AN EXPLORATION ON THE USE OF DATA ENVELOPMENT ANALYSIS IN THE PRODUCT DESIGN DOMAIN

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ABSTRACT

In the engineering design domain, product design process is a major focus. In this process, products are realized by several consecutive stages, and decision making is frequently involved. In the product design process, decision makers have to deal with multiple dimensions, criteria and uncertainties. For manufacturers, any faulty decision during the product design process would lead to enormous losses. Product design process is so complex that decision makers may need an effective tool to assist them in achieving appropriate decisions. In this study, we introduce data envelopment analysis (DEA) to the product design process in solving conceptual design problems and product family design problems. Moreover, we apply both traditional deterministic DEA and interval DEA models in this study. Three case studies are demonstrated to show how DEA can work on problems in product design domain. For the first case, deterministic DEA is applied to a product family design problem to choose the best product line. For the second and third cases, DEA is introduced to solve product conceptual design problems. The second case is a selection from multiple concept alternatives. The third case involves uncertainty issues in the decision making process. After the three case studies, the results show that DEA is applicable to problems in product design domain and can provide reasonable results for decision makers in generating appropriate product design strategies.
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Chapter 1

Introduction

Decision making is a critical process in engineering design domain. It usually involves selection from multiple strategies, including strategies for determining materials, suppliers, manufacturers or product alternatives, and also allocation of resources. Generally, decision makers have to deal with a variety of factors and they need to carefully evaluate all the possible factor effects and their interactions. For most of the situations, the decision process is complex and multidimensional, and negligence is not allowed. False judgments might lead to tragic consequences. In the engineering design domain, product design process is an area that has received increasing focus. In this study, the main objective is to explore the decision making complexities in the product design process, and explore the use of data envelopment analysis as an appropriate tool.

Product design process can be categorized into four stages, including problem definition, conceptual design, preliminary design, and detailed design (Ogot and Kremer (2006)). Decision making is involved in all these four stages. Further, because for each of the stages, any faulty decision may potentially cause huge impact on the final product, decision making in the product design process is extraordinarily important. For this reason, the quality of the acquired decisions from any of the decision making processes is significant. Faulty decisions could cause enormous investment loss, defects in product, product failure in the market, and loss in customer goodwill.

How to make appropriate decisions brings about a debate. In product design process, the decision making process often involves multiple criteria, including both quantitative and qualitative data, along with uncertainties. Some of the criteria might be conflicting. Multiple criteria decision making is always complex and difficult. Decision maker has to consider how to
well balance the trade-offs among conflicting criteria, and try to optimize the overall objective. Currently there are plenty of tools that aim to solve these kinds of multiple criteria scenarios, which have been applied to the product design process, such as multiple attributes utility theory (MAUT) and analytical hierarchy process (AHP). These methods might achieve a final decision. However, they need to involve personal preferences and also require complicated computation efforts. Thus, an alternate method that is objective and has less computational difficulties is needed in this area.

Moreover, the general decision making situation in the product design domain generally involves a group decision making process. Under a group decision making process, the final decision needs to be achieved by converging from different parties. Each decision maker has his personal subjective preferences. The preferences from multiple decision makers usually are conflicting due to various standpoints. Given this situation, weighing different criteria might require time consuming communication procedures to reach a common standpoint or the consensus might never be approached. Therefore, the decision making environment in product design process is complicated. To solve decision making problems in this area, a good decision making tool that can efficiently handle the above mentioned possible circumstances is required. Further, a judgement on which method is most appropriate in solving such problems is also open for discussion.

Among the four stages in the product design process, the most critical and complex stage is the stage of conceptual design. In this stage, decision makers have to select a most feasible product concept from a number of possible alternatives and later carry it to the next stage. For each product concept, data contains plenty of information including product features, general specifications, components, functional modules, etc. Thus, the decision process needs to take into account all the criteria and compare the overall performance of each concept alternative. However,
while considering all the criteria, how to fairly assign weights to each criterion without involving subjective individual preference is a question. Therefore, the difficulties of this stage are the diverse types of criteria and complexity of computation. Also, as some of the criteria might be conflicting, how to compromise to reach a final decision is always confusing to decision makers.

Besides the conceptual design stage, for the manufacturers, how to generate proper product offerings (customization) in the detailed design stage is also a widely discussed topic. This problem is also known as the product family design problem. In this problem, decision makers need to face the selection of an appropriate product variant sub-set among a variety of product alternatives. For products chosen to be in the product family, a balance between product commonality and differentiation for each targeted market segment is sought. How to select a family of products that can maximize the profit and provide coverage for market segments while minimizing production cost is the main objective. Consequently, similar to the conceptual design problem, multi-criteria with conflicting objectives present difficulties in solving product family design problems.

To effectively solve problems in product design process, especially focusing on the conceptual design problem and product family design problems, an appropriate decision making tool should have the following properties: 1) deals with multiple criteria, 2) compromises among conflicting criteria, and 3) prevents from subjectively weighing the criteria.

In this study, we propose using data envelopment analysis (DEA) as a tool to solve design decision making problems. DEA has two major advantages that make it a good tool in solving problems in product design process. First, DEA is noted for its ability to deal with problems involving multiple inputs and outputs. DEA distinguishes among criteria as input or output indices based on their inclination. Thus, using DEA, conflicting criteria could be set to different type of indices. This feature aims to approach an overall best compromise solution for each alternative. Further, by considering different objectives or managerial usages, decision
makers can choose from different models for a specific purpose. Secondly, DEA avoids the
difficulty of determining weights for each of the criteria. For each alternative, it automatically
generates best weights for each of the criteria to optimize the overall performance. This feature
makes DEA a fair and objective tool without taking the preference of decision makers into the
decision making process.

In this study, we demonstrate three case studies applying DEA in solving problems in the
product design domain. The first case study is adopting DEA to solve a product family design
problem. In this case, we define product family design problem as a product line selection
problem. A five-step procedure that systematically adopts DEA to solve the product line selection
problem is proposed. An illustrative application based on real industrial data of selecting the best
product line for a stapler manufacturing company is demonstrated and solved by a five-step
procedure.

For the second case study, we use the proposed five step procedure to solve a conceptual
design problem. In this case, we propose using four indices: cost, functionality, compatibility, and
DFA index to input into the DEA model. An electronic toothbrush concept selection is used to
demonstrate our methodology. The implication of this case study is that the manufacturing
concern is carried into the conceptual design stage. The acquired best concept is a compromising
solution that has the feasibility of all the functional modules, the leading functional performance
and cost level, and also the easiness of assembly. The concept with all these features can easily
enable manufacturers confidently to decide for producing it and carry it to market.

The third case study is an extension from the second case study. It also concentrates on
the conceptual design stage with the application of DEA. However, in this case study, we focus
on the topic of integrating sustainability concerns at the conceptual design stage. Five indices are
used in this case study. Besides the four indices mentioned above, we propose a new
sustainability index, operationalized as an interval variable. The interval data is transferred from a
five-level comparative verbal description. To deal with this new interval index, we adopt the interval DEA model replacing the previously used deterministic DEA model. Moreover, a set-based design view is included into this study. The objective of this case study is to select a set of most producible product concepts that also are superior as per their environmental impact. The same electronic toothbrush concept selection problem is used to demonstrate our proposed methodology.

In this study, we propose using DEA to solve three different problems in product design domain. The results show that DEA can be an effective and beneficial tool when applying to product design problems. In comparison with existing approaches, DEA can provide similar results with less problem complexity for decision makers.

In chapter two, we provide the literature review of DEA and product design process. The methodologies that apply DEA to the three different product design stages are introduced in chapter three. Chapter four presents the implementation procedure and result analysis of the three case studies. The final conclusion of this thesis is given in chapter five.
Chapter 2

Literature Review

In this chapter, we present the literature review for this thesis. There are three sections in this chapter. For the first section, the main focus is the introduction of the main method of this thesis, the data envelopment analysis (DEA). For the second section, we will present three different topics in the product design domain, including the background of product line selection, the concept selection methods (CSMs), and the development of design for sustainability. In the last section of this chapter, we provide a review of the DEA applications in the product design domain.

2.1 Data Envelopment Analysis

DEA is first proposed by Chares et al. (1978). It is a linear programming based technique that proved to be a superior efficiency evaluation tool. DEA is commonly used to measure the relative productivity efficiency among a group of decision making units (DMUs). For a given set of DMU, DEA forms an efficient frontier by joining the most efficient DMUs. The efficiency value ($\theta$) of each DMU is measured using the relative distance projection toward the frontier. $\theta$ is usually regarded as the efficiency or the productivity index. $\theta$ values range from 0 to 1. The most efficient DMUs locate on the frontier with $\theta=1$, while the inefficient ones fall beyond the frontier with $\theta<1$.

DEA is noted for its high usability. There are various DEA models, and user can select the most appropriate model for its specific usage. Different DEA models usually differ in the ways of measuring the projection for each DMU to the efficient frontier. For example, CCR
(Charnes, Cooper, Rhodes) model (Charnes et al., 1978) and BCC (Banker, Charnes, Cooper) model (Banker et al., 1984) measure the projection to the frontier, while the additive model (ADD) measures the largest sum of the horizontal and vertical distances toward the frontier (Cooper et al., 2000).

In comparison to other multi-criteria decision making (MCDM) methods, DEA has two major advantages. First, it is able to deal with multi-dimensional problems with multiple input and output indices (variables). When applying DEA, as a first step user needs to separate indices into two different types, input or output indices, based on the characteristic of the indices and problem type. For example, indices preferred to have higher values are usually assigned to be output indices. This feature makes DEA an advantageous performance evaluation tool that can be widely applied to diverse problems in various fields since it is adjustable for different problem types. Second, DEA avoids the difficulty of deciding for potentially unequal weights for the criteria. In multi-criteria decision making (MCDM) problems, deciding appropriate weights (to show the varying importance levels for criteria) for each criterion is generally controversial and time consuming. DEA uses the weight for each input and output that will let each DMU reach its maximum possible efficiency value (Charnes et al., 1994).

There are two possible orientations of DEA models: (1) the input oriented model, and (2) the output oriented model. For the input oriented model, the performance is improved by using the inputs while we try to do the improvement by adjusting the outputs for the output oriented model. The two basic DEA models are the CCR model and the BCC model. The two models differ in the appearance of their frontiers. The CCR model is the initial DEA model developed by Charnes et al. (1978). CCR is based on the assumption of constant return to scale (CRS). The BCC model is introduced by Banker et al. (1984). The BCC model considers variable return to scale (VRS). Due to the CRS feature, the CCR model forms the frontier under the most productive scale. Each DMU compares its performance to the most productive scale and receives
an absolute efficiency value. Thus, the CCR model provides a global view for all the DMUs with a consistent standard for comparison. The efficiency scores obtained by the CCR model are generally regarded as the productive efficiency. Different from the CCR model, the BCC model with VRS feature has its frontier spanned by the convex hull of the existing DMUs (Cooper et al., 2000). Therefore, BCC model evaluates DMUs under a more conservative viewpoint so that DMUs can receive equal or higher scores under BCC model than CCR model. In addition, BCC model can be regarded as relaxation of the CCR model. To distinguish from the CCR efficiency, the BCC efficiency is generally taken as the technical efficiency.

Traditional DEA approaches can only be applied to deterministic data sets. To deal with problems involving imprecise data, Coopers et al. (1999) proposed the imprecise DEA (IDEA) method. IDEA performs a series of linear transformation and rescaling variables, and generates a deterministic efficiency value for each DMU. Despotis et al. (2002) proposed an alternate way to simplify the calculations by only applying transformations on variables. The proposed model is called interval DEA. Under this interval DEA method, the efficiency value of each DMU is no longer a deterministic value but is replaced by a set of upper and lower bounds. Wang et al. (2005) introduced a modified interval DEA model to solve interval or fuzzy input/output problems. The proposed method also avoids complex linear transformation procedures 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 (2006) constructed a two-level mathematical model to acquire the upper and lower bounds of efficiency scores. After introducing linear transformation techniques, for each DMU, initial pair of non-linear formulations is simplified, which results in interval efficiencies.

Interval DEA has been applied to a variety of areas in solving problems involving uncertainty. Despotis et al. (2006) 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. (2008), who presented a framework using interval DEA to measure overall profit efficiency from indices involving interval data.

2.2 Product Design Process

In this thesis, the main concentration is on the application of DEA in product design process. Product design process is a major concern in the engineering design field. It is a critical part of the product development process. Song and Montoya-Weiss (1998) categorized new product development process (NDP) into six stages, including 1) strategic planning, 2) idea development and screening, 3) business and market opportunity analysis, 4) technical development, 5) product testing and 6) product commercialization. Product design process belongs to the forth stage, the technical development stage, which is the most important stage receiving the most attention from companies.

As mentioned in the previous chapter, Ogot and Kremer (2006) divided the product design process into four major stages, problem definition, conceptual design, preliminary design and detailed design. During the product design process, a product is embodied from rough ideas and constraints to a physical final design. The entire process involves a series of complicated decision making processes, and decision makers need to gradually narrow the feasible design space to converge to an optimal product design.

In this study, we focus on three major problems in the product design process that require complex decision making procedures. Each of the three problems will be discussed in the following sub-sections:
2.2.1 Product Line Selection Problem

Morgan et al. (2000) defined product line selection as the determination of products mix that enables companies to compete in the marketplace and gain profits. Determining the selection of product line is a commonly met problem by companies across industries. The product line selection decision involves a number of perspectives from marketing to manufacturing. Thus, when establishing product line strategies, companies need to clarify their objectives and competencies to ensure their profitability.

Many researches have proposed to explore the product line selection decision making tools or strategies. Morgan et al. (2000) formulated product line selection problem into a mathematical programming model that maximizes the profit. Customer preferences and cost considerations for both marketing and manufacturing perspective are incorporated into this model to ensure the results can actually benefit companies in making appropriate decisions. Yunes et al. (2007) proposed a two-step framework in streamlining product lines for John Deere & Company (Deere). In this framework, for the first step, the customer migration model is applied to evaluate Deere’s customer behavior. The customer migration model enabled them to examine the customer segmentation and determine the customer potential configurations (product lines) for each customer. For the second step, a mix-integer programming (MIP) model is constructed. The MIP model takes into account all the customer configurations with several managerial factors and maximizes the total profit. The proposed framework substantially benefits Deere in consolidating product lines and increasing profit.

As designing product families is a rising topic in product design domain, more and more companies look into this field and start to develop platform-based designs to reduce product development and production costs, and diversify the product offerings (Simpson et al., 2005). To help companies in consolidating their product lines, a consistent and effective approach is
required. Li and Aazarm (2002) divided the product line selection process into two stages. At the first stage, the appropriate design alternatives are generated. The commonality among product variants is taken into account during this stage. In the second stage, product line is evaluated based on several concerns, including profitability, market share, customers’ preferences, market competitions, product life cycle and uncertainty. A multi-objective optimization model is formulated incorporating above concerns, and a genetic algorithm (GA) is adopted to generate product line candidates.

Thevenot et al. (2007) proposed a method using multi-attribute utility theory (MAUT) to solve product line selection problems. MAUT involves a single decision-maker choosing from a number of alternatives based on two or more criteria or attributes. The decision maker seeks to maximize a utility function for this complex decision making. A case study of selecting a best line of stapler product family is performed by applying the MAUT method. Dolan et al. (2008) proposed using hypothetical equivalents and inequivalents method (HEIM) on product line selection problems. They applied HEIM on the same case study of consolidating a stapler product family from Thenvenot et al. (2007). When solving product line selection problems, HEIM involves less complexity since it avoids the requirements of evaluating attribute trade-offs and the potential difficulty in aggregating the utilities. However, HEIM has its natural limitation when facing large scale problems, including either numerous product line alternatives or product attributes.

In fact, when facing real product line selection situations, companies can not avoid the involvement of a number of alternatives and criteria. For the above situation, using MAUT or HEIM is time consuming and difficult. In addition, decision making process may involve a group of decision-makers. In such situations, applying either MAUT or HEIM would become extremely complex. For the reasons indicated above, a method which can easily work on large scale multi-criteria problems and by several decision-makers is needed. Although
there have been several studies that used DEA mostly for project evaluations, it has not been applied to product line selection problems. DEA can effectively handle problems with multiple alternatives (DMUs) and criteria. Also, since no weighing procedure is required, DEA can be treated as a group decision making tool. Accordingly, in this study, DEA is proposed to be our tool in solving the complex product line selection problem.

2.2.2 Concept Selection Problem

In product design process, concept selection is an extremely important stage. King and Sivaloganathan (1999) defined that concept selection is a stage where various concepts of subsystems, such as modules, components, etc. are evaluated, rated and eventually integrated into a feasible product concept. In other words, the design is embodied and the product specifications are finalized. A poorly selected design concept can rarely be compensated at later design stages. The result is costly, since it usually requires considerable efforts to redesign the product. Attesting to this, Pugh (1996) states that the selection of the best concept with which to proceed to detail design and ultimately manufacture is one of the most difficult, sensitive, and critical problems in design. As an indication of its importance, Duffy (1993) states that nearly 60-80% of the cost is committed at this stage.

Owing to the importance of concept selection, considerable amount of research effort has been devoted to this area. Okudan and Tauhid (2009) categorized all the known concept selection methods (CSM) to date into six groups based on the core methodologies adopted, and Figure 2-1 shows all the six categories. As we can see from Figure 2-1, various decision making tools have been applied to solve problems in conceptual design stage. The reason is that problems in conceptual design stage are diverse and complex so that decision makers need to select an appropriate tool to approach the best final decision according to different problem types. There is
not a best common tool that can simultaneously work on all types of problems. In addition, in-depth reviews of these CSMs can also be found in other research as well (e.g., Okudan and Shirwaiker (2006)). Salonen et al. (2005) addressed that generally the inclusion of uncertainty and compatibility concerns makes the concept selection methods complex; accordingly, their adoption by industry practitioners becomes next to impossible. Practitioners tend to choose methods that are easy to implement. Bohm et al. (2008) proposed a new approach of concept selection by using design repository. In this approach, product designers perform a morphological search to directly search the design repository for components that match the product sub-functions transferred from customer needs.

Figure 2-1: Concept Selection Methods (Adopted from Okudan and Tauhid (2009))

Further, Wang (1997) suggested that designers should consider not only the product functionality needed, but also other criteria including life-cycle issues, such as manufacturability, ease of assembly, reliability, and maintainability during the concept selection process. In most design situations, the decision process can be even more complex because of the conflict of those criteria. Accordingly, in this thesis we focus on arriving at a method that is easy to implement and can effectively deal with the diverse criteria involved in concept selection problems. Thus we propose to adopt DEA method to deal with concept selection problems in this study.
2.2.3 Design for Sustainability Problem

The main challenge for the product designers when integrating an environmental perspective is to identify the needs that are relevant to consumers’ quality of life, design products that meet these needs, and, ensure that the product does not limit the ability of future generations to meet their needs. Figure 2 adopted from Bhander et al. (2003) presents the product life cycle starting from raw material and end with product disposal. This implies that the first sustainability consideration is at the material selection stage. Then, during the selection of manufacturing processes and functional performance, the concepts with energy efficiency, minimum discharge, emission and waste should be preferred.

![Figure 2-2: Product life cycle model (Bhander et al. (2003))](image)

When one considers sustainability issues, life cycle assessment quickly appears as an established mechanism. Life Cycle Assessment (LCA) is a well known and widely used technique that is capable of evaluating the potential environmental impact of a product throughout its entire
lifespan. The goal of the LCA is to produce sustainable products that cause relatively lower impact to the environment. Therefore, to produce sustainable products, it is necessary to integrate sustainability considerations into early stages of the product design process.

However, product design process includes a series of stages, and in each stage sustainability concern should emphasize different points. Azapagic et al. (2006) explored how to incorporate the sustainability consideration in the different stages of product design process. In the initial product design stage, particularly the problem definition and concept selection phases, sustainability guidelines are identified and evaluated for all concept alternatives. When entering the preliminary design stage, sustainability criteria are clarified and preliminarily assessed. At this stage, design concepts are simply categorized into different performance groups. Finally, in the detail design phase, full assessment of sustainability criteria is executed to determine the final design. Selection of materials and process are the two major fundamental considerations in sustainability. From an economic viewpoint: the operational efficiency, maintainability, and residual value in the end of life are determined by materials and processes. In perspective of environmental impacts: emission, energy consumption, discharge and waste are also confirmed when materials and processes are identified. Brief summaries of the prior literature on sustainable materials and process selection are provided below.

2.2.3.1 Sustainable Material Selection

Zhou et al. (2009) developed a multi-objective optimization model that incorporates Genetic Algorithm (GA) and Neural Network (NN) to select materials for sustainable product design. The mechanical properties, economic properties and environmental properties are pointed out as evaluation indicators for material selection. GA first searches through the sample data and the data are regarded as training data for NN. The optimal design concepts are determined by the NN. A complete sustainable material database is the backbone of this method. Furthermore, this
method assumes all materials and processes are binding together, but the materials data may not be representative of particular operations in production. The neglect of process analysis might result in misjudgment.

Ljungberg (2007) classified six different material groups as: metals, ceramics, synthetic polymers, natural organic materials, natural inorganic materials and composites. Each material is evaluated by a 1-3 scale scoring system to assess the potential sustainability to simplify the computational complexity. Sun et al. (2004) clustered sixteen material groups according to the physical, mechanical and environmental properties to simplify the life cycle assessment of a design concept by identifying the material groups used in the product. However, the variation of materials in these simplified methods might impact the precision of the final result. Accordingly, when taking life cycle assessment into concept selection stage, a lack of process consideration might affect the applicability of the final product concept.

### 2.2.3.2 Sustainable Process and Component Selection

Schmidt et al. (2008) introduced a process-driven tool developed by the Ford-Europe, the Product Sustainability Index (PSI), to achieve sustainability. The purposes of developing PSI are to: 1) cover key environmental, social, and economic vehicle attributes; 2) allow Ford-Europe to implement; 3) require no additional data; 4) indicate bottom line issues only; and 5) reduce to manageable amount of indicators. Eight indicators are specified as life cycle global warming potential, life cycle air quality potential, sustainable materials, restricted substances, drive-by-exterior noise, safety, mobility capability and life cycle ownership costs.

Another important consideration for current selection process is Design for Disassembly (DfD). DfD is an important consideration for repair, cannibalization, or refurbish during a product’s operational phase, and end-of-life situations such as reuse, remanufacturing, and recycle. Boothroyd et al. (1992) concluded DfD guidelines, which address product structure,
design of functional units, material selection, minimizing waste, and harmful contaminating materials were presented so that the residual value of a product can be efficiently acquired. In addition, DfA method might be compatible with DfD if incorporated with some environmental criteria such as ease of removal and selection of recycle material. However, in applications, minimization of environmental impact should be taken into account along with maximal financial benefits.

2.2.3.3 Sustainability Index

To evaluate the sustainability issues, proper sustainability performance indices or indicators are necessary to be developed. 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. (2002) 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 contains several basic attributes. A 0-10 scoring system is used to evaluate the performance of each attribute, where higher values represent the greater penalty level.

Hur et al. (2004) 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. (2007) 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 also used to assess each key indicator.

To sum up, the sustainability considerations should contain both material and process at the early design stage to assure the sustainable development for the future generations. However, taking sustainability consideration into early design stage usually results in decision making among a number of diverse types of criteria. Those criteria might be quantitative, qualitative or even fuzzy. Accordingly, general optimization skills may not be applicable to solve problems involving sustainability considerations. In most prior studies, approaches settle for compromise solutions instead of seeking win-win solutions (Bhander et al. (2003), Azapagic et al. (2006)). In this thesis, interval DEA method is chosen to perform the selection among product concepts under a series of functional requirements, economical requirements and environmental requirements. The proposed method will automatically provide the decision maker with the most appropriate set of concept alternatives.

2.3 DEA Application in the Engineering Design Domain

DEA has been applied to various areas as a performance evaluation tool. For example, in the engineering design area, Miyashita et al. (2002) constructed a supervisor system that used DEA to solve a collaborative design problem, Paradi et al. (2002) used DEA to analyze the performance of engineering design teams at Bell Canada, and Farris et al. (2006) adopted DEA as a project evaluation tool to analyze projects from two different engineering design processes. Cariaga et al. (2007) proposed to incorporate DEA with value analysis (VA) and quality function deployment (QFD) within the initial design stage. DEA is used to evaluate the degree of satisfaction for each design alternative in meeting the relative customer requirements.
Although traditional DEA has been used in the engineering design domain, very rare studies focused on solving product line selection problems and concept design problems. The complexity of both problems is relatively high and may cause critical impacts on many operational outcomes of a company (e.g., manufacturing cost, inventory levels, profit, market coverage and customer satisfaction). In addition, since a large amount of uncertainty might be involved in the decision making process during product design process, an effective tool that is able to efficiently handle problems involving uncertainties is necessary. In fact, DEA is appropriate to be applied to problems with uncertainties. By setting uncertainties into interval or fuzzy data set, decision makers can apply interval or fuzzy DEA models to execute the performance evaluation procedure. In this study, we transfer uncertainties into interval data and use interval DEA as our tool for solving the conceptual design problem. However, interval DEA has never been introduced in this domain. For the above reasons, in this study, we use deterministic DEA and interval DEA in solving problems in the product design process.
Chapter 3

Methodology

In this chapter, we introduce our methodologies to apply DEA to solve three different problems in the product design domain. The three problem types have been mentioned in the previous chapter. The three problems belong to different stages in the product design process. The reason why we propose using DEA to solve problems in this area is that most problems in product design process involve multiple criteria. Decision makers usually need to deal with complex problems involving a number of conflicting criteria. As we mentioned in the chapter 2, DEA is a superior multiple criteria decision making tool that is capable of fairly handling a number of criteria with no individual preferences involved. Decision makers can save time in discussing appropriate weights for all the criteria. DEA directly makes trade-offs among conflicting viewpoints, and automatically reaches a quality final decision converging from diverse viewpoints. Above stated features can significantly help reduce both problem complexity and difficulty. Moreover, there are numerous of DEA models that have been developed in the literature, and each model features a specific mathematical property and is best suited for applying to a particular data set or problem type. Therefore, decision makers can choose an appropriate model based on their objectives.

In the following sections, we demonstrate how to apply DEA to solve different product design problems. Three types of product design problems are discussed. The first problem is a product line selection problem. The main objective is to help a company consolidate its product lines in order to generate a best product family offering. The other two problems are both product concept selection problems but with different types of variables involved. All the criteria in the second problem are deterministic data sets while an interval (uncertain index) is introduced to the
third problem. Owing to different problem types, different DEA models and decision processes are prepared and developed to deal with the three problems.

3.1 Product Line Selection Problem

For manufacturers, how to consolidate their product lines is a critical problem. Any fault in product line selection decision would result in a wrong market strategy and lead to tremendous loss. For product line selection problems, decision makers usually need to determine a smaller set of metrics from several market performance measures, such as revenue, profit, and market share along with some technical indices, like product commonality index (PCI).

In this section, we develop a five-step framework incorporating DEA method to solve product line selection problems. The overall flow of this framework is provided in Figure 3. Below we explain each of the steps in detail:

1. **Data collection**: For each component of the different product family alternatives, all pertaining information on potential variables (e.g., costs, revenues etc.) should be collected and recorded. For example, calculating the PCI would require detailed information about all the components, processes, materials, etc. The quality of the collected data will in part determine the quality of the eventual decision.

2. **Identify model indices (variables)**: The main question to answer at this stage is “What are the main indices that could directly affect the decision?” One word of caution is that the set of indices should be limited in size, and accordingly, only the main factors, which significantly affect the decision, should be included in the set. Too many indices will cause the result of loosing discriminatory power (Paradi et al., 2002). The recommended maximum number of input and output indices for DEA is equal to one-half the number of DMUs (Dyson et al., 2001).
Figure 3-1: The decision process for product line selection using DEA

3. **Model selection**: According to the property of the indices and the decision purpose, we need to select the most appropriate DEA model as our approach. Model types that change based on the calculation of the projection (CCR, ADD), or problem/variable characteristics (such as input-oriented or output oriented models) may dictate the selection of the model. Steps 2 and 3 of the methodology should be treated very carefully as the property of the indices would have strong influence on the model to be used.

4. **Run the DEA model**: There are several software packages for DEA calculations such as Frontier Analyst, DEA Frontier, etc. In addition, generic software could be programmed to complete the calculation. For example, in this study, we used Excel VBA. The code for our programs can be seen in Appendix B.
5. **Result analysis**: Tie in multiple most efficient DMUs is a commonly met result for DEA calculations. Thus, to break the ties and differentiate the actual performance, a ranking of the results with a specific DEA ranking method, such as cross-efficiency method, or the Andersen-Petersen method might be necessary. During the analysis of the results, special attention should be concentrated on explaining the meaning of the model parameters such as \( \theta, \eta, \mu \) etc., to obtain the most appropriate result.

In this study, we will adopt the data from Thevenot et al. (2007). To effectively solve product line selection problem, a method which can easily work on large scale multi-criteria problems and by several decision-makers is needed. Although there have been several studies that used DEA mostly for project evaluations, it has not been applied to product line selection problems. DEA can effectively handle problems with multiple alternatives (DMUs) and criteria. Also, since no attribute weighing procedures are required, DEA can be treated as a group decision making tool. Accordingly, in this study, DEA is proposed to be our tool in solving the complex product line selection problem. The detailed case study implementing the proposed five steps framework is demonstrated in chapter 4. In the next section, we will discuss the proposed methodology for solving product concept selection problems.

### 3.2 Concept Selection Problem

Conceptual design stage is extremely important in the product design. As mentioned in chapter 2, most of the product development cost incurs at this stage. Thus, decision makers have to be careful in choosing the appropriate product concept at this stage to prevent from faulty products.
For the concept selection problem, we propose to follow the five-step framework we proposed in the previous section. However, because of the different objectives and the problem type, in this section we introduce four new indices. The four indices are as follow:

A. **Design for Assembly (DFA) Index**: The DFA index provides a comparative measure that indicates the degree of easiness for parts assembly. The DFA index is derived from the ranking system first developed by Rampersad (1994). To obtain the DFA index, 13 criteria are used to evaluate the relative assembly easiness (Rampersad (1994), Hsu et al. (1998)). Equation (8) provides the formula for calculating the DFA index adopted from Hsu et al. (1998). The DFA index ranges from 0-10, and the lower values show increasing ease of assembly. Manufacturers prefer less assembly difficulty during the manufacturing process, thus product concept with a lower DFA index is preferable. For the above reason, we treat this index as an input index.

\[
\text{DFA index} = 10 \left( \frac{\sum P_i - \sum V_{\text{min},j}}{\sum V_{\text{max},j} - \sum V_{\text{min},j}} \right)
\]  

(8)

\( P_i \): point value for each criterion, \( i = 1 \ldots 13 \).

\( V_{\text{min},i} \): minimum value for each criterion.

\( V_{\text{max},i} \): maximum value for each criterion.

B. **Functionality Index**: The functionality index is derived from the concept of Quality Function Deployment (QFD) matrix. It represents the potential customer satisfaction for varying product concept alternatives. In this study, we develop a procedure to arrive at the functionality index. As per this process, first of all, one relates customer requirements to product functions. Second, function weights are assigned (totaling 1) to represent relative importance of functions. Third, all product modules (or components) are weighed. The entire modular weights should sum up to 1. Fourth, for each module concept alternative, one
uses a 1-9 scoring system to measure functional fulfillment by the module. A score of 9 represents that the alternative completely satisfies the certain function while a score of 1 indicates that alternative conflicts with the function. The final step is to calculate the functionality index. For this step, two procedures are involved. First, we calculate the weighed functional score for each module concept alternative. We multiply the function weights by the functional scores of each module alternative and sum up all the weighted scores. The acquired sum is the weighted functional score of each module concept alternative. Next, we calculate functionality index for each product concept. We select a product concept composition with certain components, multiply weighed functional scores of all its components by the respective modular weights and then calculate the sum. The acquired value is the functionality index for the certain product concept, which 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.

C. **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 scoring system to arrive at relative cost indicators. For evaluating the cost index, the first step is deciding relative weights for each module variant (component). After weighing all the components by their relative cost level, we can obtain more accurate cost estimation. At this step, all the weights need to sum up to 1. Second, for each module (component) in a concept, we use a 1 – 9 scoring system to indicate the relative cost. We assign 1 to the module with the lowest cost and 9 to the most expensive one. In the final step, cost index for a certain product concept is obtained by multiplying the cost scores of each of its component to the relative weight and sum all the weighted value. The cost index also uses a scale of 1 – 9. The cost index is an input index.
An alternative with lower value is the better choice.

**Compatibility Index:** For each product concept, we need to consider the compatibility issue of all its components. In this study, we develop a systematic process to generate an index to indicate the inter-component compatibility. The first step is to set up the compatibility matrix. We use three levels of weights to show the compatibility of each component pair: (1) If two components are incompatible, we assign a score of “0”. (2) If two components are compatible, it receives a score of “1”. (3) If two components are completely suitable for each other, a score of “2” is assigned. We populate all module concept alternatives, rate their pairwise compatibilities and record all the weights into the compatibility matrix. After determining the compatibility matrix, in the next two steps we calculate the compatibility index. By multiplying all the compatibility values among all the components, we first obtain a compatibility value for the certain product concept alternative. Further, we eliminate incompatible product concepts. To scale the remaining concepts into a proper level, we take their base-2 logarithm, and add 1 to the result. Consequently, the integer obtained is the compatibility index for a certain product concept. Overall, for a product concept having a high compatibility score may indicate an increased ease for it to be realized. Thus, choosing high compatibility product concepts is preferred by manufacturers. Accordingly, in this problem, compatibility index is set to be an output index.

The detailed application of the proposed method is shown in chapter 4. In the next section, we introduce our extended method that incorporates sustainability consideration into product conceptual design stage.
3.3 Design for Sustainability at Conceptual Design Stage

Nowadays, the increasing concerns on the environment related issues have forced manufacturers to reconsider their new product design processes. To produce sustainable products, considering product sustainability in the earlier stage of the design process is necessary. However, the sustainability consideration frequently involves comparison among alternatives with uncertain information, including the complex material property and qualitative features. Therefore, formulation of this kind of problem is difficult. In addition, the computation difficulties for conceptual design problems with uncertainty is rather high. Therefore, taking sustainability into the earlier design stages is not easily achievable.

In this section, we quantify sustainability concern by formulating it as interval data. To deal with interval data, traditional DEA is not usable since it only can be applied to deterministic data sets. Thus, in this section, we propose using an interval DEA model introduced by Despotis et al. (2002) to solve the concept selection problem with an interval sustainability index.

In the case study, we use five indices to support our decision process. The first four indices are extended from the previous section. These are the design for assembly index, the functionality index, the cost index and the compatibility index. A new sustainability index is proposed in this section to measure the sustainability of each product module. We specifically focus on the issues of material, energy and production process of the functional modules. First, we use a five level comparable descriptive vocabulary to evaluate each component: Very low (0 – 30/11), Low (20/11 – 50/11), Moderate (40/11 – 70/11), High (60/11 – 90/11), and Very high (80/11 - 10). Each level is represented by an interval score system which ranges from 0 to 10. For each level of the scores, we assume that there is a 1/3 interval overlap between the higher and lower levels. The reason for the overlap is that we consider the decision to be potentially biased. Thus, this approach can reduce the effect of bias. Using interval rather than fuzzy membership
function has two main advantages. First, it is easier to calculate, and hence can reduce the complexity of the problem. Second, using interval data would lead to relaxing the feasible solution region. In the conceptual design stage, the objective is to review the possible product concepts. Traditionally, during the conceptual design stage, decision makers try to pick the best product concept and directly carry it to the preliminary design stage. However, as uncertainty is introduced to the conceptual design stage, decision makers can no longer converge to an optimal concept from existing criteria. To account for this situation, we propose adopting set-based design concept for this scenario.

Sobeck (1996) mentioned that set-based design is a systematic method for converging design ideas. The designer eliminates clearly unworkable alternatives rather than pick a single idea, and develop a subset of potential solutions to greater resolution before making a specific decision. The set of ideas are narrowed after more information is gathered.

Therefore, adopting set-based logic at the conceptual design stage is to select a group of product concepts with highest possibility to be realized in the later stages and enable manufacturers to delay the decision making and consider more information in order to reach a more complete design. Actually, interval DEA can effectively select a set of DMUs with highest overall performance. It separates DMUs into three levels of performance groups. DMUs in the highest performance group can be directly regarded as the set of most applicable product concepts.

In the next chapter, we provide the result of the implementations of three case studies.
Chapter 4

Results

In this chapter, three case studies are demonstrated using the proposed methodologies in the previous chapter. For the following three sections, the case study for each of the product design problems is explained in detail.

4.1 Product Line Selection Problem

In this section, we utilize the data set pertaining to a product family adopted from Thevenot et al. (2007) (see Table 4-1). The background of the problem introduced was the following: a company produces three different types of staplers (numbered 1, 2, 3 in the Product Mix column in Table 4-1). Business leaders in the company would like to add a new model to their product line to expand their market coverage. However, additional criteria and issues (e.g., costs, inventory levels, etc.) should also need to be taken into consideration while introducing a new product. Thus, the goal in this case is to decide which product mix would result in high profits while minimizing product proliferation and maintaining competitive market coverage. Note that this case study is based on real data from the company, even though the provided strategy analyzed is only for illustrative usage and will not be implemented.

From a manufacturing point of view, along with the high profit and wide market coverage, the company might prefer to produce a product family with high product commonality. High commonality in products would reduce the complexity in manufacturing processes, and also reduce the production costs and inventory level. On the other hand, high commonality would cause products to be less unique. From a consumer point of view, a reduction in product variety
may lessen customer interest for purchasing. Accordingly, making the product line selection decision is a trade-off situation, which may lead to losing customers or increasing costs and production complexity. In this section, we also generate suggested decisions based on the two contradicting viewpoints.

Table 4-1: Stapler product families with predicted market information (adopted from Thevenot et al. (2007))

<table>
<thead>
<tr>
<th>Product Mix</th>
<th>PCI (%)</th>
<th>Profit ($)</th>
<th>Market Coverage (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 2 3 4</td>
<td>36.5</td>
<td>$45,543,018</td>
<td>80</td>
</tr>
<tr>
<td>1 2 3</td>
<td>40.7</td>
<td>$36,280,518</td>
<td>70</td>
</tr>
<tr>
<td>1 2 4</td>
<td>40.7</td>
<td>$26,389,514</td>
<td>60</td>
</tr>
<tr>
<td>2 3 4</td>
<td>43.1</td>
<td>$48,793,824</td>
<td>80</td>
</tr>
<tr>
<td>1 3 4</td>
<td>43.1</td>
<td>$39,817,768</td>
<td>80</td>
</tr>
<tr>
<td>1 2</td>
<td>59.2</td>
<td>$17,127,014</td>
<td>50</td>
</tr>
<tr>
<td>1 3</td>
<td>42.9</td>
<td>$30,555,268</td>
<td>70</td>
</tr>
<tr>
<td>1 4</td>
<td>42.9</td>
<td>$20,664,264</td>
<td>60</td>
</tr>
<tr>
<td>2 3</td>
<td>42.9</td>
<td>$39,531,324</td>
<td>70</td>
</tr>
<tr>
<td>2 4</td>
<td>42.9</td>
<td>$29,640,320</td>
<td>60</td>
</tr>
<tr>
<td>3 4</td>
<td>63.3</td>
<td>$28,416,004</td>
<td>30</td>
</tr>
</tbody>
</table>

Now we start applying our proposed five-step framework on the stapler product line selection problem. As provided in Table 4-1, we have data related to the problem that fulfills the first step. The overall data set contains information on product line commonality index (PCI), profit, and market coverage for varying product mixes. In Table 4-1, each product mix is represented with a collection of integers each representing a product variant (e.g., 23 would mean that product mix involves product 2 and product 3. All indices available are used in the DEA (Step 2).

In Step 3, we make DEA model decisions. Regardless of the point of view we take, our ultimate goal is to find the product mix with the best performance in profit and market coverage given the PCI values. Thus, output oriented DEA model with two outputs, profit and market coverage along with the only input, PCI, is selected as our model. Notice that choosing the most
efficient product family is our objective, and accordingly the performance measure in
determining the overall efficiency in a global view from the total eleven product family
alternatives is important to us. Therefore, we decide to use the CCR output oriented model
pertaining constant return to scale (CRS) property as our approach. The CCR output oriented
model is given in Eq. (1):

$$\text{Min} \quad \eta_k = \frac{\sum_{i=1}^{m} v_i x_{ik}}{\sum_{r=1}^{s} u_r y_{rk}}$$

s.t. $$\sum_{i=1}^{m} v_i x_{ij} \leq 1, \quad j = 1, \cdots, n,$$
      $$\sum_{r=1}^{s} u_r y_{rj} \leq 1, \quad j = 1, \cdots, n,$$
      $$v_i \geq \varepsilon > 0, \quad i = 1, \cdots, m,$$
      $$u_r \geq \varepsilon > 0, \quad r = 1, \cdots, s.$$  \hspace{1cm} (1)

In Eq.(1), \(\eta_k\) is the efficiency value of the \(k^{th}\) DMU, and \(\eta_k = 1 / \theta_k\). \(x_{ik}\) and \(y_{rk}\) represent
the input and output indices of the \(k^{th}\) DMU. \(v_i\) and \(u_r\) are the weights, which are generated
automatically during the computation process. The dual linear programming model is shown in
Eq. (2):

$$\text{max} \quad \eta_k$$

s.t. $$x_k - \sum_{j=1}^{n} x_{ij} \mu_j \geq 0 \quad (i = 1, 2, \cdots, m)$$

$$\sum_{j=1}^{n} y_{rj} \mu_j \geq \eta y_{rk} \quad (r = 1, 2, \cdots, s)$$

$$\mu_j \geq 0 \quad (j = 1, 2, \cdots, n)$$ \hspace{1cm} (2)
Since $\eta$ is increasing from 1 and that is difficult to distinguish the degree of difference, we represent the score by $1/\eta$ as $\theta$ for easiness in comparison. The DEA scores of the 11 product family alternatives based on two conflicting points of view (manufacturer’s, and consumer’s) are shown in Tables 4-2 and 4-3.

Table 4-2: The DEA result for manufacturer’s viewpoint

<table>
<thead>
<tr>
<th>Product Mix</th>
<th>100-PCI</th>
<th>Profit (dollar)</th>
<th>Market Coverage (100%)</th>
<th>DEA Score</th>
<th>Cross Efficiency</th>
<th>Ranking</th>
</tr>
</thead>
<tbody>
<tr>
<td>1234</td>
<td>63.5</td>
<td>45543018</td>
<td>0.8</td>
<td>0.896063</td>
<td>0.885209</td>
<td>3</td>
</tr>
<tr>
<td>123</td>
<td>59.3</td>
<td>36280518</td>
<td>0.7</td>
<td>0.839587</td>
<td>0.816654</td>
<td>6</td>
</tr>
<tr>
<td>124</td>
<td>59.3</td>
<td>26389514</td>
<td>0.6</td>
<td>0.719646</td>
<td>0.683155</td>
<td>10</td>
</tr>
<tr>
<td>234</td>
<td>56.9</td>
<td>48793824</td>
<td>0.8</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>134</td>
<td>56.9</td>
<td>39817768</td>
<td>0.8</td>
<td>1</td>
<td>0.966553</td>
<td>2</td>
</tr>
<tr>
<td>12</td>
<td>40.8</td>
<td>17127014</td>
<td>0.5</td>
<td>0.87163</td>
<td>0.802155</td>
<td>7</td>
</tr>
<tr>
<td>13</td>
<td>57.1</td>
<td>30555268</td>
<td>0.7</td>
<td>0.871935</td>
<td>0.826859</td>
<td>5</td>
</tr>
<tr>
<td>14</td>
<td>57.1</td>
<td>20664264</td>
<td>0.6</td>
<td>0.747373</td>
<td>0.688218</td>
<td>9</td>
</tr>
<tr>
<td>23</td>
<td>57.1</td>
<td>39531324</td>
<td>0.7</td>
<td>0.871935</td>
<td>0.860189</td>
<td>4</td>
</tr>
<tr>
<td>24</td>
<td>57.1</td>
<td>29640320</td>
<td>0.6</td>
<td>0.747373</td>
<td>0.721548</td>
<td>8</td>
</tr>
<tr>
<td>34</td>
<td>36.7</td>
<td>28416004</td>
<td>0.3</td>
<td>0.90291</td>
<td>0.639859</td>
<td>11</td>
</tr>
</tbody>
</table>

Table 4-3: The DEA result for consumer’s viewpoint

<table>
<thead>
<tr>
<th>Product Mix</th>
<th>PCI</th>
<th>Profit (Dollar)</th>
<th>Market Coverage (100%)</th>
<th>DEA Score</th>
<th>Cross Efficiency</th>
<th>Ranking</th>
</tr>
</thead>
<tbody>
<tr>
<td>1234</td>
<td>36.5</td>
<td>45543018</td>
<td>0.8</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>123</td>
<td>40.7</td>
<td>36280518</td>
<td>0.7</td>
<td>0.784705</td>
<td>0.765535</td>
<td>4</td>
</tr>
<tr>
<td>124</td>
<td>40.7</td>
<td>26389514</td>
<td>0.6</td>
<td>0.672604</td>
<td>0.630889</td>
<td>7</td>
</tr>
<tr>
<td>234</td>
<td>43.1</td>
<td>48793824</td>
<td>0.8</td>
<td>0.907316</td>
<td>0.863354</td>
<td>2</td>
</tr>
<tr>
<td>134</td>
<td>43.1</td>
<td>39817768</td>
<td>0.8</td>
<td>0.846868</td>
<td>0.817833</td>
<td>3</td>
</tr>
<tr>
<td>12</td>
<td>59.2</td>
<td>17127014</td>
<td>0.5</td>
<td>0.385346</td>
<td>0.343487</td>
<td>10</td>
</tr>
<tr>
<td>13</td>
<td>42.9</td>
<td>30555268</td>
<td>0.7</td>
<td>0.744464</td>
<td>0.697107</td>
<td>6</td>
</tr>
<tr>
<td>14</td>
<td>42.9</td>
<td>20664264</td>
<td>0.6</td>
<td>0.638112</td>
<td>0.569365</td>
<td>9</td>
</tr>
<tr>
<td>23</td>
<td>42.9</td>
<td>39531324</td>
<td>0.7</td>
<td>0.744464</td>
<td>0.74284</td>
<td>5</td>
</tr>
<tr>
<td>24</td>
<td>42.9</td>
<td>29640320</td>
<td>0.6</td>
<td>0.638112</td>
<td>0.615098</td>
<td>8</td>
</tr>
<tr>
<td>34</td>
<td>63.3</td>
<td>28416004</td>
<td>0.3</td>
<td>0.359774</td>
<td>0.25538</td>
<td>11</td>
</tr>
</tbody>
</table>
Owing to different points of view, we use two different input indices: 100-PCI and PCI. For manufacturer’s view, we set the 100-PCI as the input, thus a higher PCI value results in a smaller input and that product line with higher commonality is preferred. On the other hand, for consumer’s view, since a lower PCI value represents a higher distinctness among the members of the product family, setting the PCI as the input will assign higher efficiency to the most distinctive product family alternative.

We use Excel-VBA to program our software, for which the code is presented in Appendix A. As mentioned before, DEA might involve the problem of having multiple DMUs tie with the same score, as in Table 4-2 (i.e., product family alternative 234 and 134 are both efficient with the same score while DMU 14 and 24 are less efficient and have equal scores). Accordingly, to provide better managerial resolution, it is necessary to distinguish DMUs in a detailed ranking. There are many studies discussing various ranking methods used to rank DEA results. For this study, the cross efficiency ranking method is selected to rank all the product family alternatives.

The cross-efficiency matrix was first proposed by Sexton et al. (1986). For each DMU, the ranking method calculates the mean efficiency scores of the product of its attributes to the best weights of every DMU, as in the Eq. (3) (Adler et al., 2002). In Eq. (3), $h_{kj}$ is the efficiency score for DMU j when applying weights from DMU k. $u_{rk}$, $v_{ik}$ are weights from DMU k.

After each DMU acquires the efficiency scores when adopting weights from every DMU, a $n \times n$ matrix, called the cross-efficiency matrix, is formed. Eq. (4) is the cross-efficiency matrix. In the cross-efficiency matrix, each element’s value ranges from 0 to 1, and the diagonal represents the original DEA score. The cross-efficiency score of each DMU is obtained by averaging the sum of each row in the cross-efficiency matrix, which is shown in Eq. (5). $\overline{h}_k$ is the cross efficiency score for DMU k. Under cross-efficiency method, the most efficient DMU
might obtain a score lower than 1. If a DMU gets a cross-efficiency score of 1, it indicates that this DMU dominates all the others in performance.

\[
h_{kj} = \frac{\sum_{r=1}^{s} u_{rk} y_{rj}}{\sum_{i=1}^{m} v_{ik} x_{ij}}
\]

\[k = 1, \cdots, n\]

\[j = 1, \cdots, n\]

(3)

\[
h_{11} \quad h_{12} \quad \cdots \quad h_{1n}
\]

\[
h_{21} \quad h_{22} \quad \cdots \quad h_{2n}
\]

\[
\cdots \quad \cdots \quad \cdots \quad \cdots
\]

\[
h_{n1} \quad h_{n2} \quad \cdots \quad h_{nn}
\]

(4)

\[
\overline{h}_k = \frac{\sum_{j=1}^{n} h_{kj}}{n}
\]

\[k = 1, \cdots, n\]

(5)

In Step 5, an analysis of results is necessary. The cross-efficiency scores and the ranking are shown in the last two columns of Table 2 and Table 3. For manufacturer’s view, product family alternative (234) is our best choice. However, for the consumer’s view, the results indicate that the product mix 1234 to be the recommended choice. Since Table 2 and Table 3 are from two conflicting points of view, the corresponding ranking orders still cannot facilitate making a final
decision. Accordingly, we introduce a compromising viewpoint to assist the decision-makers in choosing the best product family alternative.

In this compromising solution, we consider the two different points of view to have equal importance and thus we assign a weight of 0.5 for each. Accordingly, we create a new compromise PCI index and set it to the input to replace the original PCI or 100-PCI index. The formulation of the new compromise PCI index is shown in Eq. (6). We first transfer the PCI to the absolute distance from the average PCI, and then rescale the absolute distance by adding another average PCI. For this viewpoint, we assume that the average PCI is the more reasonable value for both manufacturer and consumer to compromise. The new ranking of all the product family alternatives under the newly introduced compromise PCI can be seen in Table 4.4. We see in the table that product mix with product variants 2, 3 and 4 is recommended.

\[
\text{Compromise PCI} = \text{Avg PCI} + |\text{Avg PCI} - \text{PCI}|
\]  

(6)

Further, the resultant rankings of the three different points of view (manufacturer’s, consumer’s, and compromise) are compared to the ranking achieved using MAUT in Thevenot et al. (2007) in Table 5. As a measure of comparison for the ranking, Spearman’s “footrule” (Spearman, 1904) is used, which is calculated as provided in Eq. (7). In Eq. (7), \(R_i\) and \(Q_i\) represent the ranks for \(n\) items in a set. This relative distance measures disagreement in rankings, and it takes on its minimum value (0) if and only if \(R_i=Q_i\) for \(i=1,\ldots,n\). In general, a smaller value represents a smaller disagreement between rankings.

\[
F = \sum_{i=1}^{n} |R_i - Q_i|
\]  

(7)
In Table 4-4, three Spearman’s footrule distances revealing the disagreement between all three DEA-based rankings introduced in this thesis and MAUT-based ranking (from Thevenot et al. (2007)) are provided as 14, 12 and 10 for the manufacturer’s, consumer’s and the compromise points of view, respectively. Accordingly, the ranking result from the compromise view has the least difference from the MAUT-based ranking order. Moreover, among the three viewpoints, the ranking under compromise viewpoint reproduces the most number of equal ranks with the MAUT result (4). Therefore, based on the Spearman’s footrule distances, we conclude that the compromise view offered is an acceptable method in selecting a product line, where the decision-makers would like to avoid complexity of MAUT calculations and exploit advantages of DEA.

Table 4-4: The comparison of ranking results from the three different views and MAUT

<table>
<thead>
<tr>
<th>Product Family</th>
<th>Ranking under Manufacturer’s view (R1)</th>
<th>Ranking under Consumer’s view (R2)</th>
<th>Ranking under Compromise view (R3)</th>
<th>Ranking under MAUT (R4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Rank</td>
<td></td>
<td>Rank</td>
<td></td>
</tr>
<tr>
<td>1234</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>123</td>
<td>6</td>
<td>1</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>124</td>
<td>10</td>
<td>1</td>
<td>7</td>
<td>2</td>
</tr>
<tr>
<td>234</td>
<td>1</td>
<td>0</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>134</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>12</td>
<td>7</td>
<td>3</td>
<td>10</td>
<td>0</td>
</tr>
<tr>
<td>13</td>
<td>5</td>
<td>1</td>
<td>6</td>
<td>0</td>
</tr>
<tr>
<td>14</td>
<td>9</td>
<td>2</td>
<td>9</td>
<td>2</td>
</tr>
<tr>
<td>23</td>
<td>4</td>
<td>0</td>
<td>5</td>
<td>1</td>
</tr>
<tr>
<td>24</td>
<td>8</td>
<td>1</td>
<td>8</td>
<td>1</td>
</tr>
<tr>
<td>34</td>
<td>11</td>
<td>3</td>
<td>11</td>
<td>3</td>
</tr>
</tbody>
</table>

Moreover, we want to verify the correlation between the rank orders of each of the three different viewpoints and the MAUT result. To assess the relation between two set of rankings, Spearman’s rank correlation test is a good tool that is able to effectively provide a valuable measure in testing the correlation between two sets of rankings. Accordingly, we apply the Spearman’s rank correlation test to calculate the Spearman’s rank correlation coefficient, ρ, between the rankings R1 to R3 and R4. Eq. (8) is the formula for acquiring ρ, where $d_i$ is the rank

$$\sum(|R1-R4|)=14$$

$$\sum(|R2-R4|)=12$$

$$\sum(|R3-R4|)=10$$
difference between two set of ranks and n is the number of values in each data set. Table 4-5 shows the Spearman’s rank correlation test result. We can see that the ρ values indicate that all the three rankings generated by DEA have fairly high correlation with the MAUT result. In addition, the result also shows that the rankings from consumer’s view and compromise view both have slightly higher correlation with the MAUT result. This Spearman’s rank correlation test provides us with confidence that when working on product line selection problems, DEA can be a replacement tool for MAUT and can generate credible results with simpler calculations.

\[
\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \]

Table 4-5: The result from Spearman’s rank correlation test

<table>
<thead>
<tr>
<th>Product Family</th>
<th>Correlation between R1 and R4</th>
<th>Correlation between R2 and R4</th>
<th>Correlation between R3 and R4</th>
</tr>
</thead>
<tbody>
<tr>
<td>ρ</td>
<td>0.872727</td>
<td>0.9</td>
<td>0.9</td>
</tr>
</tbody>
</table>

4.2 Concept Selection Problem

In this section, we implement the proposed five-step method on the second case study, an electronic toothbrush concept selection problem that belongs to the conceptual design stage of the product design process. Five newly introduced indices mentioned in the previous chapter are considered to play important roles in the decision making process.

The case study in this section is extended from the relevant work of our research team on the concept selection of electronic toothbrushes (Gupta et al., 2008). We study two electronic
toothbrushes, Oral-B™ Vitality Series (Dual Clean), and Crest™ Spin Brush Pro. By dissection procedure, both products are grouped into six categories of functional modules, including Brush head, Coupler/De-coupler, Actuator, Oscillation generator, DC motor and Battery. In the case study, we assume that there is a need to create a new electronic toothbrush model selected from existing modules. Accordingly, we demonstrate the concept selection decision making process for choosing the best electronic toothbrush design concept from a set of concept alternatives. For simplicity, we limit the concept components to those that come from the two existing electronic toothbrushes mentioned before. Accordingly, we have two alternatives for each of the six functional modules, and a total of $2^6 = 64$ concept combinations.

In this case study, we want to minimize the input indices (DFA and cost) based on existing output levels (functionality and compatibility), CCR-input oriented model is selected as our approach for solving this concept selection problem. The CCR-input oriented dual linear programming model is shown in Eq. (9):

$$\max \theta_k$$

$$\text{s.t.} \quad \theta_k x_k - \sum_{j=1}^{n} x_j \lambda_j \geq 0 \quad (i = 1, 2, \cdots, m)$$

$$\sum_{j=1}^{n} y_j \lambda_j \geq y_{rk} \quad (r = 1, 2, \cdots, s)$$

$$\mu_j \geq 0 \quad (j = 1, 2, \cdots, n)$$

In Eq. (9), $\theta$ is the efficiency value ranging from 0 to 1. Under the CCR-input oriented model, the most efficient DMU has the score of $\theta = 1$. We also apply the cross efficiency ranking method to rank all the concept alternatives after the DEA calculations. The software code written by Excel VBA is provided in Appendix B. Table 4-6 shows all the indices, the DEA and cross efficiency score and the detailed ranking order of all the 32 feasible product concept alternatives.
We eliminate the incompatible product concepts after acquiring the compatibility index, thus there are only 32 possible concepts left to choose from. As seen in the table, DMU 20 is the most efficient product concept among the 64 alternatives. Although DMU 20 does not dominate in any of the four indices, it still leads in the ranking by having the best overall performance in comparison to others.

In this section, DEA is introduced to conceptual design stage for solving product concept selection problems. The results presented above demonstrate that DEA indeed can sufficiently be used for multi-criteria concept selection problems. DEA reduces the complexity of the problem and provides reasonable overall evaluation for all the product concepts. The final result also shows one important feature of DEA. Under DEA, the final result may not be the dominant DMU for any one index (attribute). However, based on the overall view of all the criteria, it naturally selects a balanced solution that is most competitive across all criteria. The above feature enables managerial level to arrive at an overall best decision that properly considers the trade-offs among factors, and can substantially benefit companies in achieving their potential goals.
4.3 Design for Sustainability at Conceptual Design Stage

In this section, the case study is extended from the previous section and is based on the same electric toothbrush selection data set from Gupta et al. (2008). In conceptual design stage,
sometimes choosing only one most applicable product concept might not be sufficient. In fact, during the conceptual design stage, some factors or criteria might be roughly determined or might involve uncertainties, thus more information is required to converge to a final best product concept. Set-based design concept can be applied to above situations. As we mentioned in chapter 3.3, the goal of adopting set-based design concept is to select a set of most applicable concept alternatives at a time to delay the final decision making at current stage. The objective of this case study is to select a set of product concepts that simultaneously satisfies all the functional requirements, economical consideration, feasibility and sustainability concerns. We propose a new framework to solve the set-based product concept selection problem using interval DEA. We adopt the interval DEA model from Despotis et al. (2002). The input oriented interval DEA model is shown in Eq. (10) and (11). Eq. (10) is the model for upper bound efficiency and Eq. (11) provides the lower bound efficiency model.

\[
\begin{align*}
\text{Max} & \quad H_{j_0}^U = \sum_{r=1}^{s} u_r y_{rj_0}^U \\
\text{s.t.} & \quad \sum_{i=1}^{m} v_i x_{ij_0}^L = 1, \\
& \quad \sum_{r=1}^{s} u_r y_{rj}^U - \sum_{i=1}^{m} v_i x_{ij}^L \leq 0, \\
& \quad \sum_{r=1}^{s} u_r y_{rj}^L - \sum_{i=1}^{m} v_i x_{ij}^U \leq 0, \quad j = 1, \ldots, n, \quad j \neq j_0, \\
& \quad u_r, v_i \geq \varepsilon > 0, \quad \forall r, i.
\end{align*}
\]
By inputting interval data into the interval DEA model, both interval efficiency bounds for each DMU can be calculated. Similar to traditional DEA results, while evaluating interval efficiency bounds, the most efficient DMUs for each bound receive an efficiency value equal to 1. Further, since the interval efficiencies under interval DEA cannot be ranked with any known traditional DEA ranking methods, Despotis et al. (2002) also mentioned a way to classify all the DMUs into three groups of efficient sets. For the highest set $E^{++}$, both the upper and lower bound efficiency scores are required to be 1 ($E^{++} = \{j \in J/ H^U = H^L = 1\}$). DMUs categorized in this set are most efficient in both efficiencies and superior to all the other DMUs. For the second set of DMUs ($E^+$), they are most efficient in the upper bound efficiency, but inefficient in the lower bound efficiency ($E^+ = \{j \in J/ H^L < 1 \text{ and } H^U = 1\}$). Thus, these DMUs can still be improved in some aspects. However, for the DMUs with the worst performance ($E^-$), they are inefficient for both bounds ($E^- = \{j \in J/ H^U < 1\}$). DMUs in this set require immediate reconsideration of their performance in each index, and perhaps elimination from the dataset.

As mentioned in the previous section, for the electronic toothbrush design selection case, initially we have 64 product concepts. We first generate the five indices that are used in the DEA model. The first four indices, including DFA, functionality, cost and compatibility index, are adopted from the previous section. In this study, we define a new sustainability index for
measuring the relative sustainability for product concepts. Each individual module concept receives a comparable descriptive vocabulary which later is translated into an interval sustainability score. For the next step, the overall product concept sustainability score is acquired by adding up all the interval scores from each functional module. In this thesis, our comparison standard is based on the environment impact driver adopted from Sun et al. (2003). The environment impact driver differentiates concepts based on their material type. In this case, the material type of each module and values are shown in Table 4-7. Following that the next step is to assign the comparable descriptive vocabulary for each module. In this case study we do not consider the sustainable production process for each module since most of the modules in this are simply made by injection molding and no complicated production process is involved.

By comparing the environmental impact driver of each module, the comparable descriptive vocabulary of each model can be assessed as provided in Table 4-8. In Table 4-8, we can see that for actuator, no significant difference exists between the two modules since the environmental impact driver for the two material types are located in the same category and with similar weights. For brush head and coupler/decoupler, despite the fact that the material types of the two modules are equal, the quantity of material used differs in the two modules. Given this, we assign a relatively higher level in comparable descriptive vocabulary for the module with less material. Moreover, when the two modules of oscillation generator are analyzed, a significant difference is seen. Module of Oral B obtained a lower level of environmental rating since additional material (steel) is used, and it has more consumption in the common material. The difference in DC motor is also caused by the noticeable difference in the amount of material used. Furthermore, the alkaline battery and rechargeable battery have relatively high difference in environmental considerations. The major materials used in rechargeable batteru (Ni and Cd) belong to the category that might cause higher environmental harm. Responding to that, we
assign a relatively “very high” rating in the comparable descriptive vocabulary for the rechargeable battery module.

<table>
<thead>
<tr>
<th>Module</th>
<th>Crest Spin Brush Pro</th>
<th>Oral-B Vitality: Dual Clean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brush head</td>
<td>Major material</td>
<td>Weight</td>
</tr>
<tr>
<td>Coupler/Decoupler</td>
<td>Nylon/ABS plastic</td>
<td>20.6g</td>
</tr>
<tr>
<td>Coupler/Decoupler</td>
<td>ABS plastic</td>
<td>1.1g</td>
</tr>
<tr>
<td>Actuator</td>
<td>ABS plastic</td>
<td>2.4g</td>
</tr>
<tr>
<td>Oscillation generator</td>
<td>ABS plastic</td>
<td>2.4g</td>
</tr>
<tr>
<td>DC Motor</td>
<td>Metal</td>
<td>30.83g</td>
</tr>
<tr>
<td>Battery</td>
<td>Zn-Mn (Alkaline)</td>
<td>46.5g</td>
</tr>
</tbody>
</table>

Table 4-8: The comparable descriptive vocabulary of each module

<table>
<thead>
<tr>
<th>Module</th>
<th>Crest Spin Brush Pro</th>
<th>Oral-B Vitality: Dual Clean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brush head</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Coupler/Decoupler</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Actuator</td>
<td>Moderate</td>
<td>Moderate</td>
</tr>
<tr>
<td>Oscillation generator</td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td>DC Motor</td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td>Battery</td>
<td>Very High</td>
<td>Very Low</td>
</tr>
</tbody>
</table>

After acquiring all the indices, we first eliminate all the concepts with a value of 0 in their compatibility index. After this elimination process, there are 32 possible product concepts remained as candidates. We input data into the interval DEA to obtain the efficiency intervals for each DMU. Note that only sustainability index has interval values. Thus, for the rest of the indexes, we put the same deterministic values to both upper bound and lower bound. The interval DEA result is shown in Table 4-9, and the software code written by Excel VBA is provided in Appendix C. In Table 4-9, we can see that the performance of all the feasible DMUs are divided into two different groups. DMU 17, 20, 32, 52 and 64 acquire the high efficiency scores in both
bounds and are categorized into the most efficient set ($E^{++}$). These five most efficient DMUs are the final most appropriate set-based concepts in this case, and they are worth taking to the next design stage for further discussion.

The detailed components of the five most applicable product concepts are provided in Table 4-10. It is noted that the brand name under each module indicates the origin of the module. From Table 4-10, after looking into each of the components from the five best final product concepts, we can see that DEA is based on overall performance rather than the effect on a single criterion. For example, for the battery, even though alkaline battery dominates rechargeable battery in sustainability score, rechargeable battery is still used in DMU 52 and 64. The reason is that the considerations from other criteria still make rechargeable battery a better component rather than adopting alkaline battery. In this application, sustainability consideration is taken into concept selection process. However, it is still an auxiliary criterion with no strict impact to the final decision. Currently, as the industry stresses on the importance of producing more sustainable products, the proposed method can provide reasonable result generating appropriate sustainable product concepts. However, if sustainability consideration is the first priority, we suggest that more constraints (e.g. adopting DEA assurance region model to set weight constraints.) should be added to our model to increase the judgment of sustainability index.
Table 4-9: The interval DEA result of the 32 possible electronic toothbrush concepts

<table>
<thead>
<tr>
<th>DMU</th>
<th>DFA</th>
<th>Cost</th>
<th>Functionality</th>
<th>Compatibility</th>
<th>Sustainability LB</th>
<th>Sustainability UB</th>
<th>Interval Efficiency Score LB</th>
<th>Interval Efficiency Score UB</th>
<th>Efficient Set</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>40.5</td>
<td>6.3</td>
<td>8.0195</td>
<td>5</td>
<td>21.82</td>
<td>38.18</td>
<td>0.975612</td>
<td>1</td>
<td>E'</td>
</tr>
<tr>
<td>4</td>
<td>36.72</td>
<td>7.05</td>
<td>7.8825</td>
<td>3</td>
<td>25.45</td>
<td>41.82</td>
<td>0.97423</td>
<td>1</td>
<td>E'</td>
</tr>
<tr>
<td>5</td>
<td>42.12</td>
<td>6.75</td>
<td>7.8935</td>
<td>2</td>
<td>21.82</td>
<td>38.18</td>
<td>0.912491</td>
<td>1</td>
<td>E'</td>
</tr>
<tr>
<td>8</td>
<td>38.34</td>
<td>7.5</td>
<td>7.7565</td>
<td>4</td>
<td>25.45</td>
<td>41.82</td>
<td>0.950875</td>
<td>1</td>
<td>E'</td>
</tr>
<tr>
<td>9</td>
<td>40.23</td>
<td>6.8</td>
<td>7.925</td>
<td>4</td>
<td>21.82</td>
<td>38.18</td>
<td>0.940236</td>
<td>1</td>
<td>E'</td>
</tr>
<tr>
<td>12</td>
<td>36.45</td>
<td>7.55</td>
<td>7.788</td>
<td>2</td>
<td>21.82</td>
<td>38.18</td>
<td>0.965979</td>
<td>1</td>
<td>E'</td>
</tr>
<tr>
<td>13</td>
<td>41.85</td>
<td>7.25</td>
<td>7.799</td>
<td>3</td>
<td>21.82</td>
<td>38.18</td>
<td>0.881121</td>
<td>1</td>
<td>E'</td>
</tr>
<tr>
<td>16</td>
<td>38.07</td>
<td>8.0</td>
<td>7.662</td>
<td>5</td>
<td>21.82</td>
<td>38.18</td>
<td>0.974692</td>
<td>1</td>
<td>E'</td>
</tr>
<tr>
<td>17</td>
<td>39.42</td>
<td>6.1</td>
<td>7.9935</td>
<td>5</td>
<td>18.18</td>
<td>34.55</td>
<td>1</td>
<td>1</td>
<td>E''</td>
</tr>
<tr>
<td>20</td>
<td>35.64</td>
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<td>7.8565</td>
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<td>0.934828</td>
<td>1</td>
<td>E'</td>
</tr>
<tr>
<td>24</td>
<td>37.26</td>
<td>7.3</td>
<td>7.7305</td>
<td>4</td>
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<td>38.18</td>
<td>0.975483</td>
<td>1</td>
<td>E'</td>
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<td>25</td>
<td>39.15</td>
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<td>7.899</td>
<td>4</td>
<td>18.18</td>
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</tr>
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<td>7.762</td>
<td>2</td>
<td>21.82</td>
<td>38.18</td>
<td>0.991591</td>
<td>1</td>
<td>E'</td>
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<tr>
<td>29</td>
<td>40.77</td>
<td>7.05</td>
<td>7.773</td>
<td>3</td>
<td>18.18</td>
<td>34.55</td>
<td>0.902083</td>
<td>1</td>
<td>E'</td>
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<tr>
<td>32</td>
<td>36.99</td>
<td>7.8</td>
<td>7.636</td>
<td>5</td>
<td>21.82</td>
<td>38.18</td>
<td>1</td>
<td>1</td>
<td>E''</td>
</tr>
<tr>
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<td>7.3</td>
<td>8.132</td>
<td>5</td>
<td>21.82</td>
<td>38.18</td>
<td>0.97</td>
<td>1</td>
<td>E'</td>
</tr>
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<tr>
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<td>8.006</td>
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<td>0.921762</td>
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<td>E'</td>
</tr>
<tr>
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<td>8.5</td>
<td>7.869</td>
<td>4</td>
<td>25.45</td>
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<td>E'</td>
</tr>
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<td>8.0375</td>
<td>4</td>
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<td>38.18</td>
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<td>E'</td>
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<td>44</td>
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<td>8.55</td>
<td>7.9005</td>
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<td>25.45</td>
<td>41.82</td>
<td>0.969535</td>
<td>1</td>
<td>E'</td>
</tr>
<tr>
<td>45</td>
<td>42.12</td>
<td>8.25</td>
<td>7.9115</td>
<td>3</td>
<td>21.82</td>
<td>38.18</td>
<td>0.851286</td>
<td>1</td>
<td>E'</td>
</tr>
<tr>
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<td>5</td>
<td>25.45</td>
<td>41.82</td>
<td>0.974851</td>
<td>1</td>
<td>E'</td>
</tr>
<tr>
<td>49</td>
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<td>7.1</td>
<td>8.106</td>
<td>5</td>
<td>18.18</td>
<td>34.55</td>
<td>0.993802</td>
<td>1</td>
<td>E'</td>
</tr>
<tr>
<td>52</td>
<td>35.91</td>
<td>7.85</td>
<td>7.969</td>
<td>3</td>
<td>21.82</td>
<td>38.18</td>
<td>1</td>
<td>1</td>
<td>E''</td>
</tr>
<tr>
<td>53</td>
<td>41.31</td>
<td>7.55</td>
<td>7.98</td>
<td>2</td>
<td>18.18</td>
<td>34.55</td>
<td>0.894358</td>
<td>1</td>
<td>E'</td>
</tr>
<tr>
<td>56</td>
<td>37.53</td>
<td>8.3</td>
<td>7.843</td>
<td>4</td>
<td>21.82</td>
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<td>0.974354</td>
<td>1</td>
<td>E'</td>
</tr>
<tr>
<td>57</td>
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<td>7.6</td>
<td>8.0115</td>
<td>4</td>
<td>18.18</td>
<td>34.55</td>
<td>0.952188</td>
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<td>E'</td>
</tr>
<tr>
<td>60</td>
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<td>7.8745</td>
<td>2</td>
<td>21.82</td>
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<td>0.995627</td>
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<td>7.8855</td>
<td>3</td>
<td>18.18</td>
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<td>7.7485</td>
<td>5</td>
<td>21.82</td>
<td>38.18</td>
<td>1</td>
<td>1</td>
<td>E''</td>
</tr>
</tbody>
</table>
Table 4-10: The components of the five most efficient product concepts

<table>
<thead>
<tr>
<th>DMU</th>
<th>Battery</th>
<th>Actuator</th>
<th>DC Motor</th>
<th>Oscillation generator</th>
<th>Coupler/Decoupler</th>
<th>Brush head</th>
</tr>
</thead>
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<tr>
<td>17</td>
<td>Crest</td>
<td>Oral-B</td>
<td>Crest</td>
<td>Oral-B</td>
<td>Crest</td>
<td>Crest</td>
</tr>
<tr>
<td></td>
<td>Alkaline Zn-Mn</td>
<td>PVC</td>
<td>Metal</td>
<td>ABS plastic/Steel</td>
<td>ABS plastic</td>
<td>Nylon/ABS plastic</td>
</tr>
<tr>
<td></td>
<td>(46.5g)</td>
<td>(2.06g)</td>
<td>(30.83g)</td>
<td>(21.3g)</td>
<td>(1.1g)</td>
<td>(20.6g)</td>
</tr>
<tr>
<td>20</td>
<td>Crest</td>
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<td>Crest</td>
<td>Oral-B</td>
<td>Oral-B</td>
<td>Oral-B</td>
</tr>
<tr>
<td></td>
<td>Alkaline Zn-Mn</td>
<td>PVC</td>
<td>Metal</td>
<td>ABS plastic/Steel</td>
<td>ABS plastic</td>
<td>Nylon/ABS plastic</td>
</tr>
<tr>
<td></td>
<td>(46.5g)</td>
<td>(2.06g)</td>
<td>(30.83g)</td>
<td>(21.3g)</td>
<td>(10.2g)</td>
<td>(7.75g)</td>
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<tr>
<td>32</td>
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<td>Oral-B</td>
<td>Crest</td>
<td>Oral-B</td>
<td>Oral-B</td>
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<tr>
<td></td>
<td>Alkaline Zn-Mn</td>
<td>PVC</td>
<td>Metal</td>
<td>ABS plastic</td>
<td>ABS plastic</td>
<td>Nylon/ABS plastic</td>
</tr>
<tr>
<td></td>
<td>(46.5g)</td>
<td>(2.06g)</td>
<td>(90.6g)</td>
<td>(2.4g)</td>
<td>(10.2g)</td>
<td>(7.75g)</td>
</tr>
<tr>
<td>52</td>
<td>Oral-B</td>
<td>Oral-B</td>
<td>Crest</td>
<td>Oral-B</td>
<td>Oral-B</td>
<td>Oral-B</td>
</tr>
<tr>
<td></td>
<td>Rechargeable Ni-Cd</td>
<td>PVC</td>
<td>Metal</td>
<td>ABS plastic/Steel</td>
<td>ABS plastic</td>
<td>Nylon/ABS plastic</td>
</tr>
<tr>
<td></td>
<td>(55.9g)</td>
<td>(2.06g)</td>
<td>(30.83g)</td>
<td>(21.3g)</td>
<td>(10.2g)</td>
<td>(7.75g)</td>
</tr>
<tr>
<td>64</td>
<td>Oral-B</td>
<td>Oral-B</td>
<td>Oral-B</td>
<td>Crest</td>
<td>Oral-B</td>
<td>Oral-B</td>
</tr>
<tr>
<td></td>
<td>Rechargeable Ni-Cd</td>
<td>PVC</td>
<td>Metal</td>
<td>ABS plastic</td>
<td>ABS plastic</td>
<td>Nylon/ABS plastic</td>
</tr>
<tr>
<td></td>
<td>(55.9g)</td>
<td>(2.06g)</td>
<td>(90.6g)</td>
<td>(2.4g)</td>
<td>(10.2g)</td>
<td>(7.75g)</td>
</tr>
</tbody>
</table>
Chapter 5

Conclusion

Product design process includes a series of stages, and each of them requires complex decision making procedures. For decision makers, when dealing with product design problems, how to choose an appropriate decision making tool is always a difficult task. In this thesis, we propose applying data envelopment analysis (DEA) to solve problems in different stages of the product design process. DEA is a linear programming based multi-criteria decision making tool which has been widely applied to various fields. It is a good performance evaluation tool, and is noted for its applicability and calculation simplicity. Decision makers have high flexibility when adopting DEA since they can select appropriate DEA models with specific indices (criteria) based on different problem types and objectives. Above features of DEA make it capable of solving problems in product design domain.

In this thesis, DEA is applied to three product design problems. DEA is first introduced to a product line selection problem. We propose a general five-step problem solving procedure incorporating DEA model with cross-efficiency ranking method for solving this product line selection problem. By changing the tendency of one of the indices, DEA generates two different set of rankings from two inverse viewpoints. The manufacturer’s view provides manufacturers with the ranking of product line combinations that have better platform sharing and resource allocation. On the other hand, the ranking from the inverse viewpoint, the consumer’s view, represents the product lines that can fulfill most customers with higher uniqueness. A compromise ranking is proposed to provide a neutral point of view between the two standpoints. After comparing the three set of rankings to the ranking result generated by the Multiple Attribute Utility Theory (MAUT) by using Spearman’s footrule distances, the ranking from the
compromise viewpoint is proved to have least difference from the MAUT ranking. This case study provides us with confidence that 1) DEA can be an effective tool when applying to product line selection problems with appropriate indices, and 2) using DEA requires relatively low calculation difficulty compared to MAUT.

In the second case study, DEA is applied to a concept selection problem to choose a best electronic toothbrush product concept. In this case study, five newly defined indices from various perspectives are input into the DEA model. When solving this concept selection problem, we also follow the five-step problem solving procedure proposed for the first case study. In this case study, DEA promptly evaluates and ranks all the product concept alternatives into a detail ranking by their overall performance. If all the values for the indices are properly gathered, the acquired ranking can enable decision makers in making most appropriate product decision. Comparing to other concept selection methods (CSMs), DEA avoids introducing decision maker’s personal preference, and reduces the complicated multiple stage decision procedures.

For the last case study, DEA is introduced to a concept selection problem involving uncertainty. In fact, at the concept design stage, since most of the product specification and functions are not yet determined, it is very difficult to have all the design criteria in deterministic values. In this case study, we create an interval sustainability index that measures relative sustainability level to work with the other five indices proposed for the second case study. To deal with interval data, we select interval DEA model as our tool for this case study. However, when problems involve uncertainty indices, it is very difficult to have only one most efficient DMU or even to rank all the DMUs. In fact, when applying interval DEA, it can generate a set of best performing DMUs. This feature satisfies the concept of set-based design, which is to select a set of most applicable product concepts with all the functions and specifications located in a feasible domain. In this case study, interval DEA successfully chooses five most applicable
product concept alternatives that are worthy of taking to the next design stage in order to incorporate more detailed information.

Referring to the three case studies illustrated in chapter 4, we can conclude that DEA is an effective tool that can provide decision makers valuable results. With relatively low computational difficulty and high applicability, DEA is undoubtedly a very good decision making tool that is superior in solving large scale decision making problems with numerous decision making units (DMUs) and controlled number of indices (attributes). For example, in the first case study, DEA outputs a very similar result in comparison with MAUT method, but with a lower computational difficulty. This result will be amplified significantly if the scale of the problem increases greatly. Above mentioned advantage makes it specifically appropriate to be applied to product design domain.

However, when applying DEA, decision makers have to be familiar with the background of the problem in order to approximately define all the indices. The selection of indices is a very critical part when implementing DEA. Mistakes in defining indices may lead to meaningless results.

Overall, after examining the acquired result from the three case studies, we recommend that DEA as a very suitable tool for applying to product design decisions.
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Appendix A

Software Code of CCR Output-Oriented Model with Cross Efficiency Ranking Method

Sub Macro2()
' Define variables
Dim a(60, 10) As Double
Dim b(60, 10) As Double
Dim c(60, 10) As Double
Dim d(60, 10) As Double
Dim p As Double
Dim q As Double
Dim v(60, 60) As Double
Dim u(60, 60) As Double
Dim ce(60, 60) As Double
Dim e As Double
Dim f As Double
Dim av(60) As Double
Dim dmu(60) As Variant
Dim si(60, 10) As Double
Dim sr(60, 10) As Double

  t = 0
  Worksheets("sheet1").Activate
'Examine data
If Cells(1, 1).Value = "DMU" Then
    For j = 2 To 61
        If Cells(j, 1).Value <> "''" Then
            t = j - 1
        End If
    Next
Else
    MsgBox "The data format is not correct"
End If

'Check number of input indices
x = 0
For j = 2 To 12
    If Cells(1, j).Value = "(I)" Then
        x = x + 1
    End If
Next

'Check number of output indices
y = 0
For j = 3 To 22
    If Cells(1, j).Value = "(O)" Then
        y = y + 1
    End If
If x > 10 Then
    MsgBox "You can't enter more than 10 inputs"
    If y > 10 Then
        MsgBox "You can't enter more than 10 inputs and outputs"
    End If
Else
    If y > 10 Then
        MsgBox "You can't enter more than 10 outputs"
    Else
        For k = 2 To t + 1
            For r = 2 To x + 1
                Cells(k, r).Interior.ColorIndex = 6
            Next
            For s = x + 2 To x + y + 1
                Cells(k, s).Interior.ColorIndex = 28
            Next
        Next
For k = 2 To t + 1
For $i = 2$ To $x + 1$

Sheets("sheet1").Select

$a(k - 1, i - 1) = Cells(k, i)$

Cells(k, i).Select

Selection.Copy

Sheets("Sheet2").Select

Cells(k, i).Select

ActiveSheet.Paste

Next

For $j = x + 2$ To $x + y + 1$

Sheets("sheet1").Select

$b(k - 1, j - x - 1) = Cells(k, j)$

Cells(k, j).Select

Selection.Copy

Sheets("Sheet2").Select

Cells(k, $10 - x + j$).Select

ActiveSheet.Paste

Next

Next

Worksheets("sheet2").Select

If $x < 10$ Then
For k = 2 To t + 1
    For l = x + 2 To 11
        Cells(k, l).Value = 0
    Next
    Next
    End If

If y < 10 Then
    For k = 2 To t + 1
        For l = 12 + y To 21
            Cells(k, l).Value = 0
        Next
        Next
    End If

Worksheets(3).Name = "Variables"
ActiveWorkbook.Sheets.Add after:=Sheets("Variables")
Worksheets(4).Name = "Weight"
ActiveWorkbook.Sheets.Add after:=Sheets("Weight")
Worksheets(5).Name = "Slacks"
ActiveWorkbook.Sheets.Add after:=Sheets("Slacks")
Worksheets(6).Name = "Cross Efficiency"
ActiveWorkbook.Sheets.Add after:=Sheets("Cross Efficiency")
Worksheets(7).Name = "Ranking"
For k = 2 To t + 1
For i = 1 To 60
  For j = 1 To 10
    c(i, j) = 0
    d(i, j) = 0
  Next
Next

Sheets("sheet2").Select
For N = 2 To 21
  Cells(k, N).Select
  Selection.Copy
  Cells(1, N).Select
  ActiveSheet.Paste
Next

Worksheets("sheet2").Activate
For m = 1 To 81
  Cells(m, 1).Value = 0
Next

For i = 2 To 1 + x
  For j = 62 To 71
    If j - 60 = i Then
      Cells(j, i) = 1
    End If
  Next
Else
  Cells(j, i) = 0
  End If
Next
Next

If x < 10 Then
  For i = 2 + x To 11
    For j = 62 To 71
      Cells(j, i) = 0
    Next
  Next
  End If

For i = 12 To 11 + y
  For j = 62 To 71
    If j - 50 = i Then
      Cells(j, i) = 1
    Else
      Cells(j, i) = 0
    End If
  Next
Next

If y < 10 Then
For i = 12 + y To 21
For j = 62 To 71
Cells(j, i) = 0
Next
Next
End If

'DEA formulation
Cells(82, 2).Value = "=sumproduct($A$62:$A$71,B62:B71)"
Cells(82, 3).Value = "=sumproduct($A$62:$A$71,C62:C71)"
Cells(82, 4).Value = "=sumproduct($A$62:$A$71,D62:D71)"
Cells(82, 5).Value = "=sumproduct($A$62:$A$71,E62:E71)"
Cells(82, 6).Value = "=sumproduct($A$62:$A$71,F62:F71)"
Cells(82, 7).Value = "=sumproduct($A$62:$A$71,G62:G71)"
Cells(82, 8).Value = "=sumproduct($A$62:$A$71,H62:H71)"
Cells(82, 9).Value = "=sumproduct($A$62:$A$71,I62:171)"
Cells(82, 10).Value = "=sumproduct($A$62:$A$71,J62:J71)"
Cells(82, 11).Value = "=sumproduct($A$62:$A$71,K62:K71)"
Cells(82, 12).Value = "=sumproduct($A$72:$A$81,L62:L71)"
Cells(82, 13).Value = "=sumproduct($A$72:$A$81,M62:M71)"
Cells(82, 14).Value = "=sumproduct($A$72:$A$81,N62:N71)"
Cells(82, 15).Value = "=sumproduct($A$72:$A$81,O62:O71)"
Cells(82, 16).Value = "=sumproduct($A$72:$A$81,P62:P71)"
Cells(82, 17).Value = "=sumproduct($A$72:$A$81,Q62:Q71)"
Cells(82, 18).Value = "=sumproduct($A$72:$A$81,R62:R71)"
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<th></th>
</tr>
</thead>
<tbody>
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<td>&quot;=sumproduct($A$2:$A$61,C2:C61)&quot;</td>
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<tr>
<td>Cells(2, 25).Value</td>
<td>&quot;=sumproduct($A$2:$A$61,D2:D61)&quot;</td>
</tr>
<tr>
<td>Cells(2, 26).Value</td>
<td>&quot;=sumproduct($A$2:$A$61,E2:E61)&quot;</td>
</tr>
<tr>
<td>Cells(2, 27).Value</td>
<td>&quot;=sumproduct($A$2:$A$61,F2:F61)&quot;</td>
</tr>
<tr>
<td>Cells(2, 28).Value</td>
<td>&quot;=sumproduct($A$2:$A$61,G2:G61)&quot;</td>
</tr>
<tr>
<td>Cells(2, 29).Value</td>
<td>&quot;=sumproduct($A$2:$A$61,H2:H61)&quot;</td>
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<tr>
<td>Cells(2, 30).Value</td>
<td>&quot;=sumproduct($A$2:$A$61,I2:I61)&quot;</td>
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<tr>
<td>Cells(2, 31).Value</td>
<td>&quot;=sumproduct($A$2:$A$61,J2:J61)&quot;</td>
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<td>Cells(3, 36).Value</td>
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<td>Cells(3, 38).Value</td>
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<td>Cells(3, 41).Value</td>
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</tr>
<tr>
<td>Cells(3, 42).Value</td>
<td>&quot;=sumproduct($A$2:$A$61,U2:U61)&quot;</td>
</tr>
</tbody>
</table>
Cells(2, 33).Value = "=sumproduct($A$1,L1)"
Cells(2, 34).Value = "=sumproduct($A$1,M1)"
Cells(2, 35).Value = "=sumproduct($A$1,N1)"
Cells(2, 36).Value = "=sumproduct($A$1,O1)"
Cells(2, 37).Value = "=sumproduct($A$1,P1)"
Cells(2, 38).Value = "=sumproduct($A$1,Q1)"
Cells(2, 39).Value = "=sumproduct($A$1,R1)"
Cells(2, 40).Value = "=sumproduct($A$1,S1)"
Cells(2, 41).Value = "=sumproduct($A$1,T1)"
Cells(2, 42).Value = "=sumproduct($A$1,U1)"

Cells(1, 33).Value = "=sum(AG2,L82)"
Cells(1, 34).Value = "=sum(AH2,M82)"
Cells(1, 35).Value = "=sum(AI2,N82)"
Cells(1, 36).Value = "=sum(AJ2,O82)"
Cells(1, 37).Value = "=sum(AK2,P82)"
Cells(1, 38).Value = "=sum(AL2,Q82)"
Cells(1, 39).Value = "=sum(AM2,R82)"
Cells(1, 40).Value = "=sum(AN2,S82)"
Cells(1, 41).Value = "=sum(AO2,T82)"
Cells(1, 42).Value = "=sum(AP2,U82)"

Cells(1, 23).Value = Cells(1, 2).Value
Cells(1, 24).Value = Cells(1, 3).Value
Cells(1, 25).Value = Cells(1, 4).Value
Cells(1, 26).Value = Cells(1, 5).Value
Cells(1, 27).Value = Cells(1, 6).Value
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Cells(1, 29).Value = Cells(1, 8).Value
Cells(1, 30).Value = Cells(1, 9).Value
Cells(1, 31).Value = Cells(1, 10).Value
Cells(1, 32).Value = Cells(1, 11).Value

Cells(3, 23).Value = "=sum(B82,W2)"
Cells(3, 24).Value = "=sum(C82,X2)"
Cells(3, 25).Value = "=sum(D82,Y2)"
Cells(3, 26).Value = "=sum(E82,Z2)"
Cells(3, 27).Value = "=sum(F82,AA2)"
Cells(3, 28).Value = "=sum(G82,AB2)"
Cells(3, 29).Value = "=sum(H82,AC2)"
Cells(3, 30).Value = "=sum(I82,AD2)"
Cells(3, 31).Value = "=sum(J82,AE2)"
Cells(3, 32).Value = "=sum(K82,AF2)"

' Call Excel solver

solverreset

solveroptions precision:=0.000001, assumelinear:=True, assumenonneg:=True
Sheets("sheet2").Select

solverok setcell:=Range("A1"), maxminval:=1, bychange:=Range("A1:A81")
solveradd cellref:=Range("W3:AP3"), relation:=2, formulatext:=Range("W1:AP1")
solversolve userfinish = False

solverfinish keepfinal:=1, reportarray:=Array(2)

Application.DisplayAlerts = False

' Acquire variable values (u and v) from the sensitivity report

For i = 94 To 93 + x
    Sheets("Sensitivity report 1").Select
    c(k - 1, i - 93) = Cells(i, 5)
    Next

For i = 104 To 103 + y
    Sheets("Sensitivity report 1").Select
    d(k - 1, i - 103) = Cells(i, 5)
    Next

Sheets("Sensitivity report 1").Delete

Sheets("sheet2").Select
Cells(1, 1).Select
Selection.Copy
Sheets("Variables").Select
Cells(k, 2).Select
ActiveSheet.Paste
For i = 2 To t + 1
    Sheets("sheet2").Select
    Cells(i, 1).Select
    Selection.Copy
    Sheets("Variables").Select
    Cells(k, i + x + y + 1).Select
    ActiveSheet.Paste
    Next

For i = 62 To 61 + x
    Sheets("sheet2").Select
    si(k - 1, i - 61) = Cells(i, 1)
    Next

For i = 72 To 71 + y
    Sheets("sheet2").Select
    sr(k - 1, i - 71) = Cells(i, 1)
    Next

Sheets("Variables").Select
For i = 3 + x + y + t To 2 + x + x + y + t
    Cells(k, i) = si(k - 1, i - 2 - x - y - t)
    Next
For \( i = 3 + x + x + y + t \) To \( 2 + x + x + y + y + t \)

\[ \text{Cells}(k, i) = \text{sr}(k - 1, i - 2 - x - y - t) \]

Next

Sheets("Slacks").Select

For \( i = 2 \) To \( 1 + x \)

\[ \text{Cells}(k, i) = \text{si}(k - 1, i - 1) \]

Next

Sheets("Slacks").Select

For \( i = 2 + x \) To \( 1 + x + y \)

\[ \text{Cells}(k, i) = \text{sr}(k - 1, i - 1 - x) \]

Next

For \( i = 3 \) To \( 2 + x \)

Sheets("Variables").Select

\[ \text{Cells}(k, i) = \text{Abs}(c(k - 1, i - 2)) \]

Next

For \( i = 3 + x \) To \( 2 + x + y \)

Sheets("Variables").Select

\[ \text{Cells}(k, i) = \text{Abs}(d(k - 1, i - 2 - x)) \]

Next

Sheets("sheet2").Select

For \( i = 2 \) To \( t + 1 \)
Sheets("Weight").Select
For j = 2 To 1 + x
    Cells(k, j) = Abs(c(k - 1, j - 1))
Next

Sheets("Weight").Select
For j = 2 + x To 1 + x + y
    Cells(k, j) = Abs(d(k - 1, j - 1 - x))
Next

p = 0
q = 0

'Collect required value for the cross efficiency calculation
For j = 2 To x + 1
    p = p + a(i - 1, j - 1) * Abs(c(k - 1, j - 1))
Next

For l = 2 To y + 1
    q = q + b(i - 1, l - 1) * Abs(d(k - 1, l - 1))
Next

v(i - 1, k - 1) = p
u(i - 1, k - 1) = q
For k = 2 To t + 1
For i = 2 To t + 1
'Calculate cross efficiency values
ce(i - 1, k - 1) = u(i - 1, k - 1) / v(i - 1, k - 1)
Sheets("Cross Efficiency").Select
Cells(i, k) = ce(i - 1, k - 1)
Next
Next k
Worksheets("Variables").Activate
Range("A1:A61") = ""
For i = 1 To 20
For j = 1 To t + 1
Sheets("sheet1").Select
If Cells(1, i) = "DMU" Then
dmu(j) = Cells(j, i)
End If
Next
Next
‘Ranking all the DMUs by the cross efficiency values

For i = 1 To t + 1

Sheets("Variables").Select

Cells(i, 1) = dmu(i)

Sheets("Weight").Select

Cells(i, 1) = dmu(i)

Sheets("Slacks").Select

Cells(i, 1) = dmu(i)

Sheets("Cross Efficiency").Select

Cells(i, 1) = dmu(i)

Next

‘Prepare all the data for the report sheet

Sheets("Variables").Select

Cells(1, 2).Value = "η"

For i = 3 To 2 + x

Cells(1, i).Value = "V" & i - 2

Next

For i = 3 + x To 2 + x + y

Cells(1, i).Value = "U" & i - 2 - x

Next
For i = 3 + x + y To 2 + x + y + t
Cells(1, i).Value = "μ" & i - 2 - x - y
Next

For i = 3 + x + y + t To 2 + x + x + y + t
Cells(1, i).Value = "S" & i - 2 - x - y - t & "."
Next

For i = 3 + x + x + y + t To 2 + x + x + y + y + t
Cells(1, i).Value = "S" & i - 2 - x - x - y - t & "+"
Next

Sheets("Weight").Select
For i = 2 To 1 + x
Cells(1, i).Value = "V" & i - 1
Next

For i = 2 + x To 1 + x + y
Cells(1, i).Value = "U" & i - 1 - x
Next

Sheets("Slacks").Select
For i = 2 To 1 + x
Cells(1, i).Value = "S" & i - 1 & "."
For i = 2 + x To 1 + x + y
Cells(1, i).Value = "S" & i - 1 - x & "+"
Next

Sheets("Cross Efficiency").Select
For i = 2 To t + 1
Cells(1, i).Value = "η" & Cells(i, 1)
Next
Cells(1, t + 2) = "Average η"

For i = 2 To t + 1
    e = 0
    For j = 2 To t + 1
        e = e + Cells(i, j)
    Next
    f = e / t
    av(i - 1) = f
Next
Cells(i, t + 2) = av(i - 1)
Next

Sheets("Ranking").Select
Cells(1, 1) = "DMU"
Cells(1, 3) = "Ranking"
For i = 1 To t - 1
    For j = 1 To t - i
        If av(j + 1) > av(j) Then
            temp = av(j + 1)
            av(j + 1) = av(j)
            av(j) = temp
        End If
    Next
    Next

For k = 1 To t
    Cells(k + 1, 2) = av(k)
Next

For i = 2 To t + 1
    For j = 2 To t + 1
        If Worksheets("Cross Efficiency").Cells(i, 2) = Worksheets("Ranking").Cells(j, 2) Then
            Worksheets("Ranking").Cells(j, 1) = Worksheets("Cross Efficiency").Cells(i, 1)
        End If
    Next
    Cells(i, 3) = i - 1
Next

Application.DisplayAlerts = False
Sheets("sheet2").Delete
End If
End If
End Sub
Start
Appendix B

Software Code of CCR Input-Oriented Model with Cross Efficiency Ranking Method

Sub Macro1()

‘Define variables
Dim a(50, 10) As Double
Dim b(50, 10) As Double
Dim c(50, 10) As Double
Dim d(50, 10) As Double
Dim p As Double
Dim q As Double
Dim v(50, 50) As Double
Dim u(50, 50) As Double
Dim ce(50, 50) As Double
Dim e As Double
Dim f As Double
Dim av(50) As Double
Dim dmu(50) As Variant
Dim si(50, 10) As Double
Dim sr(50, 10) As Double

\[ t = 0 \]
Worksheets("sheet1").Activate

'Collect input data
If Cells(1, 1).Value = "DMU" Then
    For j = 2 To 51
        If Cells(j, 1).Value <> "" Then
            t = j - 1
        End If
    Next
Else
    MsgBox "The data format is not correct"
End If

'Check the number of input indices
x = 0
For j = 2 To 12
    If Cells(1, j).Value = "(I)" Then
        x = x + 1
    End If
Next

'Check the number of output indices
y = 0
For j = 3 To 22
If Cells(1, j).Value = "(O)" Then
    y = y + 1
End If
Next

If x > 10 Then
    MsgBox "You can't enter more than 10 inputs"
Else
    If y > 10 Then
        MsgBox "You can't enter more than 10 inputs and outputs"
    End If
End If

For k = 2 To t + 1
    For r = 2 To x + 1
        Cells(k, r).Interior.ColorIndex = 6
    Next
    For s = x + 2 To x + y + 1
        Cells(k, s).Interior.ColorIndex = 28
    Next
Next

For k = 2 To t + 1
    For i = 2 To x + 1
        Sheets("sheet1").Select
        a(k - 1, i - 1) = Cells(k, i)
        Cells(k, i).Select
        Selection.Copy
        Sheets("Sheet2").Select
        Cells(k, i).Select
        ActiveSheet.Paste
    Next
Next

For j = x + 2 To x + y + 1
    Sheets("sheet1").Select
    b(k - 1, j - x - 1) = Cells(k, j)
    Cells(k, j).Select
    Selection.Copy
    Sheets("Sheet2").Select
    Cells(k, 10 - x + j).Select
    ActiveSheet.Paste
Next
Next
Worksheets("sheet2").Select
If x < 10 Then
    For k = 2 To t + 1
        For l = x + 2 To 11
            Cells(k, l).Value = 0
        Next
    Next
End If

If y < 10 Then
    For k = 2 To t + 1
        For l = 12 + y To 21
            Cells(k, l).Value = 0
        Next
    Next
End If

'Add Excel sheets
'add sheets
Worksheets(3).Name = "Variables"
ActiveWorkbook.Sheets.Add after:=Sheets("Variables")
Worksheets(4).Name = "Weight"
ActiveWorkbook.Sheets.Add after:=Sheets("Weight")
Worksheets(5).Name = "Slacks"
ActiveWorkbook.Sheets.Add after:=Sheets("Slacks")
Worksheets(6).Name = "Cross Efficiency"
ActiveWorkbook.Sheets.Add after:=Sheets("Cross Efficiency")
Worksheets(7).Name = "Ranking"

For k = 2 To t + 1
  For i = 1 To 50
    For j = 1 To 10
      c(i, j) = 0
      d(i, j) = 0
    Next
    Next
      Sheets("sheet2").Select
    For N = 2 To 21
      Cells(k, N).Select
      Selection.Copy
      Cells(1, N).Select
      ActiveSheet.Paste
    Next
    Worksheets("sheet2").Activate
  For m = 1 To 71
Cells(m, 1).Value = 0
Next

For i = 2 To 1 + x
    For j = 52 To 61
        If j - 50 = i Then
            Cells(j, i) = 1
        Else
            Cells(j, i) = 0
        End If
    Next
Next

If x < 10 Then
    For i = 2 + x To 11
        For j = 52 To 61
            Cells(j, i) = 0
        Next
    Next
End If

For i = 12 To 11 + y
    For j = 52 To 61
        If j - 40 = i Then
            Cells(j, i) = 1
        End If
    Next
Next
Else
Cells(j, i) = 0
End If
Next
Next

If y < 10 Then
For i = 12 + y To 21
For j = 52 To 61
Cells(j, i) = 0
Next
Next
End If

' DEA formulation

Cells(72, 2).Value = "=sumproduct($A$52:$A$61,B52:B61)"
Cells(72, 3).Value = "=sumproduct($A$52:$A$61,C52:C61)"
Cells(72, 4).Value = "=sumproduct($A$52:$A$61,D52:D61)"
Cells(72, 5).Value = "=sumproduct($A$52:$A$61,E52:E61)"
Cells(72, 6).Value = "=sumproduct($A$52:$A$61,F52:F61)"
Cells(72, 7).Value = "=sumproduct($A$52:$A$61,G52:G61)"
Cells(72, 8).Value = "=sumproduct($A$52:$A$61,H52:H61)"
Cells(72, 9).Value = "=sumproduct($A$52:$A$61,I52:I61)"
Cells(72, 10).Value = "=sumproduct($A$52:$A$61,J52:J61)"
Cells(72, 11).Value = "=sumproduct($A$52:$A$61,K52:K61)"
Cells(72, 12).Value = "=sumproduct($A$62:$A$71,L52:L61)"
Cells(72, 13).Value = "=sumproduct($A$62:$A$71,M52:M61)"
Cells(72, 14).Value = "=sumproduct($A$62:$A$71,N52:N61)"
Cells(72, 15).Value = "=sumproduct($A$62:$A$71,O52:O61)"
Cells(72, 16).Value = "=sumproduct($A$62:$A$71,P52:P61)"
Cells(72, 17).Value = "=sumproduct($A$62:$A$71,Q52:Q61)"
Cells(72, 18).Value = "=sumproduct($A$62:$A$71,R52:R61)"
Cells(72, 19).Value = "=sumproduct($A$62:$A$71,S52:S61)"
Cells(72, 20).Value = "=sumproduct($A$62:$A$71,T52:T61)"
Cells(72, 21).Value = "=sumproduct($A$62:$A$71,U52:U61)"

Cells(2, 24).Value = "=sumproduct($A$2:$A$51,C2:C51)"
Cells(2, 25).Value = "=sumproduct($A$2:$A$51,D2:D51)"
Cells(2, 26).Value = "=sumproduct($A$2:$A$51,E2:E51)"
Cells(2, 27).Value = "=sumproduct($A$2:$A$51,F2:F51)"
Cells(2, 28).Value = "=sumproduct($A$2:$A$51,G2:G51)"
Cells(2, 29).Value = "=sumproduct($A$2:$A$51,H2:H51)"
Cells(2, 30).Value = "=sumproduct($A$2:$A$51,I2:I51)"
Cells(2, 31).Value = "=sumproduct($A$2:$A$51,J2:J51)"
Cells(2, 32).Value = "=sumproduct($A$2:$A$51,K2:K51)"
Cells(3, 33).Value = "=sumproduct($A$2:$A$51,L2:L51)"
Cells(3, 34).Value = "=sumproduct($A$2:$A$51,M2:M51)"
Cells(3, 35).Value = "=sumproduct($A$2:$A$51,N2:N51)"
Cells(3, 36).Value = "=sumproduct($A$2:$A$51,O2:O51)"
Cells(3, 37).Value = "=sumproduct($A$2:$A$51,P2:P51)"
Cells(3, 38).Value = "=sumproduct($A$2:$A$51,Q2:Q51)"
Cells(3, 39).Value = "=sumproduct($A$2:$A$51,R2:R51)"
Cells(3, 40).Value = "=sumproduct($A$2:$A$51,S2:S51)"
Cells(3, 41).Value = "=sumproduct($A$2:$A$51,T2:T51)"
Cells(3, 42).Value = "=sumproduct($A$2:$A$51,U2:U51)"

Cells(1, 23).Value = "=sumproduct($A$1,B1)"
Cells(1, 24).Value = "=sumproduct($A$1,C1)"
Cells(1, 25).Value = "=sumproduct($A$1,D1)"
Cells(1, 26).Value = "=sumproduct($A$1,E1)"
Cells(1, 27).Value = "=sumproduct($A$1,F1)"
Cells(1, 28).Value = "=sumproduct($A$1,G1)"
Cells(1, 29).Value = "=sumproduct($A$1,H1)"
Cells(1, 30).Value = "=sumproduct($A$1,I1)"
Cells(1, 31).Value = "=sumproduct($A$1,J1)"
Cells(1, 32).Value = "=sumproduct($A$1,K1)"

Cells(3, 23).Value = "=sum(W2,B72)"
Cells(3, 24).Value = "=sum(X2,C72)"
Cells(3, 25).Value = "=sum(Y2,D72)"
Cells(3, 26).Value = "=sum(Z2,E72)"
Cells(3, 27).Value = "=sum(AA2,F72)"
Cells(3, 28).Value = "=sum(AB2,G72)"
Cells(3, 29).Value = "=sum(AC2,H72)"
Cells(3, 30).Value = "=sum(AD2,I72)"
Cells(3, 31).Value = "=sum(AE2,J72)"
Cells(3, 32).Value = "=sum(AF2,K72)"

Cells(1, 33).Value = "=sum(L72,L1)"
Cells(1, 34).Value = "=sum(M72,M1)"
Cells(1, 35).Value = "=sum(N72,N1)"
Cells(1, 36).Value = "=sum(O72,O1)"
Cells(1, 37).Value = "=sum(P72,P1)"
Cells(1, 38).Value = "=sum(Q72,Q1)"
Cells(1, 39).Value = "=sum(R72,R1)"
Cells(1, 40).Value = "=sum(S72,S1)"
Cells(1, 41).Value = "=sum(T72,T1)"
Cells(1, 42).Value = "=sum(U72,U1)"

'Call solver
      solverreset
      solveroptions precision:=0.000001, assumelinear:=True, assumenonneg:=True

Sheets("sheet2").Select
      solverok setcell:=Range("A1"), maxminval:=2, bychange:=Range("A1:A71")
      solveradd cellref:=Range("W3:AP3"), relation:=2, formulatext:=Range("W1:AP1")
      solversolve userfinish = False
      solverfinish keepfinal:=1, reportarray:=Array(2)
      Application.DisplayAlerts = False
'Collect data from the sensitivity report

For i = 84 To 83 + x
    Sheets("Sensitivity report 1").Select
    c(k - 1, i - 83) = Cells(i, 5)
Next

For i = 94 To 93 + y
    Sheets("Sensitivity report 1").Select
    d(k - 1, i - 93) = Cells(i, 5)
Next

Sheets("Sensitivity report 1").Delete

Sheets("sheet2").Select
Cells(1, 1).Select
Selection.Copy
Sheets("Variables").Select
Cells(k, 2).Select
ActiveSheet.Paste

For i = 2 To t + 1
    Sheets("sheet2").Select
    Cells(i, 1).Select
    Selection.Copy
Sheets("Variables").Select
Cells(k, i + x + y + 1).Select
ActiveSheet.Paste

Next

For i = 52 To 51 + x

Sheets("sheet2").Select

si(k - 1, i - 51) = Cells(i, 1)

Next

For i = 62 To 61 + y

Sheets("sheet2").Select

sr(k - 1, i - 61) = Cells(i, 1)

Next

Sheets("Variables").Select

For i = 3 + x + y + t To 2 + x + x + y + t

Cells(k, i) = si(k - 1, i - 2 - x - y - t)

Next

For i = 3 + x + x + y + t To 2 + x + x + y + y + t

Cells(k, i) = sr(k - 1, i - 2 - x - x - y - t)

Next
Sheets("Slacks").Select

For i = 2 To 1 + x

Cells(k, i) = si(k - 1, i - 1)

Next

Sheets("Slacks").Select

For i = 2 + x To 1 + x + y

Cells(k, i) = sr(k - 1, i - 1 - x)

Next

For i = 3 To 2 + x

Sheets("Variables").Select

Cells(k, i) = Abs(c(k - 1, i - 2))

Next

For i = 3 + x To 2 + x + y

Sheets("Variables").Select

Cells(k, i) = Abs(d(k - 1, i - 2 - x))

Next

Sheets("sheet2").Select

For i = 2 To t + 1

Sheets("Weight").Select
For j = 2 To 1 + x
Cells(k, j) = Abs(c(k - 1, j - 1))
Next

Sheets("Weight").Select
For j = 2 + x To 1 + x + y
Cells(k, j) = Abs(d(k - 1, j - 1 - x))
Next

p = 0
q = 0
‘Collect values for cross efficiency calulation
For j = 2 To x + 1
p = p + a(i - 1, j - 1) * Abs(c(k - 1, j - 1))
Next

For l = 2 To y + 1
q = q + b(i - 1, l - 1) * Abs(d(k - 1, l - 1))
Next

v(i - 1, k - 1) = p
u(i - 1, k - 1) = q

Next
Next k

For k = 2 To t + 1
For i = 2 To t + 1

'Obtain cross efficiency values

ce(i - 1, k - 1) = u(i - 1, k - 1) / v(i - 1, k - 1)

Sheets("Cross Efficiency").Select
Cells(i, k) = ce(i - 1, k - 1)

Next
Next k

Worksheets("Variables").Activate
Range("A1:A61") = ""

'Ranking all the DMUs by the cross efficiency values

For i = 1 To 20
For j = 1 To t + 1

Sheets("sheet1").Select
If Cells(1, i) = "DMU" Then
dmu(j) = Cells(j, i)
End If

Next
Next
For i = 1 To t + 1
    Sheets("Variables").Select
    Cells(i, 1) = dmu(i)
    Sheets("Weight").Select
    Cells(i, 1) = dmu(i)
    Sheets("Slacks").Select
    Cells(i, 1) = dmu(i)
    Sheets("Cross Efficiency").Select
    Cells(i, 1) = dmu(i)
    Next

'Prepare for all the reports
Sheets("Variables").Select
Cells(1, 2).Value = "θ"

For i = 3 To 2 + x
    Cells(1, i).Value = "V" & i - 2
    Next

For i = 3 + x To 2 + x + y
    Cells(1, i).Value = "U" & i - 2 + x
    Next

For i = 3 + x + y To 2 + x + y + t
Cells(1, i).Value = "λ" & i - 2 - x - y

Next

For i = 3 + x + y + t To 2 + x + x + y + t
Cells(1, i).Value = "S" & i - 2 - x - y - t & "/-
Next

For i = 3 + x + x + y + t To 2 + x + x + y + y + t
Cells(1, i).Value = "S" & i - 2 - x - x - y - t & "+-
Next

Sheets("Weight").Select

For i = 2 To 1 + x
Cells(1, i).Value = "V" & i - 1
Next

For i = 2 + x To 1 + x + y
Cells(1, i).Value = "U" & i - 1 - x
Next

Sheets("Slacks").Select

For i = 2 To 1 + x
Cells(1, i).Value = "S" & i - 1 & "."
For i = 2 + x To 1 + x + y

Cells(1, i).Value = "S" & i - 1 - x & "+"

Next

Sheets("Cross Efficiency").Select

For i = 2 To t + 1

Cells(1, i).Value = "θ" & Cells(i, 1)

Next

Cells(1, t + 2) = "Average θ"

For i = 2 To t + 1

e = 0

For j = 2 To t + 1

e = e + Cells(i, j)

f = e / t

av(i - 1) = f

Next

Cells(i, t + 2) = av(i - 1)

Next

Sheets("Ranking").Select

Cells(1, 1) = "DMU"

Cells(1, 3) = "Ranking"

For i = 1 To t - 1

For j = 1 To t - i
If \(av(j + 1) > av(j)\) Then
  
  \(temp = av(j + 1)\)
  
  \(av(j + 1) = av(j)\)
  
  \(av(j) = temp\)

End If

Next

Next

For \(k = 1\) To \(t\)

Cells\((k + 1, 2) = av(k)\)

Next

For \(i = 2\) To \(t + 1\)

For \(j = 2\) To \(t + 1\)

If Worksheets("Cross Efficiency").Cells\((i, t + 2) = Worksheets("Ranking").Cells\((j, 2)\) Then

Worksheets("Ranking").Cells\((j, 1) = Worksheets("Cross Efficiency").Cells\((i, 1)\)

End If

Next

Cells\((i, 3) = i - 1\)

Next

Application.DisplayAlerts = False

Sheets("sheet2").Delete

End If

End If

End Sub
Appendix C

Software Code of Interval DEA Input Oriented model

Sub a()
Dim counti As Integer
Dim counto As Integer
Dim count As String
Dim lowi(100, 10) As Double
Dim lowo(100, 10) As Double
Dim upi(100, 10) As Double
Dim upo(100, 10) As Double
Dim dmu(100) As String
Dim dmucount As Integer
Dim theda(100, 2) As Double

Worksheets(2).Name = "Low"
Worksheets(3).Name = "Up"
Worksheets.Add after:=Worksheets("Up")
Worksheets(4).Name = "Efficiency Score"

Sheets("sheet1").Select

'data reading and categorizing
For i = 1 To 20
    count = Cells(1, i + 1).Value
    If Mid(count, 1, 1) = "I" Then
        counti = counti + 1
    If Mid(count, 3, 1) = "L" Then
        For j = 1 To 100
            lowi(j, (counti + 1) / 2) = Cells(j + 1, i + 1)
        Next
        Else
            For j = 1 To 100
                upi(j, counti / 2) = Cells(j + 1, i + 1)
            Next
        End If
    End If
Next

For i = 1 To 20
    count = Cells(1, i + 1 + counti).Value
    If Mid(count, 1, 1) = "O" Then
        counto = counto + 1
    If Mid(count, 3, 1) = "L" Then

For j = 1 To 100
    lowo(j, (counto + 1) / 2) = Cells(j + 1, i + 1 + counti)
    Next
Else
    For j = 1 To 100
        upo(j, counto / 2) = Cells(j + 1, i + 1 + counti)
        Next
    End If
End If

Next

counti = counti / 2
counto = counto / 2

For i = 1 To 100
    dmu(i) = Cells(i + 1, 1)
    If Cells(i + 1, 1).Value <> "" Then
        dmucount = dmucount + 1
    End If
Next

'alarm
If counti = 0 Then
    MsgBox "Please insert inputs"
If counto = 0 Then
MsgBox "Please insert outputs"
End If

If counti >= 11 Then
MsgBox "You can not have over 10 inputs"
End If

If counto >= 11 Then
MsgBox "You can not have over 10 outputs"
End If

'Paste data to lowerbound sheet
Sheets("Low").Select
For i = 1 To 100
For j = 1 To 10
If lowi(i, j) <> 0 Then
Cells(i + 1, j) = lowi(i, j)
Else
Cells(i + 1, j) = 0
End If
If upo(i, j) <> 0 Then
Cells(i + 1, j + 11) = upo(i, j)
Else
Cells(i + 1, j + 11) = 0
End If
Next
Next
Next
Next

For i = 1 To dmucount
For j = 1 To 10
If i > 1 Then
Cells(i, j) = lowi(i - 1, j)
Cells(i, j + 11) = upo(i - 1, j)
End If
Cells(1, j) = upi(i, j)
Cells(1, j + 11) = lowo(i, j)
Cells(i + 1, j) = upi(i, j)
Cells(i + 1, j + 11) = lowo(i, j)
Next

For k = 1 To 21
Cells(105, k) = 0
Next

Call cal
theda(i, 1) = Cells(105, 22).Value

Next

'Paste data to upperbound sheet
Sheets("Up").Select
For i = 1 To 100
    For j = 1 To 10
        Cells(i + 1, j) = upi(i, j)
        Cells(i + 1, j + 11) = lowo(i, j)
    Next
Next

For i = 1 To dmucount
    For j = 1 To 10
        If i > 1 Then
            Cells(i, j) = upi(i - 1, j)
            Cells(i, j + 11) = lowo(i - 1, j)
        End If
        Cells(1, j) = lowi(i, j)
        Cells(1, j + 11) = upo(i, j)
    Next
Next
For k = 1 To 21
    Cells(105, k) = 0
Next

Call cal

    theda(i, 2) = Cells(105, 22).Value
Next

Sheets("Efficiency score").Select
For i = 1 To dmucount
    Cells(i + 1, 1) = dmu(i)
    Cells(i + 1, 2) = theda(i, 1)
    Cells(i + 1, 3) = theda(i, 2)
Next

    Cells(1, 1) = "DMU"
    Cells(1, 2) = "Lb eff"
    Cells(1, 3) = "Ub eff"
End Sub