DECISION MAKING FRAMEWORK FOR SUSTAINABLE PACKAGING DESIGN USING LIFE CYCLE ASSESSMENT

by

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ABSTRACT OF THE DISSERTATION

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using Life Cycle Assessment

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Packaging industry is one of the largest industries in the world and is also associated with many environmental concerns. To reduce the environmental impacts, sustainable packaging design decision has been one of the top priorities in packaging industries nowadays. One of the commonly used tools measuring and quantifying the environmental impact of a product throughout all life stages is the Life Cycle Assessment. Based on the result from Life Cycle Assessment, decision is supposed to be made for choosing the more sustainable designs from a design population. However, the decision making process is challenging because of the complexity of the problem. The complexity is incurred by the large set and multi-criteria characteristic of result from Life Cycle Assessment, the existence of trade-off of designs between different indicators, and the

uncertainty in the environmental impact indicator values. The objective of this dissertation is to aid the decision making process to cope with these challenges, find the more sustainable packaging designs alternatives, based on both deterministic environmental impact indicators values and environmental impact indicator values with uncertainty.

To achieve the research objective, to aid the decision making process, a decision making framework is developed, which consist of three research components. Component 1 efficiently finds the non-dominated designs among a large design population using Ranking Based Pareto Filter Algorithm. Component 2 concerns the trade-offs between designs on different indicators, using Design Preference Function and Ranking Based Rate of Substitution Method. Component 3 deals with the uncertainty in the environmental impact indicator values. When dealing with the uncertainty in the environmental impact indicators, the Ranking Based Pareto Selection Algorithm has been modified to the Probabilistic Pareto Filter Algorithm.

Acknowledgment

This dissertation was accomplished with the kind help from a lot of people. First and foremost, I would like to express my deepest gratitude to my advisor, Professor Hae Chang Gea. In the years of study at Rutgers, Dr. Gea has been provided continuous guidance, help, support and encouragement. Dr. Gea not only has guided and influenced me in my academic study using his erudite knowledge, rigorous attitude and persistent inspirit of pursing truth, but also navigated and lightened me in my life by sharing many of his valuable experience, respectable values and wise life philosophy. For me, Dr. Gea is not only my advisor, but also a mentor of life time. I always feel lucky and honored to have the opportunity to work with Dr. Gea.

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Dedications

To my family.

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Chapter 1.

Introduction

This dissertation presents a decision making framework for selecting the sustainable packaging designs using Life Cycle Assessment. The Life Cycle Assessment for the packaging designs is firstly performed in order to evaluate and quantify the environmental impact. The sustainable packaging design decision problem was formulated as a Multi-Criteria Decision Making problem. Then the two phase decision making framework was proposed to select the more sustainable packaging designs, by coping with the multi-dimensional feature of the environmental impact indicators from Life Cycle Assessment, trade-off among design alternatives between different design attributes, and uncertainty in the environmental impact indicators. Case studies are shown to demonstrate the function the decision making framework.

Chapter 1 provides an introduction and background for the dissertation. In this chapter, session 1.1 presents the motivation, the objective and the scope of the research. Session 1.2 contains the literature reviews in the related aspects of the research. The research contributions are illustrated in session 1.3 while the overview of the dissertation is shown in session 1.4. Session 1.5 summarizes this chapter.

1.1. Motivation and Objective

In 1987, the United Nations World Commission on Environment and Development in its report “Our Common Future” defines “sustainability”: “Sustainable

Development is development that meets the needs of the present without compromising the ability of future generations to meet their own needs [1]", pointing out that current activities should not deprives the future generations of the ability to maintain and endure. Since then, sustainability has drawn a lot of attention from many fields of the world, such as government [2][3] and non-governmental organizations [4][5][6][7], research institutions [8][9][10][11][12] and industries [13][14][15]. Later, the 2005 World Summit on Social Development identified sustainable development goals, such as economic development, social development and environmental protection [16], which now are often referred as three components of sustainability, as shown in Figure 1.1.

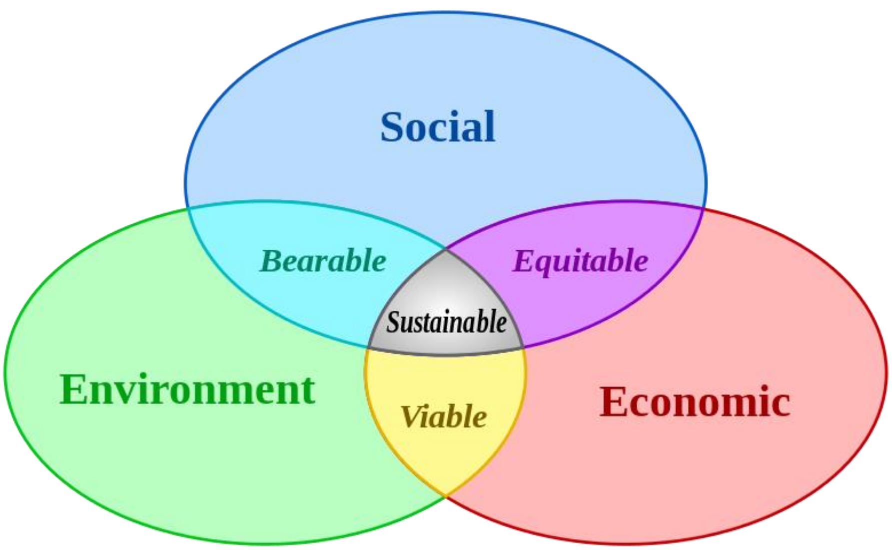


Figure 1.1. Three Pillars of Sustainability (Source: http://www.thwink.org)

A lot of efforts have been made in different fields to foster the sustainable development, including the packaging industry [17][18][19][20][21]. Packaging brings a lot of convenience to our daily life today, so the high demand makes the packaging industry one of the biggest industries in the world [22]. At the same time, packaging is associated with many sustainability issues, such as atmosphere, land use, resource consumption, energy, water, waste and so on [23]. In order to reduce the negative impact, packaging industry is making efforts to enhance the sustainability performance of packaging. Sustainable packaging development involves research multiple aspects, such as the development of new material [24][25][26], landfill waste management [27], recycling method [28], and packaging design decisions [20][21]. In this dissertation, the research is focused on the packaging design selection decision.

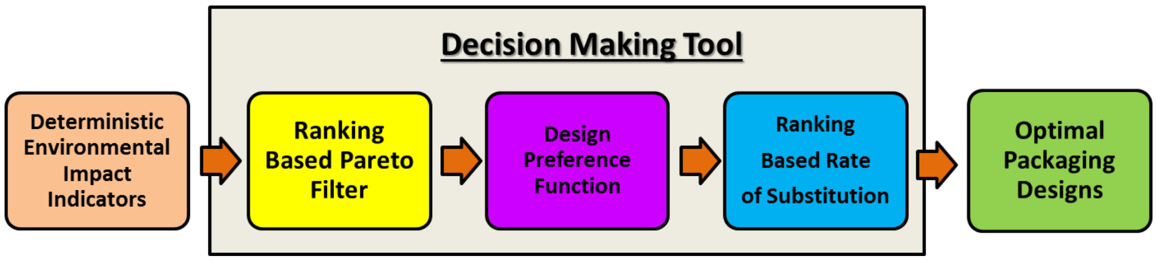
In order to find the more sustainable designs, a packaging design options set needs to be created, from which the more sustainable design will be selected. All the packaging design alternatives need to be analyzed for their environmental impact, so that decision for more sustainable design could be made. Life Cycle Assessment (LCA) is the most used method to conduct the comprehensive evaluation of the environmental impact throughout life cycle, such as climate change, human health, resource consumption, energy, water depletion, ecosystem and so on [23][29][30], thus has been broadly adopted for sustainable packaging design decisions [30][31]. In this dissertation, the Life Cycle Assessment will be conducted for all the designs, and design selection decision will be made that which designs are more sustainable based on the LCA results. A systematic decision making framework is desired to choose the most sustainable packaging from a set of packaging design alternatives. This decision making framework should be able to resolve the following questions:

- How to differentiate the “good designs” and “bad designs” from the many design alternatives?

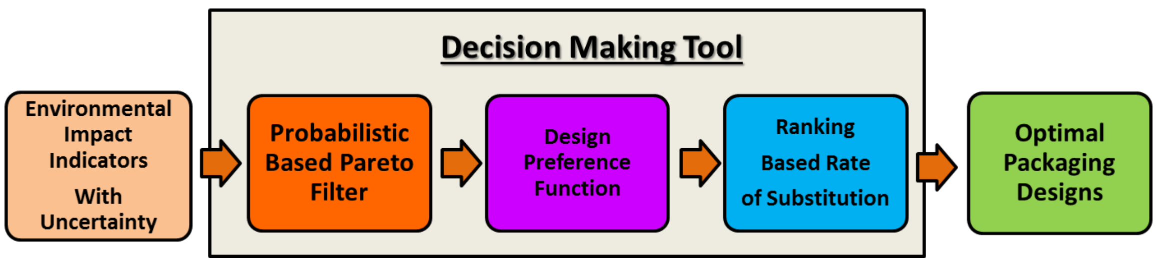
- How to implement the decision maker's preference when choosing the designs?
- How to deal with uncertainty that exists in the environmental impact indicators when choosing the "best design"?

It is challenging to answer the above questions, because of the following reasons: First, results from Life Cycle Assessment for packaging designs are a large set of multi-dimensional environmental impact indicators data, and this makes the problem a Multi-Criteria Decision Making Problem. As a result, there may not be one single best solution. Secondly, trade-off exists among designs, and different design options may excel on different environmental impact indicators that result in conflicting design solutions. As a result, design decision will highly depend on decision maker's preference. The preference is resulted from locations, environmental regulations and so on. How to implement decision maker's inclination into the selection process needs to be solved. Thirdly, the existence of uncertainty cannot be ignored. The presentence of uncertainty makes the decision making process more complicated. As a result, a systematic based decision making method is needed to aid the design selection.

To address the design decision challenges, a ranking based decision making framework using LCA for sustainable design is proposed, as shown in Figure 1.2. Pareto Optima concept is adopted first to find the possible proper design options based on the Life Cycle Assessment result. In order to find the Pareto Optimal solutions efficiently, Ranking Based Pareto Filter algorithm (RBPF) was proposed to find the Pareto Optima in the deterministic case, and Probabilistic Pareto Filter algorithm (PPF) was proposed for the non-deterministic case. Then Design Preference Function (DPF) and Ranking Based Rate of Substitution (RBRS) are proposed to implement decision maker's preference, in order to find the most preferred packaging designs among all the Pareto Optimal designs.



(a) Deterministic Decision Making Framework for Sustainable Packaging



(b) Non-Deterministic Decision Making Framework for Sustainable Packaging

Figure 1.2. Decision Making Framework for Sustainable Packaging Design

1.2. Literature Reviews

In this session, the key research components are reviewed. First, the packaging system and packaging sustainability issues are reviewed. Second, Life Cycle Assessment is then introduced as the sustainability evaluation methodology. Finally, the challenges of sustainable packaging design selection as a Multi-Criteria Decision Making Problem are discussed.

1.2.1. Packaging and Packaging Sustainability

Packaging is the coordinated complex product delivery system preparing goods for transport, distribution, storage, retailing and use [17][32]. Usually, a packaging system includes several different levels, such as primary package, secondary package, and tertiary packaging [22]. Primary package is the first wrap or containment of the product; Secondary package holds one or several primary packages; Tertiary package, also refereed as distribution package, or shipper, groups packages for manual handling and protects the product during shipping [22]. Some examples for the three stages of packaging are shown in Figure 1.3.

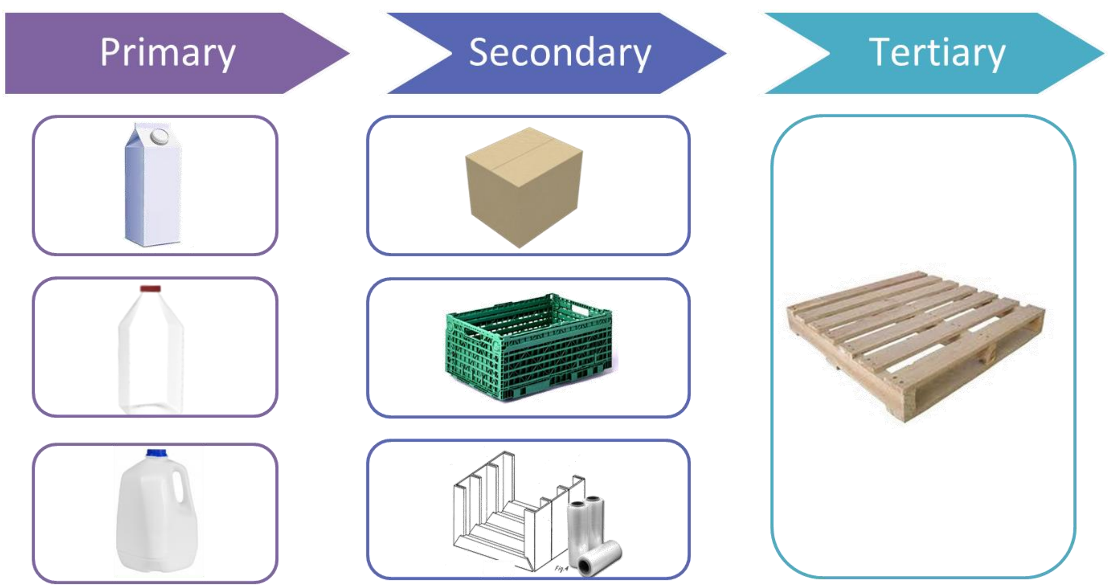


Figure 1.3. Example of Different Stages for Milk Packaging

Almost every product needs a packaging, because of the important role it plays. Packaging offers significant functions for a product, such as containment, protection, preservation, transportation, information and promotion [22]. The containing function have to successfully meet the objective of containing a product, considering the product's physical form such as mobile fluid, viscous fluid and solid/fluid, as well as product's nature such as flammable, fragile and abrasive [22]. The protect function provides the prevention of physical damage for a product, while preserve stops or inhibits chemical and biological changes [22]. The transport function enables the effective movement of goods from the point of production to the point to the point of final consumption [22]. Another function, inform and sell, is very important in today's economic scenarios, in which intensive competition exist between products, thus help customer to understand the specification of the product, hence make the best purchase decision [22]. As a result, the high demand on packaging makes the industry one of the largest in the world, since packaging plays important roles for a large range of industries as shown in Figure 1.4.

(a) Pharmaceutical Packaging (Source: http://www.pharmapackagingsolutions.com)

(b) Food Packaging (Source: http://www.brown-machine.com)

(c) Cosmetics Packaging (Source: http://blog.mjacobandsons.com)

(d) Electronic Products Packaging (Source: http://www.theguardian.com)

Figure 1.4. Packaging Examples for Different Products

However, packaging industry is associated with many environmental concerns. For example, the materials that packaging needs cost a lot of non-renewable natural resources; packaging has been considered as a main waste creator; the manufacturing and transport process cost significant energy and so on [23][33].

As a result, the packaging industry has highly regarded the sustainable development of packaging. There are many perspectives of sustainable packaging development approaches, such as the development of new recyclable and biodegradable material, landfill waste management, efficient recycling method, packaging design selection decision [24][25][26][27][28]. Among all of the perspectives, Packaging design selection decision has received high attention. In this dissertation, packaging design selection decision refers to the process of generating a set of design options, then choosing the more sustainable alternatives based on the environmental impact indicators.

1.2.2. Life Cycle Assessment

In order to evaluate the environmental impact of packaging designs, Life Cycle Assessment has been adopted. Life Cycle Assessment is the detailed analysis to assess the environmental impacts associated with all the stages of a product's life from raw materials extraction through manufacturing, distribution, use, repair and maintenance, and disposal or recycling [34][35][36][37][38][39]. Figure 1.5 shows a typical the life cycle of a packaging, from the extraction of raw material, materials processing, manufacturing, product packaging, transportation, on shelf, delivery to consumer, use, to after disposal activities (recycle, reuse, recover or waste management).

Figure 1.5. Illustration of the Life Cycle for a Packaging Product

Life Cycle Assessment provides a comprehensive approach of investigating the potential environmental impacts of a product [34]. It becomes an important method in sustainability management and decision making, because it has expanded the scope of environmental impact analysis for product to include all burdens and impact in the whole life cycle a product generates, not only focusing the emissions and wastes created only by any of one step of the whole life cycle [40][41]. The result from Life Cycle Assessment can be used to compare design alternatives, and select the most sustainable design alternatives from a generated design set [40]. Thus it can assist in various decision-making activities in industrial, governmental, and non-governmental organizations (such as strategic planning, setting policies, and making choices) [38].

Recently, Life Cycle Assessment has been widely used in packaging design field as an effective tool to quantify and measure the environmental impact of design alternatives [23] [36][38], from where the environmental impact data could be generated, and used as the foundation for making sustainable packaging design decisions.

In this dissertation, the Life Cycle Assessment is performed by utilizing the Life Cycle Assessment packaging database Software. By inputting the design information, such as materials selection, manufacturing process option, and transportation manner, the environmental impact indicators are generated for each design. Those environmental impact indicators are aimed to provide complete information of a packaging design regarding sustainability. For the Life Cycle Assessment Software that is utilized in this research dissertation (PackageSmart from Earthshift [29]), the Impact Assessment categories are descripted below:

Human Health

The damage analysis for “human health” links six impact categories (Climate change, Human toxicity, Photochemical oxidant formation, Particulate matter formation, Ionizing radiation and Ozone depletion) to the DALYs (Disability Adjusted Life Years, the sum of years of potential life lost due to premature mortality and the years of productive life lost due to disability) [29].

Ecosystems

Climate change, terrestrial acidification, freshwater eutrophication, Eco toxicity, agricultural land occupation, urban land occupation, Natural land transformation are the impact categories that apply to ecosystem [29]. The damage to ecosystems is measured by considering the species that disappear in a given time period [29].

Resources

Resources take Fossil depletion and Metal depletion into consideration [29]. The quantification of the damage is based on the marginal increase of cost due to extraction of resources, measured as dollars per kilogram [29].

Water Depletion

Water depletion category quantifies the total water consumed by a process/ product. It is measured as the volume of water consumed (m^3) [29].

Climate Change

There are several gaseous emissions that cause global warming, such as carbon dioxide, methane, nitrous oxides and fluorinated gases [29]. This category combines the effect of differing greenhouse gases remain in the atmosphere and their relative effectiveness in absorbing outgoing infrared radiation [29]. The concentration of greenhouse gases is measured as kg equivalents of CO_2, i.e. the relative global warming potential of a gas as compared to CO_2, and the unit of measure for this category is kg CO_2 equivalents [29].

Cumulative Energy Demand

Cumulative energy demand measures the cumulative energy resources required (total MJs) throughout the life cycle of a package, including energy non-renewable fossil, non-renewable nuclear, non-renewable biomass, renewable biomass, renewable wind, solar, geothermal and renewable water [29].

When making the decision of more sustainable packaging design options in this dissertation, all of the six mentioned environmental impact indicators are desired to be minimized.

1.2.3. Decision Making Challenges for Sustainable Packaging using Life Cycle Assessment

After Life Cycle Assessment was conducted for all the designs, decision need to be made that which designs are more sustainable based on Life Cycle Assessment results. However, the decision making process of chooses the optimal design from many design alternatives that serve the same function is challenging, because of the following reasons: First, Life Cycle Assessment results in a large set of multi-dimensional conflicting environmental impact indicators data, therefore a single best solution may not exist. Secondly, trade-off exists among designs between different indicators; different design options may excel on different indicators that result in conflicting design solutions. As a result, design selection decision will highly depend on decision maker's preference, which results from locations, environmental regulations and so on. Finally, the evaluation of environmental impact indicator often involves uncertainty, which makes the selection more complicated.

Multi-Criteria Characteristic

The environmental impact indicators obtained from the Life Cycle Assessment are multi-dimensional and conflicting data. This makes the sustainable packaging selection process a Multi-Criteria Decision Making problem [42][43][44][45][46]. A Multi-Criteria Decision Making problem refers to a decision making problem that has multiple, usually conflicting criteria, which are the environmental impact indicators in this dissertation. In general, there are two different types of Multi-Criteria Decision Making Problem due to the different problems settings: in the first type, there are a finite number of alternative solutions and in the second type there are an infinite number of solutions. The infinite solutions come from the continuous range of design variables, while when the design inputs are discreet, only finite number of solutions will be generated [47][48][49]. In this research dissertation, because the design variables are materials selection, manufacturing process selections, and transportation manners, the focus is the Multi-Criteria Decision Making problem with a finite number of alternatives.

To better illustrate the challenge, a simple example of Multi-Criteria Decision Making problem is considered here, as shown in Figure 1.6. There are four design options that are analyzed by the Life Cycle Assessment tool whose results include six environmental impact indicators, f_1 to f_6 , as climate change, energy demand, ecosystem, human health, resources, and water depletion, as the radar chart plotted. In our study, the smaller value of each indicator represents a better performance towards sustainability. From the radar chart, comparing the four designs' environmental impact indicators, it is obvious that options D4 has a larger value than D1, D2 and D3 on every indicator, so will not be considered as a good design. However, decision of determining which is better among D1, D2 and D3 is very difficult, because each of them have trade-off. D1 has good performance on all criteria but f_1; D2 is better than D1 on f_1 but worse on all other criteria, while it presents equal or better performance on f_1, f_2, f_4, f_5 than D3; D3 is better than D1 only on f_1, and better than D2 on f_3 and f_6. In such a situation, no single optimal solution exists.

Therefore, instead of searching for the one best design, finding all "good packaging options" is obviously necessary. These "good designs' refers to Pareto Optimal design in this dissertation, which will be introduced in the next chapter. In the example showed above, all D1, D2 and D3 are called Pareto Optimal designs for the original design alternatives set of four. The whole subset set that containing all Pareto Optimal designs of D1, D2 and D3, is called Pareto Front. In reality, the design options set could be much larger; as a result, it is important to have an efficient algorithm to search for the Pareto Optimal designs since one package could have a variety of design options.

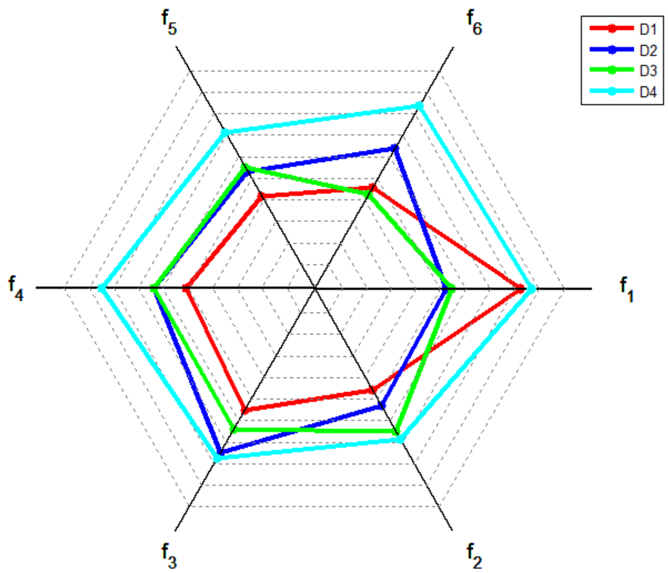


Figure 1.6. Multi-Criteria Decision Making Example

Trade-off between Solutions

After the Pareto Front is found from the original design set, the selection of the best packaging options among the Pareto Front become necessary since there is no one single best design exists, and the "best solution" varies according to different decision maker's inclination. In general, designers make decisions depending on their preference from Life Cycle Assessment results. For example, in Figure 1.7, D1, D2, and D3 are all Pareto Optimal designs, and comparison for them will depend on the inclination of the decision maker. If f_1 is a very important indicator, then D1 should not be considered as a good candidate, since it has a significant bad performance on f_1; but D2 should be considered as a good choice, as well as D3. Similarly, D1 and D2 should be selected if the designer has a higher priority about f_2.

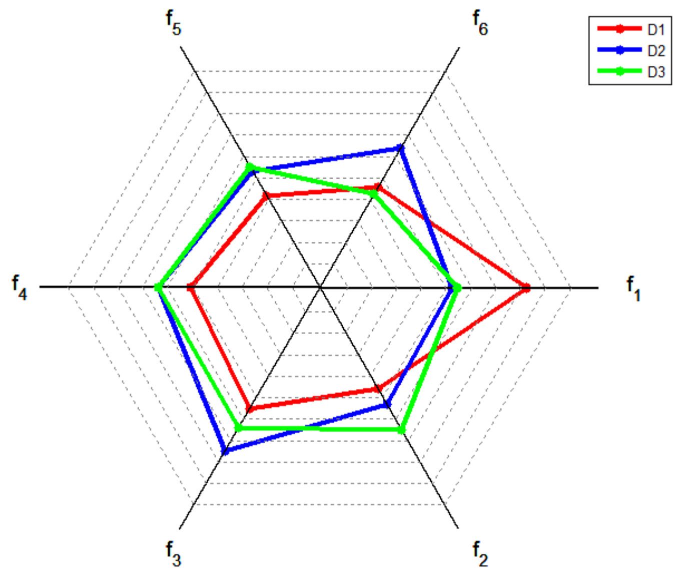


Figure 1.7. Pareto Front of the Multi-Criteria Decision Making Problem

The implementation of decision maker's preference is necessary and challenging. Also, the large number of Pareto Optimal Designs also makes this process complicated to handle. Therefore, it is critical to have a systematic way to incorporate the designer's preference into the decision making process to select the most sustainable packaging designs.

Presence of Uncertainty

The environmental impact indicator value from Life Cycle Assessment may not be deterministic. Instead, the environmental impact indicator values may involve uncertainties due to many reasons. For example, the LCA data has uncertainty because of lack of data collection or unrepresentative data. Moreover, the design model itself also has uncertainty because of manufacturing process, or some other factors. Additionally measurement errors can also affect to the uncertainty of LCA results. The presence of uncertainty may not be ignored. And design selection under uncertainty makes decision process more complicated.

To better illustrate this challenge, Figure 1.8 shows an example of the presence of the uncertainty in one environmental impact indicator. Assume that the water depletion follows normal distribution, and two designs' (D1 and D2) water depletion is plotted in Figure 1.8. The mean value (μ^{D1}) of 'design D1 shows lower water depletion tan mean value (μ^{D2}) of design D2. However, from the distribution curve, there is a possibility that the water depletion of D2 design can be lower than design D1. Therefore, depending on the criteria of probability from the decision maker, D2 design can be also selected which in a deterministic comparison cannot be the case.

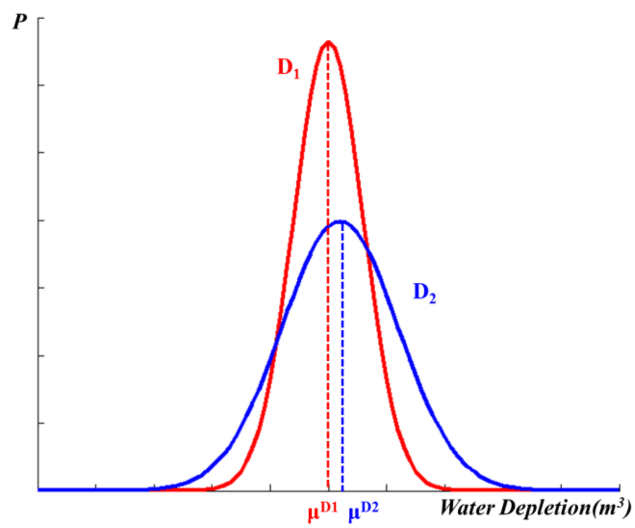


Figure 1.8. Uncertainty in the Environmental Impact Indicator of Water Depletion which is assumed to be normally distributed

1.2.4. Current Existing Methods for Multi-Criteria Decision Making Problem

Research for Multi-Criteria Decision Making problem could be back to 1950's, and has been continuously growing since then. There are different types of approaches for solving a Multi-Criteria Decision Making problem, which are briefly reviewed here [42][45][47][50][51][52][53][54][55][56]. Mainly, there are two concepts of finding optimal solutions for a Multi-Criteria Decision Making Problem. First type of approach converts the multi-dimensional data into single-dimensional data, and then creates an order based on the single dimensional data. So the decision maker could choose "the best solution" or choose several solutions from top order to bottom order. The other type of approach finds all the good solutions, which are refereed as Pareto Optimal solutions, and then do analysis about the good solutions, thus further find the best solutions.

In the first category, there are different families of methods such as the weighting methods, similarity to ideal point method, the outranking Method, utility theory. The weighting method includes Weighted Sum Method and Weighted Product Method [51]. In the case of minimizing all objectives, the Weighted Sum Method converts the multiple objectives into one objective by assign a set of weights to each of the objective, and finds one best solution that has the smallest weighted sum of all objective values. Similarly, the Weighted Product Method finds the smallest weighted product of all objective values [51]. However, there are several drawbacks of the weighting methods: First, the weighting methods are only applicable when all the objectives are expressed in exactly the same unit; however, the six environmental impact indicators are in different unit and scale. Secondly, the weighting method finds only one solution, however, when choosing the sustainable packaging designs, it is important to provide a small set of designs, in the case that more decision factors will be considered that are beyond the Life Cycle Assessment indicators. Thirdly, an inherent problem of weighting methods is that the weighting is difficult to decide among the objectives.

The similarity to ideal point method , which includes The Technique for Order Preference by Similarity to Ideal Solutions (TOPSIS) and Compromise Programming (CP) [51][54]. The methods of finding the similarity to ideal point also will fail when the objectives are not in the same scale, because the larger scaled objectives will weaken the effects of smaller scaled objectives, so is not a good options for the sustainable packaging decision making problem, due to the significant of scale different between the environmental impact indicators.

The outranking method, which includes The Preference Ranking Organization Method for Enrichment Evaluation method (PROMETHEE) and The Elimination and Choice Translating Reality method (ELECTRE) [51][54]. Both of PROMETHEE and ELECTRE perform pair-wise comparison of alternatives in order to rank them with respect to a number of criteria.

The utility theory includes mainly Multi-Attribute Utility Theory (MAUT). This method could solve the problem that Weighted Sum Method could not resolve that different scale of decision attributes could not add up, by convert the real decision attribute values into the utility value, then the total utility will be summed up, and all designs could be ordered. But the weight is usually very hard to define for all of the design attributes [51][54].

All methods in the first category try to order and rank the design from the best to the worst, according to specific index the method created. However, those designs that are dominated by the better designs have not been eliminated, and the ranking may vary according to different methods and difference decision parameters, also the order and ranking will fail to present the trade-offs between the solutions, as a result, decision made based on the order may not be reliable.

In the second category, the Pareto Optimal solutions are the solutions that cannot be improved on any attribute without sacrificing on other attribute. This method could help the decision maker to avoid choosing any design that still can be improved by another solution.

As a result, a systematic decision making process need to be created to first get rid of the “bad solutions”, and then analyze the advantage and disadvantage between solutions over the design attributes. To achieve this goal, this dissertation constructed such a decision making framework, and the detailed research contribution is introduced in the next session.

1.3. Research Contributions

The principal goal of this dissertation is the development of decision making framework for sustainable packaging design selection, based on the environmental impact indicators produced from the Life Cycle Assessment of a design alternatives set. Selecting the most sustainable designs from a design alternatives set is achievable by understanding how to differentiate good designs and bad designs, how to implement the decision maker’s preference, and how to cope with the uncertainty.

One key contribution of this dissertation is that it formulates the sustainable packaging design problem as a Multi-Criteria Decision Making Problem, develops a decision making framework, integrating Pareto Optima Concept, Design Preference Function, Ranking Based Rate of Substitution, Probabilistic Pareto Filter Algorithm on the decision making for sustainable design, provides a foundation for different stages of decision making process. Even there are existing work related to Multi-Criteria Decision Making Problem, not any of them could solve the entire problem for the Sustainable Packaging design selection problem, because the design have to satisfy many decision factors, such as regulation, decision maker's preference due to local situation and so on. So according to the practical need of packaging design selection scenario, the two phases decision making framework was formulated.

Inside of this decision making framework, one contribution of the research is the Ranking Based Pareto Filter algorithm, which employees the ranking concept to improve efficiency of Pareto Front filter process, to find the "good designs" among the design options set.

Another contribution in the decision making framework is the Design Preference Function and Ranking Based Rate of Substitution, which incorporate the decision maker's preference, to find the most preferred designs from the Pareto Optimal designs. By implementing decision maker's preference using these two methods, several preferred sustainable design can be obtained, giving the flexibility to the decision maker to finalize the choice according to some decision factors beyond the Life Cycle Assessment, such as resource accessibility, and avoided to generate only one solution which many Multi-Criteria Optimization methods do.

Finally, the development of Probabilistic Pareto Optima Filter algorithm helps to facilitate the design decision when uncertainty exists.

Figure 1.9 schemes the systematic strategy to aid the decision making process to find the most sustainable packaging designs using the proposed decision making framework, in both the deterministic and non-deterministic scenario.

At the beginning, a set of design alternatives are necessary to be generated. Then the Life Cycle Assessment is performed for all the designs, and the environmental impacts are obtained. The environmental impact indicators may be deterministic or non-deterministic. In the deterministic case, the Ranking Based Pareto Selection Method eliminates the “bad design”, and Design Preference Function and Ranking Based Rate of Substitution choose the decision maker’s preferred sustainable designs. In the non-deterministic case, the uncertainty was addressed in the first phrase of the decision making framework. Probabilistic Pareto Filter algorithm was proposed to find the “good designs”, Ranking Based Rate of Substitution were utilized to deal with the environmental impact indicators variation, thus find the most decision maker preferred designs.

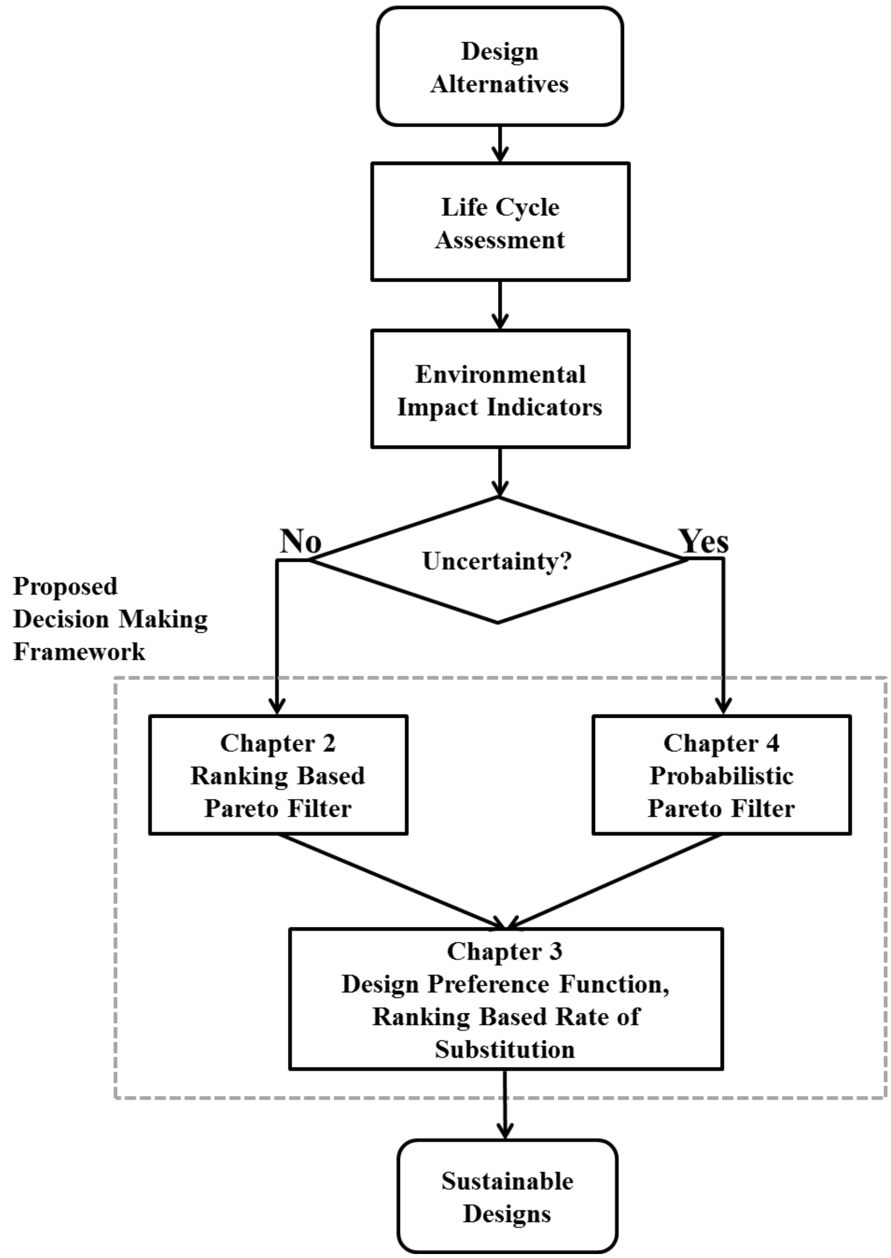


Figure 1.9. Research Component of Decision Making Framework for Sustainable Packaging Design

1.4. Overview of the Dissertation

The reminder the dissertation is organized as below:

In Chapter 2, the first phase of the decision making framework- Pareto Optima is discussed. Ranking Based Pareto Filter algorithm was proposed to improve the efficiency of Pareto Front filter algorithm, as well as to improve the flexibly of choose only part of the Pareto Optima. Chapter 3 presents how to implement decision maker’s preference, to find the “best design’. Design Preference Function and the Ranking Based Rate of Substitution method were proposed to achieve this goal. In Chapter 4, probabilistic Pareto Filter algorithm is proposed based on the Ranking Based Pareto Selection method, to address the uncertainty in the Pareto Optima search process. In Chapter 5, the proposed decision making framework is utilized to solve the Multi-Criteria Decision Making problem for sustainable packaging selection, to illustrate the effectiveness of the whole decision making framework by showing two case studies, including deterministic case and non-deterministic case. In Chapter 6, a conclusion is provided for this study and a future research plan is proposed.

1.5. Summary Remarks

This chapter has provided an introduction of the dissertation on decision making framework for sustainable design using life cycle assessment. The motivation and research background were first introduced. Then the challenges for the sustainable packaging design decision problem were discussed. There are mainly three challenges. First, LCA results are a large set of multi-dimensional environmental impact indicators data, there may not exist a single best solution. Secondly, trade-off exists among designs between different indicators, and each non-dominated design has its advantage and disadvantage. As a result, decision will highly depend on decision maker’s preference.

The preference results from locations, environmental regulations and so on. Finally, the uncertainty existence makes the selection more complicated.

In the next chapter, the Multi-Criteria Decision Making formulation and Pareto Optimal solutions will be introduced, and the first research component- Ranking Based Pareto Selection method will be discussed, to address the first challenge-how to differentiate the good designs and bad designs efficiently.

Chapter 2.

The Pareto Optimal Solutions for Multi-Criteria Decision Making Problem

2.1. Introduction

The selection of sustainable packaging design needs to be based on the environmental impact indicators, which can be acquired by performing Life Cycle Assessment. The multi-dimensional, often conflicting data from Life Cycle Assessment make the sustainable packaging design decision problem a Multi-Criteria Decision Making problem. As a result, among many design alternatives, "one single best solution" may not exist. Instead, the search for all "good designs" is of significant importance. This refers to the Pareto Optimal solutions, or non-dominated solutions. When the design alternatives population is big, an efficient algorithm to find the Pareto Optimal solutions is imperative. This chapter is directed at the first challenge of the decision making problem for sustainable packaging designs, which is how to differentiate the "good designs" and the "bad designs". The overview of Multi-Criteria Decision Making Problem, definition and terminology, and current existing method of Pareto Front search algorithm are discussed. Then the Ranking Based Pareto Filter algorithm is proposed, with an example explaining the process of the method.

2.2. Multi-Criteria Decision Making Problem (MCDM)

As mentioned in the introduction, because the results from Life Cycle Assessment are multi-dimensional characteristic of the environmental impact indicators, the design selection process is a Multi-Criteria Decision Making Problem, and we are trying to choose the most sustainable designs from a set of design alternatives, each with multiple environmental impact indicators. Here some terminologies are introduced for Multi-Criteria Decision Making Problem, which will be used in this dissertation:

The Multi-Criteria Decision Making problem of N objectives in the sustainable packaging design selection context can be formulated as follows in Equation (2.1):

$$
\begin{aligned}
\min_{X} \quad & f_i(\vec{X}) & i = 1, \ldots, N \\
\text{s.t.} \quad & g_l(\vec{X}) \leq 0 & l = 1, \ldots, L \\
& h_q(\vec{X}) = 0 & q = 1, \ldots, Q
\end{aligned}
\tag{2.1}
$$

Where f_i is the i^{th} objective function, $X=(x_1,\ldots x_I)$ is the vector of discrete design variables, g_l is the l^{th} inequality constraint function, and h_q is the q^{th} equality constraint function.

Design Variable Space

The I-dimensional vector X is the components of the discrete design variable. In the sustainable packaging design selection context, the design variable includes the materials selection, manufacturing process selection, and transportation manner.

Design Alternatives Space

The combination of design variables, forms a design alternative. In other words, a vector of design variables can represent a design alternative. For example, a water bottle was made from PET, manufactured by injection molding, and transported by diesel truck is a design alternative, and the material-PET, manufacturing method -injection molding, and the transportation manner –diesel truck are the design variables. Any feasible change of the design variables will form a new design alternative. All of the design alternatives form the design alternatives space.

Design Attribute (Objective) Space

The N-dimensional space whose coordinates are design objectives functions (i.e. $f_{1,\ldots}f_n$). In this dissertation, each point in this space represents the environmental impacts indicators of a design alternative. The performance attribute of a design alternative are evaluated by inputting the design variable information into Life Cycle Assessment in this space [57]. The relation between the Design Alternatives Space and Design Attribute Space is pitched in Figure 2.1. Let Di designate a feasible alternative and denote the set of all feasible design alternatives by D. To an element Di in D, there are n indices of value associated with it: f_1 (Di) ,…, f_n (Di). We can think of the n evaluators f_1 ,…, f_n as mapping each Di in D into a point in an n-dimensional consequence space [57].

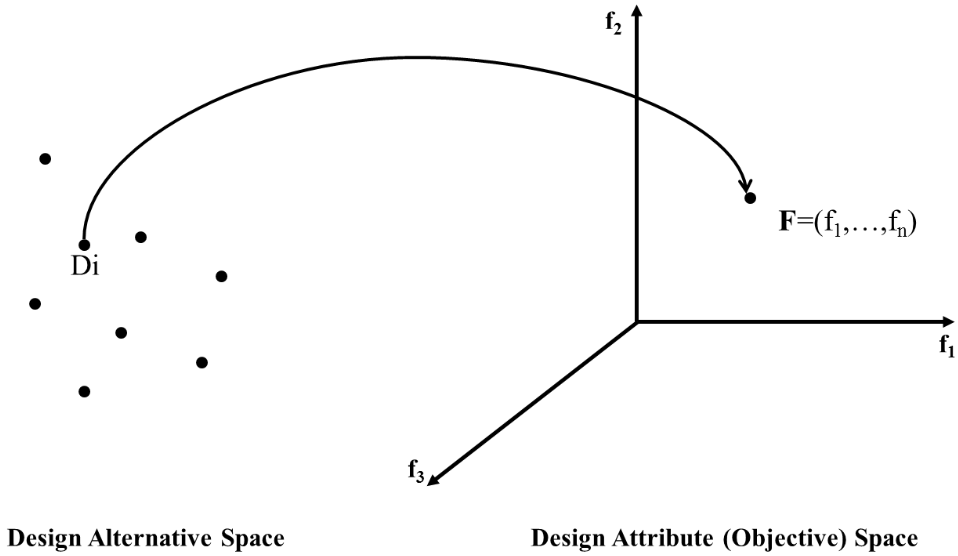


Figure 2.1. Mapping from Design Alternative Space to Design Attribute Space

2.3. Solution of Multi-Criteria Decision Making Problem: Pareto Optimum

In order to select the more sustainable packaging designs, a set of packaging design will be generated. In order to get the objective values, which are the environmental impact indicator value, of every design on each criterion, the designs are evaluated by Life Cycle Assessment. The results from Life Cycle Assessment are multiple dimensional data. When there are multiple conflicting objectives, the optimal solutions could not be the unique solution any more, since different design could be excel at different environmental impact, and not any of them could be considered as absolutely bad or good. Instead, a subset of all the good design options needs to be found. These solutions are called “Pareto Optima”.

In order to define the Pareto Optima, the definition of dominance is first introduced here:

A design decision vector $\vec{f}^1 = [f^1_1, f^1_2, ..., f^1_N]^T$ is said to dominate the decision vector $\vec{f}^2 = [f^2_1, f^2_2, ..., f^2_N]^T$, in a minimization context, if and only if [58]:

$$\begin{aligned} & f^1_i \le f^2_i,\ \forall i \in \{1,...,N\} \\ \text{and} \quad & f^1_i < f^2_i,\ \exists i \in \{1,...,N\} \end{aligned} \tag{2.2}$$

Where N is the number of decision attributes.

In this dissertation, a design decision vector is the environmental impact indicators for a design alternative. Figure 2.2 shows an example of the dominance relation between some data points, in a two-dimensional space. In the case that both f_1 and f_2 to be minimized, solution A dominates solution B, since on both f_1 and f_2, A is smaller than B. Similarly, C also dominates B for the same reason. But A does not dominates C, and C does not dominates A, because neither A is better than C on both f_1 and f_2, nor C is better than A on both f_1 and f_2.

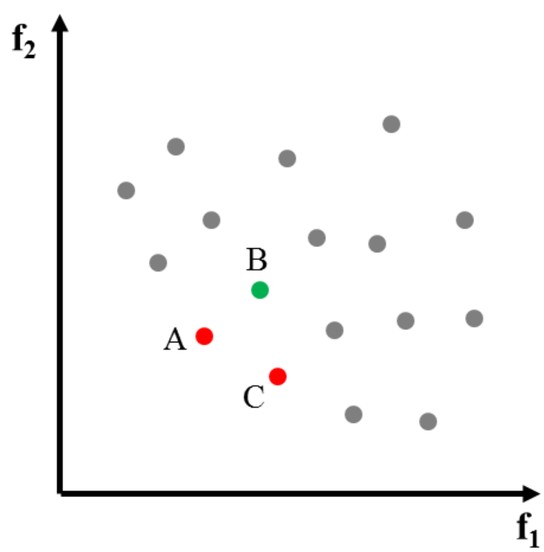


Figure 2.2. Illustration of Dominance Relation between Designs

After the dominance relation is introduced, then the Pareto Optimum can be easily defined as follows: a design Di is said to be Pareto optimum if and only if there does not exist another design that dominates it. In other words, within the design alternatives set, solution Di cannot be improved by another solution in any objective without adversely affecting at least one other objective. The corresponding objective vector $\vec{F}(\vec{D}i)$ is called a Pareto dominate vector, or non-inferior or non-dominated vector [58][59]. The set of all Pareto Optimal solutions is called the Pareto Optima Set, or Pareto Front [55][56]. Pareto Optima is named after Vilfredo Pareto (1848-1923), an Italian economist who used built the fundamental in modern theory of Multi-Criteria Analysis [60].

Figure 2.3 shows an illustration of Pareto Front of a set of two-dimensional data. The red points dominate all of the grey points. Thus, the red points construct the Pareto Front of the original data.

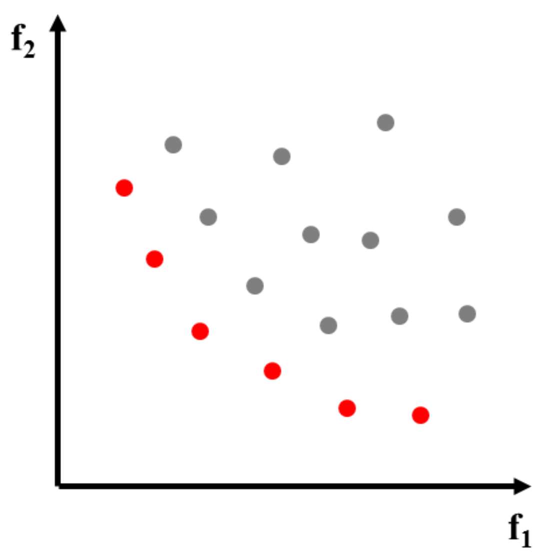


Figure 2.3. Pareto Front for a Two Dimensional Case

2.4. Pareto Optimal Search Algorithm

Literature review shows that in the Multi-Criteria Decision Making problem with a finite number of decision vectors, the Pareto Front are usually found by the conventional method-Exhausting Search method [61]. The flow is shown in Figure 2.4 [61].

This Pareto Filter Algorithm is described below in four steps [61]:

Step-1: Initialize

Initialize the algorithm indices and variables:

i=0, j=0,k=1, and m=number of generated solutions.

Step-2: Set i=i+1; j=0.

Step-3: (enclosed in dashed box): Eliminate non-global Pareto points by doing the following:

j=j+1

If i=j go to the beginning of Step 3

Else Continue

If $\vec{f}^{\,i} \neq \vec{f}^{\,j}$ and $(\vec{f}^{\,i} - \vec{f}^{\,j})_s > 0$, $\forall s$

Then f^i is not a Pareto Point.

Go to Step 4.

Else if j=m

Then f_i is a Pareto Point.

$\vec{P}^k = \vec{f}^{\,i}$

k=k+1

Go to Step 4.

Else go to the beginning of Step 3

Step-4: If i≠m, go to Step 2, else end.

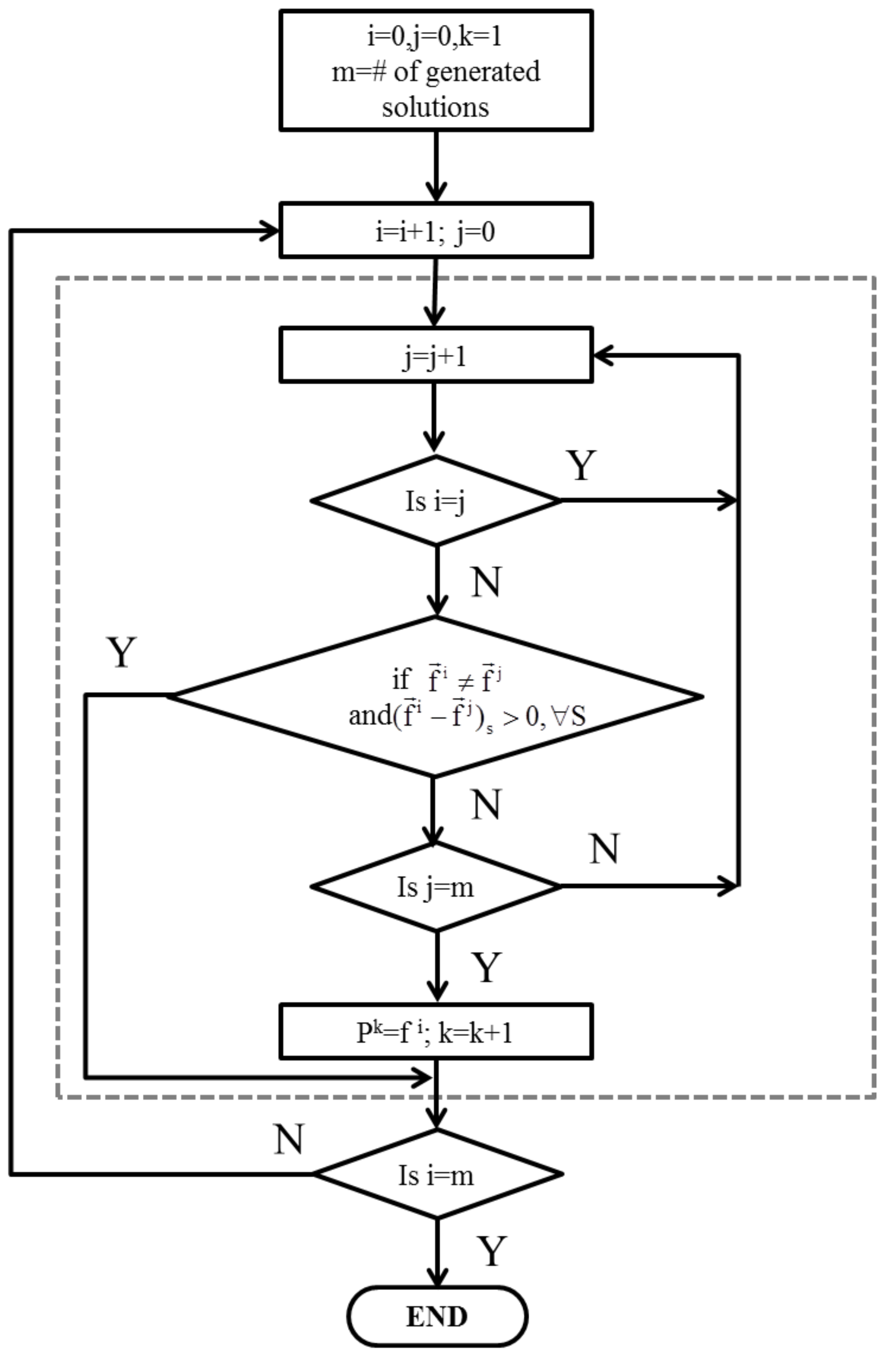


Figure 2.4. Flow Diagram of Exhausting Search Pareto Filter [40]

This algorithm is very simple but is not efficient because every option much be compared again the entire set of design options until all Pareto optimal solutions are found. It finds the Pareto Front by checking every point with other point, on each dimension, to determine the dominance relation between one design and another. In this process, a data point will be picked randomly, and then compared with other data point in a random sequence. If a data point is investigated to be a Pareto Optima, it will be marked as Pareto Optimum, then put back to the whole set of data, and the next data will be picked randomly from the data set, randomly, repeat the same procedure. Eventually, all the Pareto Front is found.

For the decision making problem for the sustainable packaging design, the design alternatives set is usually large. When apply the Pareto Filter Algorithm, if not all the Pareto Optimal solutions are not necessarily to be found, and instead, only the top choices according with respect to an indicator are need to be found out, this algorithm obviously are not efficient enough.

In order to improve the efficiency of the Pareto Front filter algorithm, at the same time, finding Pareto Front with integrating decision maker's preference, Ranking Based Pareto Filter Algorithm was proposed, which is introduced in session 2.5.

2.5. Ranking Based Pareto Front Filter Algorithm

From the previous sections, we know that the exhausting searching Pareto Front filter algorithm is widely used to find the Pareto Optimal Designs from a set of design options because the algorithm is simple. This algorithm is straightforward but not efficient enough, since some of the non Pareto Optima are kept in the comparing process until the entire Pareto Front is found. To improve the efficiency of generating the Pareto Front, a new algorithm could aim to eliminate the unnecessary design comparison, by excluding some undesired designs during the process. The Ranking Based Pareto Filter algorithm is proposed to meet this goal.

The development of this algorithm is based on the natural extension of the definition of dominance, as follows:

Assume none of any two designs in the set have the same value on any decision attribute, then a design decision vector $\vec{f}^1 = [f^1{}_1, f^1{}_2, ..., f^1{}_N]^T$ does not dominate the decision vector $\vec{f}^2 = [f^2{}_1, f^2{}_2, ..., f^2{}_N]^T$, in a minimization context, , if and only if:

$$f^1{}_i > f^2{}_i,\ \exists\, i \in \{1, ..., N\} \tag{2.3}$$

Where N is the number of decision attributes.

Now assume there are M designs, we sort them according to one decision attribute, for example f_1, in a descending order. So the first design D1 after the sorting is the best design with respect to f_i , which is a Pareto Optimal Solution. Also, after the sorting, any design Dn will not dominate any design before it, that is Di (i=1~ n-1), because it is certain that Dn is worse than Di on the fi, where fi is the attribute that all the data sorted about. So we know that if a design Dn is dominated by any Pareto Optimum before it, then it is not a Pareto Optimum. If a design is not dominated by any Pareto Optimum before it, then it is not dominated by any other design, thus it is a Pareto Optimum.

To apply the Ranking Based Pareto Filter Algorithm, the top prioritized environmental impact indicator needs to be selected, and sort all the designs with respect to it. The indicator is determined by preference of decision maker or importance of environmental considerations. After sorting, it is obvious that the first design is a Pareto Optimum, which has the best performance on the most prioritized environmental impact indicator. Since the latter design will not dominate the designs before it, one design only needs to be compared to the higher ranked Pareto Optimal design to check whether it is Pareto Optimum or not.

To further explain the mechanism of the proposed algorithms, an example is shown in Figure 2.5 to Figure 2.7, where packaging design options are plotted for the two dimensional cases. If designer defines f_1 as the most important indicator, then all data can be ranked based on f_1. So we can get the ID of the designs from 1 to 17. Therefore D1 is a Pareto Optimum, and here we plot all Pareto Optima in red, and initialize the Pareto Front ={D1}. Then we need to move to the next point, D2, to check it is a Pareto Optima or not. D2 only needs to be compared with only higher ranked Pareto Optimal design, which in this case is D1, to check if it is dominated by D1 and do not need to be compared with lower ranking points. In the two dimensional case, to apply the dominance check, we only need to compare D2 with D1 on f_2 . Since D2 has a worse performance than D1, so we can conclude, that D2 is dominated by D1, so it is also a not Pareto Optimum. So the updated Pareto Front ={D1}.

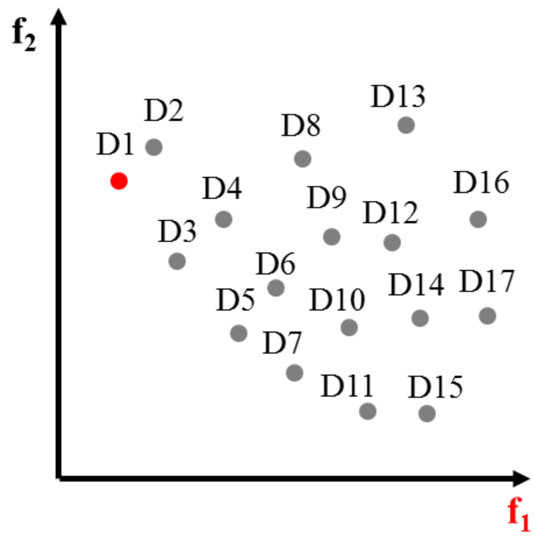


Figure 2.5. Illustration 2D Ranking Based Pareto Selection Method

Figure 2.6 illustrates the next step, exam D3 is a Pareto Optimum or not. When checking D3, we only need to compare D3 with D1. And D3 is not dominated by D1, so is a Pareto Optimum. The Pareto Front is updated as {D1, D3}. Then the dominance check continues until all the data are checked, in the case the all Pareto Optima are desired to be found.

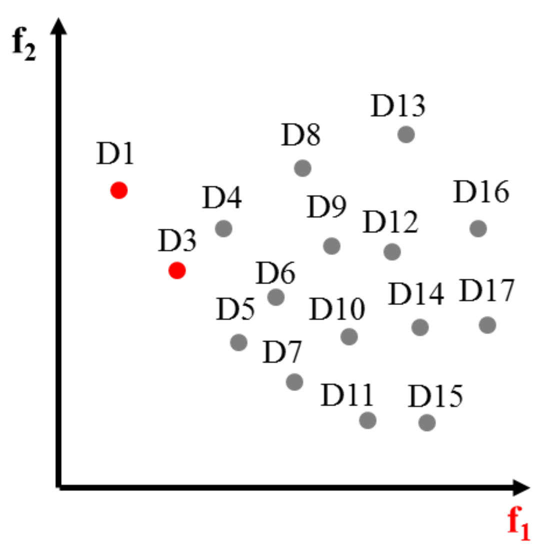


Figure 2.6.Illustration 2D Ranking Based Pareto Selection Method

Through ranking a design based on one of the indicator, the Pareto Front selection can be found more efficiently. The whole Pareto Front consists of Design D1, D3, D5, D7, D11 and D15 are identified as Pareto Optimal design, as shown in Figure 2.7.

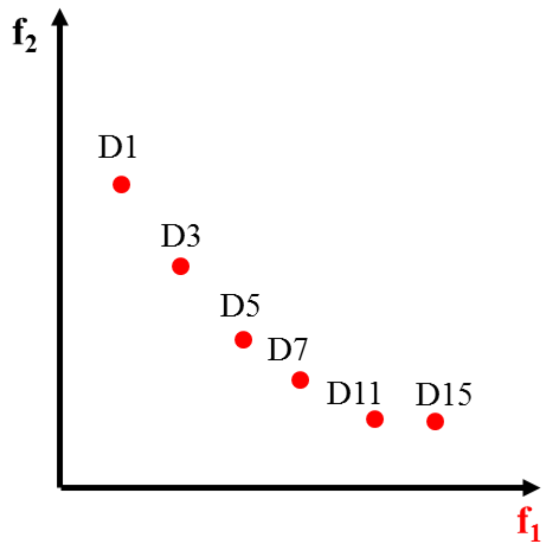


Figure 2.7. Pareto Front of Obtained Using Ranking Based Pareto Filter Algorithm

The Ranking Based Pareto Filter algorithm is summered below step by step, for finding the whole Pareto Front case, and followed with the flow chart in Figure 2.8.

Step-1: Set the most prioritized design attribute fq, q is any number from 1 to n,

n=number of design decision attribute.

Rank all designs with respect to fq, to get the design's ID D_i,

i=[1,…,m]， m=number of designs.

Step-2: Initialize the algorithm indices and variables:

i=1, j=1, k=1, l=1

P=[D_1],

l is the number of Pareto Optima

Step-3: Set i=i+1; j=1

Step-4: Set j=j+1

Step-5: Check one design is dominated by the current Pareto Optima set or not by checking:

If $Di \neq Pk$

and $(Di-Pj)s \geq 0, \forall s$

Then Di is dominated by P^k

Go to step-6

Else if k=l

Update Pareto Set P, P ={D1, Di}

Else go to step-4

Step-6: If i=m, go to step-3, else end.

In a case that not all the Pareto Optima are need to be found, step-6 is not necessary to be checked, and Pareto Search process could stop at the step that qualified number of Pareto Optima are found.

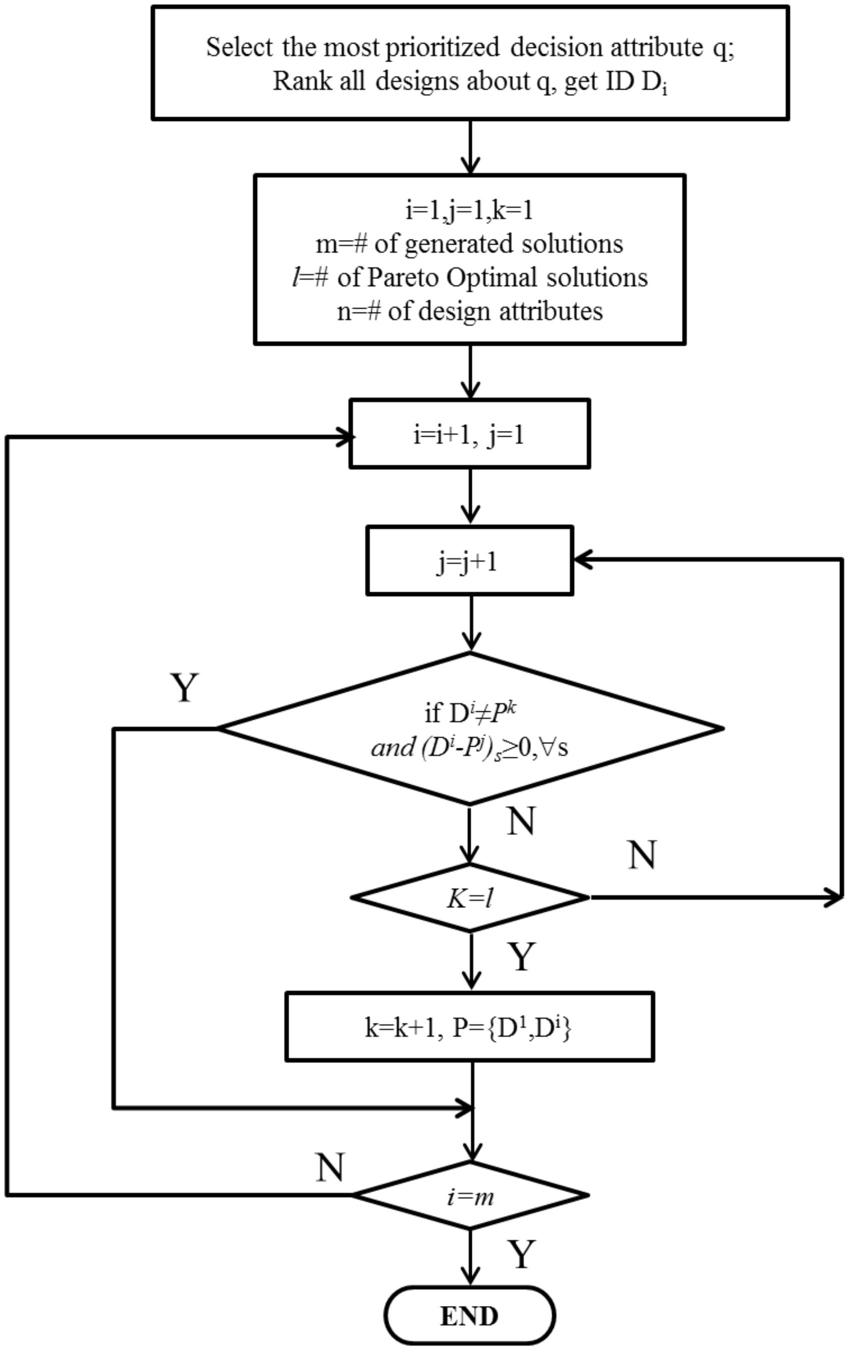


Figure 2.8. Flow Chart for Ranking Based Pareto Filter Algorithm

The Ranking Based Pareto Filter algorithm could significantly improve the efficiency of the Pareto Front search process, when all the Pareto Optimal Solutions needs to be found, because those dominated design have been eliminated to avoid any repeated and unnecessary comparison. Comparing with the Exhausting Search Filter

Algorithm, the computation cost could be reduced from n^2 to $n*\log(n)$. When only part of the Pareto Optimal need to be found, this algorithm could avoid doing unnecessary comparison.

2.6. Example

Here we show an example as a demonstration for the Ranking Based Pareto Filter algorithm.

Assume there are 6 six-dimensional design vectors, which is plotted in Figure 2.9. We will find all of the Pareto Optima according to the f_1 dimension, using Ranking Based Pareto Filter Algorithm. Here we use different color to represent different designs. Assume all dimensions' values are in the range of (0~10).

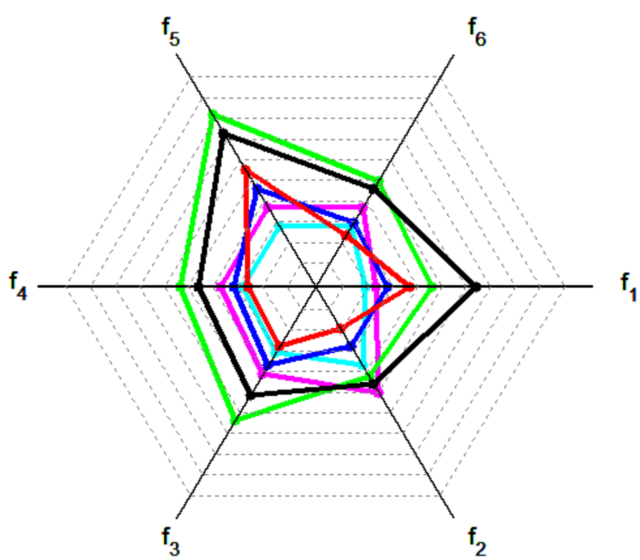


Figure 2.9. Radar Chart of the Environmental Impact Indicators of All Design Alternatives

First, we demonstrate how to use this algorithm to find the whole Pareto Front:

Step-1: Pick up the top prioritized design attribute, rank, initialize

Pick up the most important indicator; here assume f_1.Then rank all the design vectors according to f_1 in the ascending order, as D1, D2, D3, D4, D5 and D6, as shown in Figure 2.10.

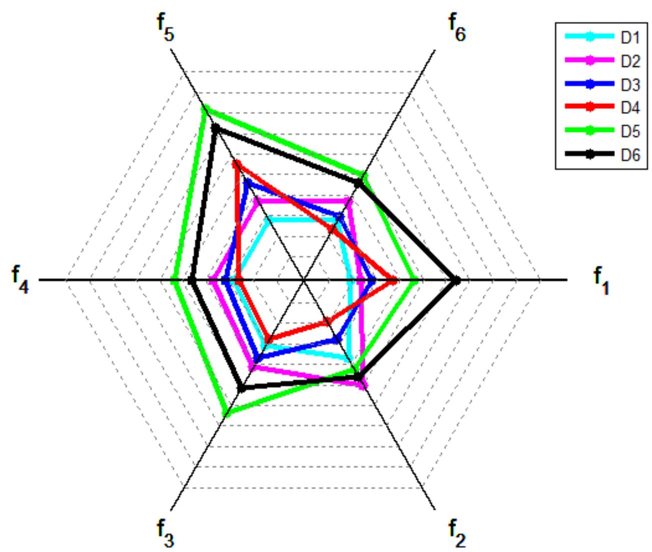


Figure 2.10. Ranking of Whole Set of Design Alternatives with respect to f_1

Step-2: Dominance Check

Since D1 has the best performance on f_1 among all the design vectors, so it is automatically a Pareto Optimum. Then we need to check the dominance of D2: compare D2 with the current updated Pareto Front, which is D1, on all of the rest of the environmental impact indicators, f_2-f_6.Then D2 is found to be dominated by D2, so it is not a Pareto Optimum. In Figure 2.11, we use dashed line to indicate a design is a Pareto Optimal design; the dominated design will remain in solid line. So up to this step, only D1 is found a Pareto Optimum.

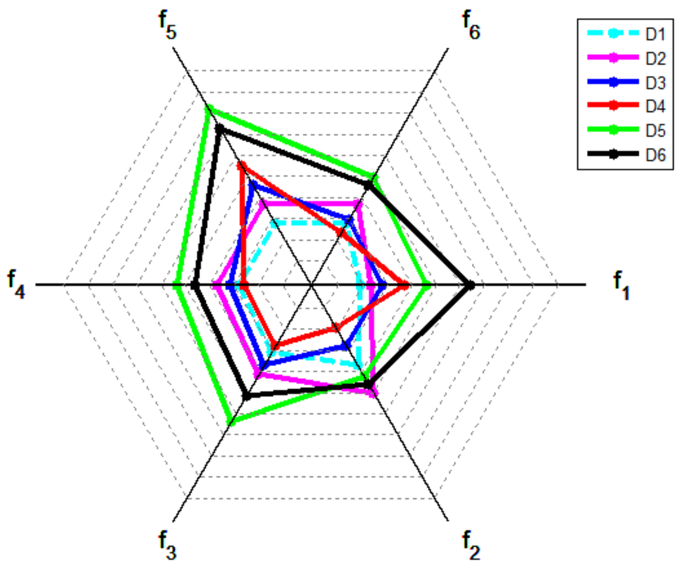


Figure 2.11. Update the Pareto Optimal Solutions

Step-3: Dominance check for all of the rest designs

Then move to the next design vector, D3, compare with the current Pareto Optima Set, that is, D1. Then we found s3 is not dominated by D1, since on f_2, D3 has a smaller value than D1.so we update the Pareto Optima Set as {D1, D3}.Then repeat to the next design vector, until to D6.

Finally, the result has been plotted in Figure 2.12. All Pareto Optima have been plotted in dashed line, and non-Pareto Optima have been plotted in solid line. From the figure we can see, D2 is not a Pareto Optimum, because it is dominated by D1. D5 is not a Pareto Optima, because it is dominated by D1, D3 and D4. Similarly, D6 is not a Pareto Optima, because it is dominated by D1, D3 and D4. So the whole Pareto Front consists of D1, D3 and D4.

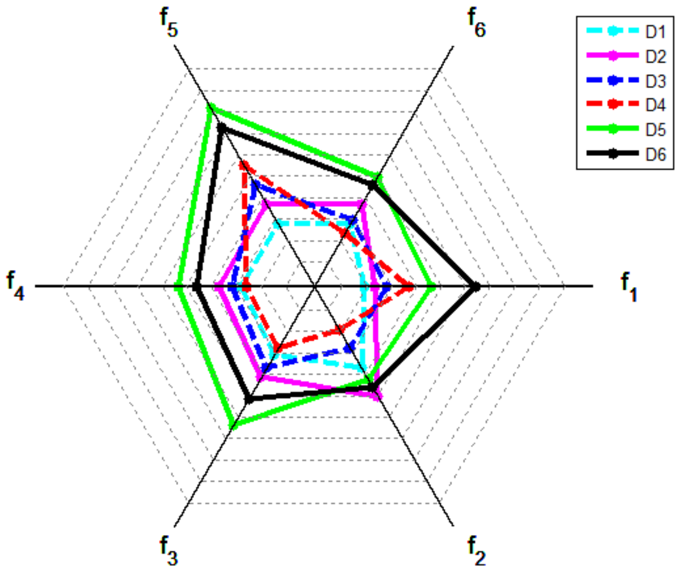


Figure 2.12. Final Pareto Optimal Solutions

In some cases, the design options set may be very large, and the Pareto Front consist many designs, even more than needed. Then it is not necessary to find all the Pareto Optima. Assume in this example, two Pareto Optimal designs are desired to be found, then the search process could stop after D3 were found a Pareto Optimum. So part of the Pareto Front, D1 and D3 were found efficiently.

2.7. Conclusion and Remarks

This chapter discussed about the first phase of the decision making framework, which is the Pareto Optima search. The basic concept and terminology of Multi-criteria Decision Making problem formulation was introduced. The conventional exhausting search Pareto Filter algorithm was introduced, as well as the drawback of the algorithm. Then the Ranking Based Pareto Selection method was proposed, aimed at improving the efficiency of the Pareto Optima search algorithm and providing the flexibility of finding partial of the Pareto Front. The advantaged of the proposed Ranking Based Pareto Selection algorithm was discussed. An example was demonstrated to illustrate the effectiveness of the algorithm.

In the next chapter, the second phase of the decision making framework, how to cope with the conflicting performance of designs in different environmental impact indicator, find the decision maker's preferred design will be discussed. In order to find the preferred designs, the implementation of decision maker's preference is necessary. To achieve this goal, Design Preference Function, and the Ranking Based Rate of Substitution are proposed, to help to guide to the most sustainable designs.

Chapter 3.

Implementation of Decision Maker's Preference

3.1. Introduction

From the first phase of the decision making tool, all the Pareto Optimal designs were found. After the Pareto Optimal solutions are found from the original design options set, there still may remain a lot of "all good" solutions left. Further design decision needs to be made, but all the Pareto Optimal solutions have trade-offs again each other on the environmental impact indicators, and there is no absolute the "best" solution. Instead, the most "preferred designs" could be selected, according to decision maker's preference. It is necessary to cope with the decision maker's preference, because practical situation that for different decision maker varies. As a result the design selected may be different to meet the different decision maker's preference. So how to deal with the trade-offs between these designs, and how to differentiate among those designs about their advantage and disadvantage will highly depend on the decision maker's preference. The preference could include the priority about different indicators, satisfactory value and so on. How to implement these preferences into the decision making process, guide the most preferred solutions needs to be addressed. In this chapter, Design Preference Function is introduced to classify the satisfactory level according to the environmental impact criteria; Ranking Based Rate of Substitution was developed to integrate decision maker's preference of the environmental impact priority, to guide to the most "preferred optimal design decisions".

3.2. Design Preference Function

The first type of decision maker's preference is involved to the criteria for each environmental impact indicator. In practical cases, satisfying designs need to meet some criteria for the environmental impact indicators' values in a certain range. These criteria may be resulted from many factors, such as regulation and policy from government, business partner requirement. The criteria can be expressed as a threshold value. For example, a decision maker will be satisfied if the energy demand f_i is lower than a certain value f_i^1 according to the environmental regulation. If there is no single value of f_i determined by any law or regulation, instead, it came from a practical situation according to a specific scenario, then it could be expressed as a range, enable a buffer zone. For example, the decision maker may feel the environmental impact indicator f_i of one design is excellent as long it is smaller than f_i^1, and is not acceptable if it is higher than f_i^2, and between f_i^1 and f_i^2 is acceptable, as pitched in Figure 3.1. In order to represent the preference and normalize the different indicator values, any indicator value f_i smaller than f_i^1 could be converted to a smaller value P_i^1 which is within the preference range, for example, (0,1), and if it is between f_i^1 and f_i^2, be assigned another value P_i^2, which is larger than P_i^1, but still in the range of (0,1), and for any f_i that is larger than f_i^2, it will be converted to P_i^3, which is larger than P_i^3, in the range of (0,1). As a result, the Design Preference Function is a step function, as shown is Figure 3.1.

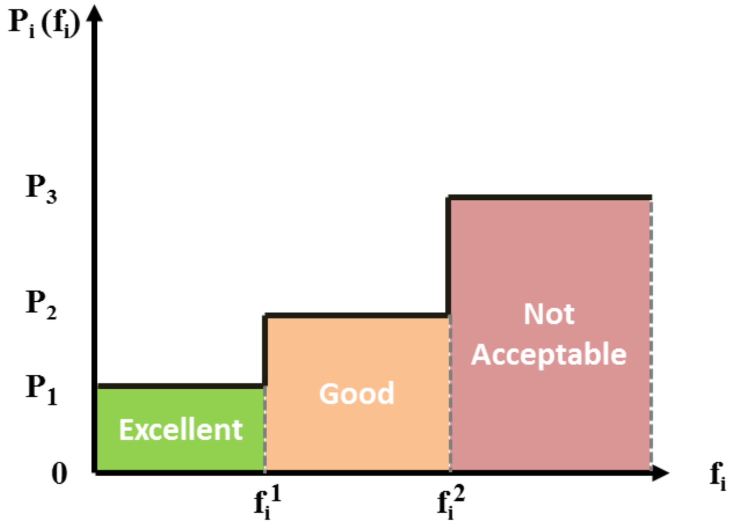


Figure 3.1. Design Preference Function example 1

The Design Preference Function that expressed in the will classify the design on one indicator into three groups; this sometimes will ignore some small difference of the performance within the same range. To reflect the difference more precisely, this preference function could be constructed in a different way, such as linear function, to present the performance, as pitched in Figure 3.2. But the choice of Design Function format could depend on the specific need of a decision making situation.

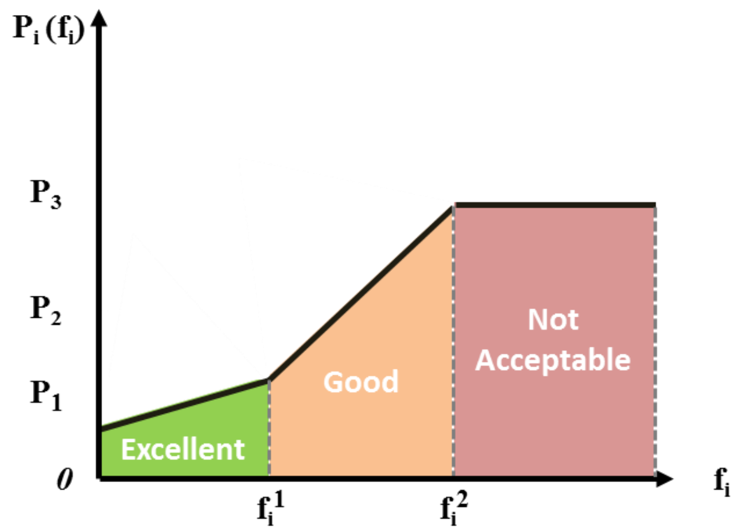


Figure 3.2. Design Preference Function Example 2

Through the Designer Preferences Function, all environmental impact indicator values f_i can be normalized into the predefined preference values P_i range. The preference values of each indicator can be used to guide decision making process since it represents performance of a design according to the preference of specific decision makers. In this paper, lower P_i value represents higher preferred environmental impact performance.

Through Design Preference Function, all the Pareto Optimal designs have been classified and converted from environmental impact indicators (f_i) to the preference value (P_i), for each design, as shown in Figure 3.3. In the environmental impact indicator domain, because each indicator may have a different unit, and a different range that has huge difference between different indicators, the performance of a design in each indicator is not easy to understand. The design preference value could help the decision maker to understand more clearly of the performance of one design on every specific indicator.

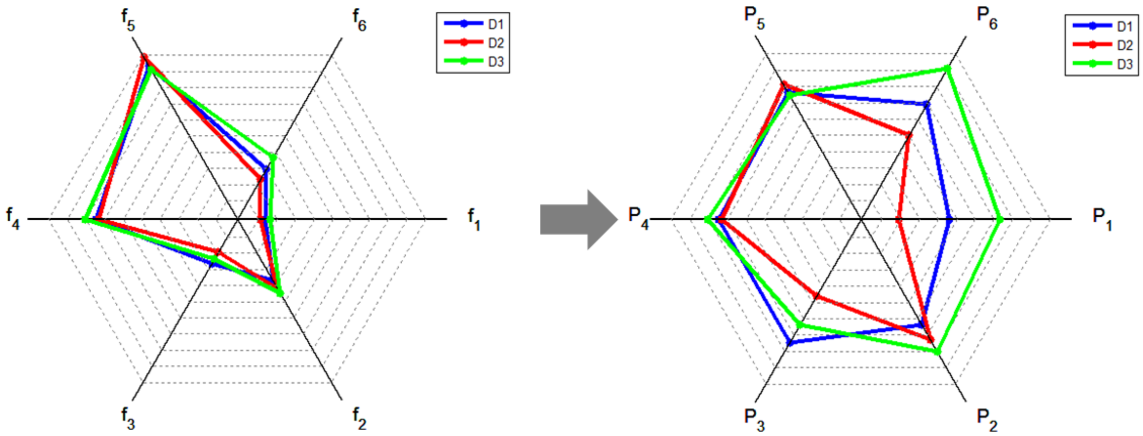


Figure 3.3. Environmental Impact Indicator Values Converted to Design Preference Value

3.3. Ranking Based Rate of Substitution

After the Design Preference Function was applied, the Pareto Optimal designs are classified and normalized. But the Design Preference Function does not compare designs about their trade-offs over different environmental impact indicators to further help to select the most sustainable designs. In order to investigate the trade-off of the designs, further differentiate the performance, find the most sustainable designs subset, decision maker's priority about different environmental impact indicators needs to be incorporated.

The conventional method to corporate with the priority about the different attributes for a Multi-Criteria Decision Making Problem is the Weighted Sum Method [39], that is, assign a set of weight for all of the decision attributes, according to the importance, thus, each multi-dimensional design objective vector is converted into a single value. However, The Weighted Sum method has two drawbacks: First, the weight between all environmental impact indicators is hard to set; Secondly, this method generates only one optimal solution which has the best performance. But in the case of selecting the sustainable packaging designs, a small set of solutions to the decision maker is necessary, because there may still be other decision factors that are not included in the environmental impact indicators from Life Cycle Assessment, such as materials accessibility.

Thus, a method that can engage the preference of priority about the environmental impact indicators, and compare the trade-off between different designs, also provide a set of optimal designs is highly needed. To do so, Marginal Rate of Substitution was adopted, based on which Ranking Based Rate of Substitution is proposed.

3.3.1. Marginal Rate of Substitution

In this session, the basic concept about Marginal Rate of Substitution is first introduced below:

In order to simplify the visualization, we suppose there is a two-dimensional design vector where f_1 and f_2 are the two attributes, as shown in Figure 3.4. In the case that both f_1 and f_2 are to be minimized as an objective, the Marginal Rate of Substitution reflects the rate between the amount f1 has to decrease in order to remain indifferent and the amount f_2 is increased. Specifically, in Figure 3.4, at design D1, let Δf_2 be the amount that the decision maker would compromise in the environmental impact f_2 in order to gain an improvement Δf_1 in environmental impact f_1 while maintaining constant value, according to the preference. The Marginal Rate of Substitution, R_{12}^1, between the two environmental impact indicators f_1 and f_2 at design D1 is the ratio $-\Delta f_1/ \Delta f_2$. Similarly, the Marginal Rate of Substitution, R_{ij}^t, between any two environmental impact indicator f_i and f_j at design Dt can be defined as the ratio $-\Delta f_i/ \Delta f_j$.

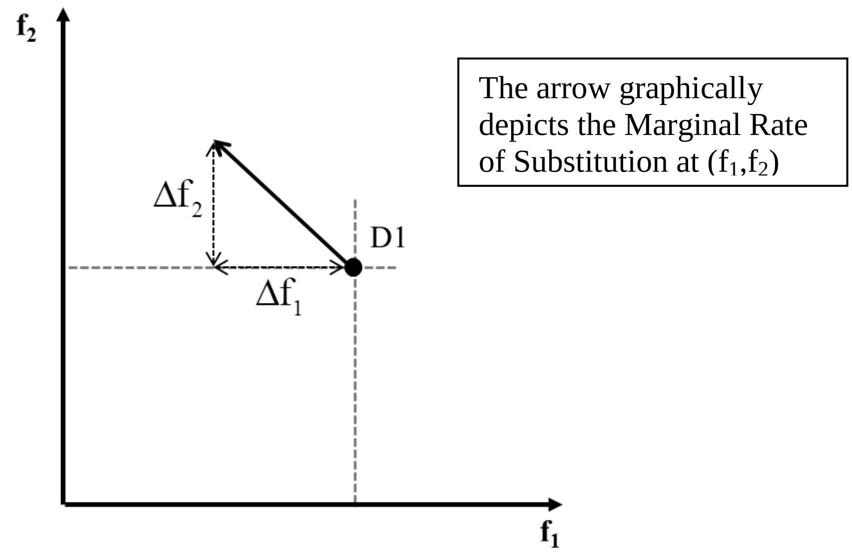


Figure 3.4. Redraw of General Case of Marginal Rate of Substitution. [41]

The concept of Marginal Rate of Substitution can be extended to compare any two design vectors about the trade-off between two attributes. For example, as shown in Figure 3.5, in a two dimensional objective space, there are three designs D1, D2 and D3. Comparing to D1, both of D2 and D3 have a worse performance on f_1, while have a better performance on f_2. Assume for the given attribute values for D1, We could compare both D2 and D3 with D1, by calculating the Marginal Rate of Substitution, to check that, which design between D2 and D3, compensates better on f_2 for the loss on f_1. At D1, the desired Marginal Rate of Substitution is λ. So when it comes to how good is another design compared to D1, we need to compare the Marginal Rate of Substation of D2, which is $\Delta f_2^{2,1}/\Delta f_1^{2,1}=\lambda_{2,1}$. If $\lambda_{2,1}$ is better than λ, then it means, even D2 has a worse performance on f_1 than D_1, but it could be considered as good, because of its qualified improvement on f_2. Similarly, we could get $\lambda_{3,1}$, if it is not better than λ , then it will be considered as no good, because it did not improve enough on f_2 to compensate the loss on f_1.

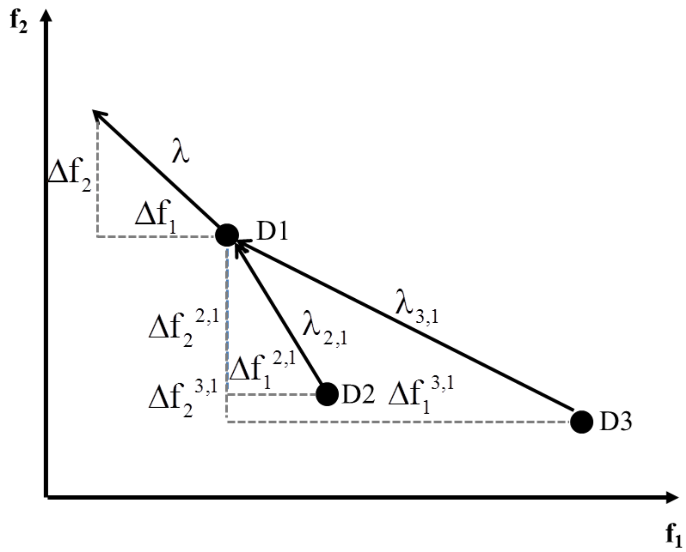


Figure 3.5. Criteria of Rate of Substitution

In this dissertation, since the design environmental impact indicators have been normalized in to the preferred value through the Design Preference Function, R_{ij}^{t} is dimensionless.

3.3.2. Ranking Based Rate of Substitution

As last session mentioned, the concept of Marginal Rate of Substitution can be utilized to compare any two designs, between any two design decision attributes. But in the decision making problem for sustainable packaging design, there are more than two attributes and more than two designs to compare. In order to extend the Marginal Rate of Substitution concept to the Multi-Criteria Decision Making problem with more than two attributes, the Ranking Based Rate of Substitution is proposed. The Ranking Based Rate of Substitution method implements the ranking of the priority of the environmental impact indicators, by comparing all other environmental impact indicators with one selected environmental impact indicator, also comparing all other designs with the one selected Pareto Optimal design.

The operation of Ranking Based Rate of Substitution is based on the trade-off between two Pareto Designs. The trade-off, R_{jp}^{ik} can be calculated in form of equation (3.1)

$$R_{j,p}^{ik} = -\frac{f_j^i - f_j^k}{f_p^i - f_p^k} \qquad i = 1 \cdots m,\ k = 1...m, j = 1...n, \text{ and } j \neq p \tag{3.1}$$

Where f represents the value of environmental indicators; the subscripts j and p represent the j^{th} and p^{th} indicators; the superscripts i and k denote two design options. $R_{j,p}^{ik}$ is the trade-off substitution design option i for design options k in terms of the gain of f_j over the loss of f_p. If the trade-off is greater than a pre-defined minimum trade-off value, then the substitution of design option i for k is acceptable. Decision maker can first select an acceptable Pareto Design, f^k, as the baseline. If the trade-off of substituting another Pareto design, $f^{i,}$ is acceptable, then f^i will be included in the set of possible solutions otherwise it will be rejected. The comparison process continues until the entire Pareto Front set is evaluated and a final reduced Pareto Set is obtained. To control the number of possible Pareto solutions in the final set, the designer can choose a different baseline design and/or define different minimum trade-off value for each environmental impact indicator.

The decision maker could also define the priority of the environmental impact indicators along with the implementation of trade-off to further reduce the size of final possible solution set. Thus, the baseline design will be chosen as the Pareto Optimal design that has the best performance on the top prioritized indicator. This refers to the Ranking Based Rate of Substitution, and the Rate of Substitution can be obtained from (3.2):

$$R_{j,p}^{i1} = -\frac{f_j^i - f_j^1}{f_p^i - f_p^1} \qquad i = 1 \cdots m,\ j = 1 \ldots n, \text{ and } j \neq p \tag{3.2}$$

Here $R_{j,p}{}^{i1}$ is a ratio between i^{th} design and the 1st ranked design. Once current design's rates of substitution are calculated, then the designer can eliminate some of the designs when the rate dose not satisfied criteria. The criterion is defined by the designer according to the priority about different environmental impact indicators.

It is only necessary to calculate the Ranking Based Rate of Substitution between any pair of designs when they have trade-off s between two environmental impact indicators, since substitution only exists in such situation. In the case that smaller objective value represents a better design, the Ranking Based Rate of substitution is a positive dimensionless number, and the larger it is, the better of the performance of trade-off.

In a N dimensional case where N is equal or greater than three, one design will generate N-1 Ranking Based Rate of Substitution, where N-1 is equal or greater than two. In this case, a good design is considered as good if there is at least one indicator has a Ranking Based Rate of Substation that is better than the desired number. We say this design is not dominated by the most preferred design, thus should be one of the optimal designs. If in none of the environmental impact indicator, a design satisfies, and is not better the criteria of Marginal Rate of Substitution, then it is not an Optimal Design.

Depending on the priority of each environmental impact, the designer can set different criteria for different environmental impact indicators, which can reflect the priority about the importance of the design objectives. A simple example is shown in Figure 3.6, all D1, D2 and D3 has six decision attributes, 5 Ranking Based Rate of Substitution is produced. In order to use Criteria of Ranking Based Rate of Substitution to determine a design is optimal or not, in terms of tradeoff between different design attributes, comparing to the most preferred design. D1 is not considered as a preferred, since none of the 5 Ranking Based Rate of Substitution satisfies the criteria. While D2 is considered a decision maker preferred design, because it has a satisfying Ranking Based Rate of Substation $R_{2,1}$, $R_{4,1}$ and $R_{5,1}$, which means it has a good compensation on both f_2 , f_4 and f_5, comparing to the performance of f_1.Similary, D3 could be considered as a good design, because on f_5 and f_6, it has satisfactory Ranking Based Rate of Substitution.

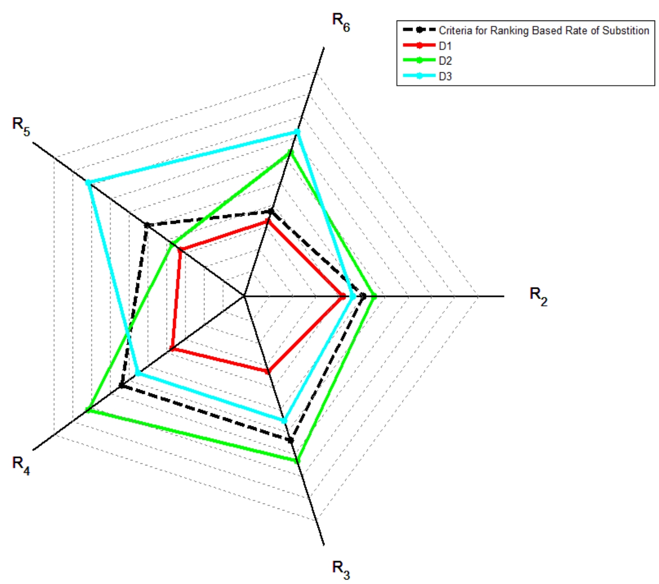


Figure 3.6. Example of Selecting Designs using Ranking Based Rate of Substitution

A table will better help us to visualize the performance of the three designs in terms of the Ranking Based Rate of Substitution, as shown in Table 3.1. The highlighted cell in red represents the Ranking Based Rate of substitution that satisfies the criteria, so D1 has no satisfying performance on any of the environmental impact indicators. However, D2 and D3 can be considered as optional designs.

	$R_{2,1}$	**$R_{3,1}$**	**$R_{4,1}$**	**$R_{5,1}$**	**$R_{6,1}$**	**Optimal Design?**
Criteria	**0.50**	**0.65**	**0.65**	**0.5**	**0.38**	**—**
D1	**0.41**	**0.32**	**0.38**	**0.34**	**0.35**	**No**
D2	**0.55**	**0.74**	**0.83**	**0.37**	**0.65**	**Yes**
D3	**0.47**	**0.56**	**0.57**	**0.82**	**0.74**	**Yes**

Table 3.1. Solutions Obtained by Ranking Based Rate of Substitution Considering All Environmental Impact Indicators

If the optimal design set needs to be further narrowed, then the priority of the environmental impact indicators can help to do so. By reducing the less prioritized environmental impact indicators, the designs that have good performance will be found. For example, in Table 3.2, the less prioritized environmental impact indicators f_5 and f_6 , has been reduced by ignoring the Ranking Based of Rate of Substitution $R_{5,1}$ and $R_{6,1}$, then D2 was found the only one satisfies the criteria, thus will be considered as an Optimal Design.

	$R_{2,1}$	$R_{3,1}$	$R_{4,1}$	Optimal Design?
Criteria	**0.50**	**0.65**	**0.65**	**—**
D1	**0.41**	**0.32**	**0.38**	**No**
D2	**0.55**	**0.74**	**0.83**	**Yes**
D3	**0.47**	**0.56**	**0.57**	**No**

Table 3.2. Solutions obtained using Ranking Based Rate of Substitution after Reducing Indicators

3.4. Example

In order to illustrate how the Design Preference Function and Ranking Based Rate of Substitution Method facilitate the selection of decision maker's preferred designs, an example is shown below.

Assume there are 5 Pareto Optimal Designs, which were selected from the original design alternatives set. The six design objective values of each design are plotted in Figure 3.7. First, the Design Preference Function will be applied, to apply the indicator preference. Then the Ranking Based Rate of Substitution is applied, to further select the designs that have satisfying compensation.

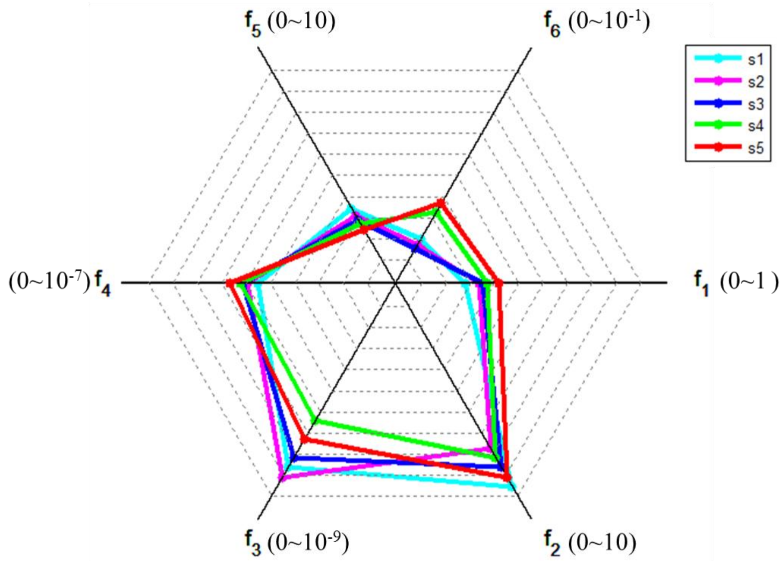


Figure 3.7. Whole Set of Pareto Optimal Designs

3.4.1. Design Preference Function

The first step to integrate the decision maker's preference is the Design Preference Function, which has been plotted in Figure 3.8.

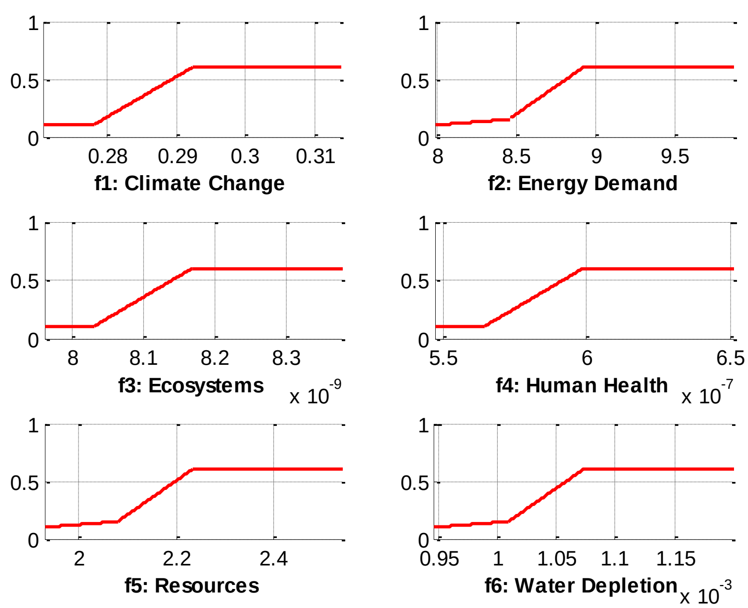


Figure 3.8. Design Preference Function

The Design Preference Functions converts the environmental impacts indicator to the design preference value, which is in the range of [0,1] ,as shown in Figure 3.9.

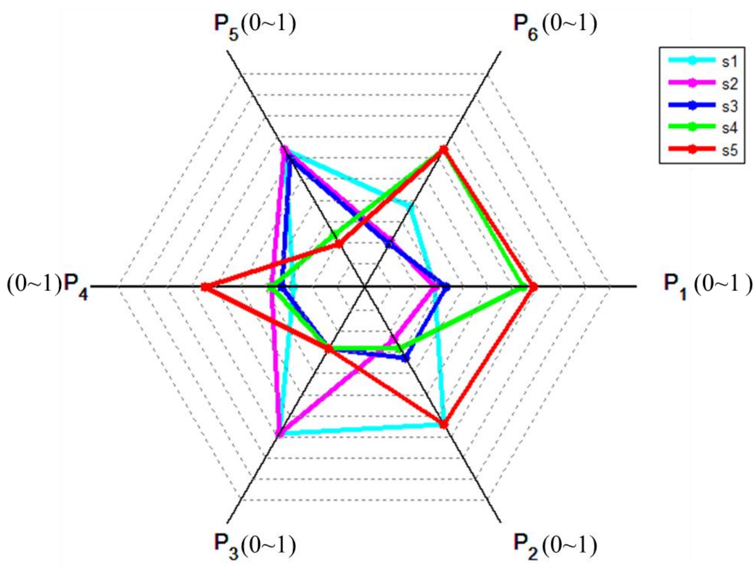


Figure 3.9. Preference Value for the Whole Set of Pareto Optimal Designs

3.4.2. Ranking Based Rate of Substitution

After the Design Preference Function, the preference value has been calculated from the environmental impact indicator values. Next, Ranking Based Rate of Substation will be utilized to compare all the "good designs". The Ranking Based Rate of Substitution will be calculated using Equation (3.2) from the normalized preference value, so it is dimensionless. The most important indicator here is assumed to be P_2 , then the Ranking Based Rate of Substitution will be calculated for all others designs but D_2, which has the best performance on D_2 and selected as the baseline. So the results are shown in Table 3.3.

	P2	P4	P3	P6	P5	P1	Optimal Design?
Criteria	—	0.15	0.2	0.25	0.5	0.8	
D2	—	—	—	—	—	—	
D4	—	-0.5	10	-11	10.5	-8.75	Yes
D3	—	0.12	10	0.25	7.25	-8.75	Yes
D1	—	0.25	0	-0.45	0.025	0.025	Yes
D5	—	-0.95	1	-1.1	1.175	-0.975	Yes

Table 3.3. Final Selected Optimal Designs after Design Preference Function and Ranking Based Rate of Substitution

To further narrow down to a smaller set of optimal selection, reducing the decision attributes will help. By reducing the least prioritized decision attribute P_5 and P_1, D5 is eliminated from the optimal designs set. As a result, D4, D3 and D1 are found to be the most sustainable packaging designs, as shown in Table 3.4.

	P2	P4	P3	P6	Optimal Design?
Criterion	—	0.15	0.2	0.25	
D2	—	—	—	—	
D4	—	-0.5	10	-11	Yes
D3	—	0.12	10	0.25	Yes
D1	—	0.25	0	-0.45	Yes
D5	—	-0.95	1	-1.1	No

Table 3.4. Final Selected Optimal Designs after Design Preference Function and Ranking Based Rate of Substitution

3.5. Conclusion and Remarks

In this Chapter, two components-Design Preference Function and Ranking Based Rate of Substitution were introduced, to implement decision maker's preference, including criteria for environmental impact indicators and priority between environmental impact indicators, thus to choose the most preferred designs.

The Design Preference Function classifies and normalizes the environmental impact indicators and Ranking Based Rate of Substitution could implement decision maker's indicator priority, by comparing all other designs with the most preferred design, thus find the most preferred designs.

The environmental impact indicators from the Life Cycle Assessment could involve uncertainty due to lack of information, system variation. In the next chapter, uncertainty will be taken into account the decision making process.

Chapter 4.

Non-Deterministic Pareto Front

In chapter 2, Ranking Based Pareto Filter algorithm was proposed to successfully facilitate the Pareto Optimal design search process for base on deterministic environmental impact indicators. However, evaluation of the environmental impact indicator often involves uncertainty. The uncertainty in environmental impacts indicator values will make the Pareto Optimal design filter process more complicated, because the original definition for Pareto Optimum no longer applies. To this end, the Probabilistic Pareto Front Filter algorithm has been developed, based on the Ranking Based Pareto Front Filter algorithm.

4.1. Uncertainty in the Environmental Impact Indicators

Through the whole process of Life Cycle Assessment, they are many potential resources of uncertainty, which will influence the accuracy of the environmental impact indicator values. Uncertainty in Life Cycle Assessment results may be resulted from many typical factors as discussed below [62][63][64][65][66]:

Database Uncertainty

The uncertainty in database refers to the uncertainty and inaccurate information collected, as a result, the data in an LCA software database may not exactly represent the actual quantity [67]. For example, for one environmental impact indicator, there are multiple values or distributions of data collection due to geographical , temporal and technological difference of a product, so an accurate quantity is hard to be determined [62][68].

Model Uncertainty

The model uncertainty refers to some aspects that cannot be modelled within the present Life Cycle Assessment structure, such as the spatial and temporal characteristic lost [62]. Different Life Cycle Assessment software may generate different environmental impact indicator values for the same design, and this is because of the model they used varied. The simplified models may not capture exact cause-and-effect mechanisms, or data regression may have the wrong functional form [67].

Statistical/ Measurement Error on Product Parameters

The statistical error may be resulted from a limited set of sample set [67]. Measurement errors may also exist in the sample data, as well as the unknown standards used to collect and quantify the data [67].

Because of the possible existence of the uncertainty in the whole process of Life Cycle Assessment, it is very likely that the environmental impact indicators are also involved with uncertainty as the Life Cycle Assessment output. This means that actual environmental impact indicator values gained from the Life Cycle Assessment software is not an accurate single value, but a value with uncertainty. The uncertainty in the environmental impact indicators could be represented in many formats, such as a probabilistic distribution.

4.2. Decision Making with Uncertainty in Environmental Impact indicators

From the last session, we know that the environmental impact indicator values from Life Cycle Assessment may not be able to present the accurate measurement of a design options, but involve uncertainty which cannot be avoided.

When these uncertainties are considered during the sustainable packaging selection decision making process, the comparison between designs becomes very challenging. First, to illustrate the challenge for decision making while environmental impact indicators has uncertainty, Figure 4.1 is shown to explain the comparison in a one dimensional case. Assume for two designs D1 and D2, the water depletion environmental impact indicator values are no longer an accurate value, but instead, data that are normally distributed, with mean value (μ^{D1}) and standard deviation σ^{s1} for design S_1, and mean value (μ^{D2}) standard deviation σ^{D2} for D2. The figure shows D1 has a lower mean value than D2 on water depletion. In a deterministic case, in which only the mean value is given, D1 naturally will be considered to be better than D2, since μ^{D1} is smaller than μ^{D2}. However, we cannot simply conclude that design D1 is always better than D2 because the variation of both options need to be considered too. Depending on the criteria of probability, which is decided by the decision maker, D2 design can be also considered has a good performance on the water depletion attribute.

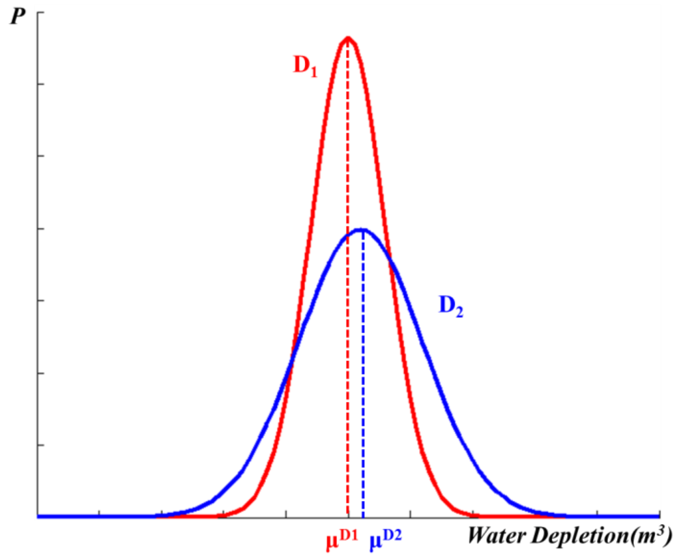


Figure 4.1. Normal Distribution of Water Depletion of Two Different Designs

The challenges that uncertainty caused extends to the Pareto Front search, when there are multiple attributes to consider in order to find the optimal designs from all the alternatives. In the deterministic case of finding Pareto Front, one design D1 dominates another design D2, if on all the environmental impact indicators; D1 has at least one environmental impact indicator value smaller than D2. But in the non-deterministic case, the definition of dominance is no longer valid, since the uncertainty exists.

Literature review shows that there are related research try to resolve the challenge of uncertainty in Multi-Criteria Decision Making [69][70][71][72] . There are mainly two streams of approaches to deal with uncertainty by directly comparing the mean and variance values, such as the "Mean-Variance" method [69] ,"Minimize Mean Value Approach", or "Minimize Mean + K* Standard Deviation Approach" [70]. However, these methods could only handle when there are significant difference between two data, since they investigated the mean value and standard deviation, not the probability between two data. Also, for “Minimize Mean + K* Standard Deviation Approach”, the determination of K for decision maker is difficult.

Another stream of approach to deal with uncertainty is to determine the Pareto Front by defining probabilistic dominance [71][72]. By defining the probabilistic dominance, the Pareto under uncertainty could be found by checking the dominance criteria. Also, the probabilistic dominance allows the use of Pareto filter algorithm that has been developed. J.E Fieldsend’s definition of probabilistic dominance calculates the sum of degree of confidence, which fail to investigate the design on each individual decision attribute’s performance [71]. H. Eskandari’s definition of probabilistic dominance calculates the product of degree of confidence , which also fail to investigate each individual attribute’s performance, also the criteria is for threshold value is hard to determine for the decision maker [72].

To overcome the drawback of current existing methods of dealing uncertainty in Multi-Criteria Decision Making problem, the probabilistic dominance is redefined in the next session.

4.3. Probabilistic Dominance and Probabilistic Pareto Optimum

When there is uncertainty in the environmental impact indicators, the equation (2.2) for dominance, and equation (2.3) for non-dominance are not valid anymore. In order to cope with the uncertainty using the Ranking Base Pareto Front Filter algorithm, and include all the designs that potentially good designs, the definition of non-dominance that concluded in chapter 2 has been modified into the Probabilistic Non-Dominance, which is stated as below:

A decision vector $\vec{f}^{A} = [f^{A}_{1}, f^{A}_{2}, ..., f^{A}_{N}]^{T}$ is said to not probabilistically dominate the decision vector $\vec{f}^{B} = [f^{B}_{1}, f^{B}_{2}, ..., f^{B}_{N}]^{T}$, in a minimization context, if and only if:

$$P_i^{AB}(f_i^A > f_i^B) > P_{ic}\,,\ \exists i = 1, ..., n \tag{4.1}$$

Where $P_i^{AB}(\cdot)$ is a probability operator, f_i^A is an environmental impact indicator of design A, f_i^B is an environmental impact indicator of design B, n is the number of indicators, P_{ic} is the probabilistic criteria. We can call the P_i^{AB} "probabilistic non-dominance factor", which could reflect the probability that A does not dominate B. In other words, if design option A has at least one attribute probabilistically worse than design B, then design A is said to probabilistically does not dominated design B.

The difference between deterministic Pareto dominance and Probabilistic Pareto dominance is illustrated in Figure 4.2. Dominance Relation in Deterministic Case (Left), and Probabilistic Dominance Relation (Right) for a two dimensional case. The left figure demonstrate a deterministic case, in which the dominance relation is determined by comparing the mean values. The mean values for area represented by the coordinate of the black dots. As a result, design A absolutely dominates B. The figure on the right illustrates the non-deterministic case, where not only the mean values are to be considered, but also the uncertainty. The dark black dots stills represent the mean value, and the gray circles represent the uncertainty. As a result, we first can conclude that A is not dominated by B or C, because its means value is smaller both of B and C. But, by adopting the probabilistic dominance, C has a higher chance to be dominated by A, while B has a high probability not to be dominated by A. By setting different value of P_{ic}, the probabilistic Pareto Front may contain different solutions.

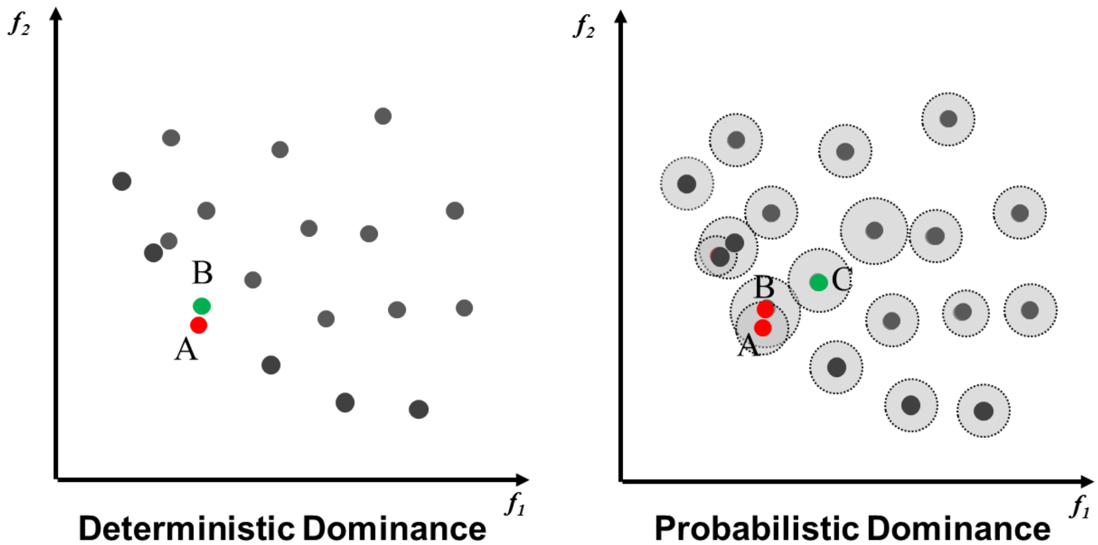


Figure 4.2. Dominance Relation in Deterministic Case (Left), and Probabilistic Dominance Relation (Right)

After the Probabilistic Dominance has been defined, Probabilistic Optimum can be further defined. If one design option is not probabilistically dominated by any other design, then this design can be considered as a Probabilistic Pareto Optimum. All the Probabilistic Pareto Optima construct the Probabilistic Pareto Front. By incorporating the probabilistic dominancy comparison, we will be able to cope with the uncertainty of Life Cycle Assessment results during the Pareto Front selection process. As a result, some of the design which has large mean value but still can be selected into the Pareto set if it satisfies the probabilistic criteria. Furthermore, the Pareto Front selection will be more flexible depending on the designer's preference by adjusting the probabilistic criteria, P_c.

A comparison between the deterministic Pareto Front selection and the probabilistic Pareto Front is illustrated in Figure 4.3. In the left figure, the red points are the designs on the Pareto Front in a deterministic case. In the right figure, red points are the design on Pareto Front, from which we can see that, two more designs has been considered Probabilistic Pareto Optima, due to their high probability of not being dominated.

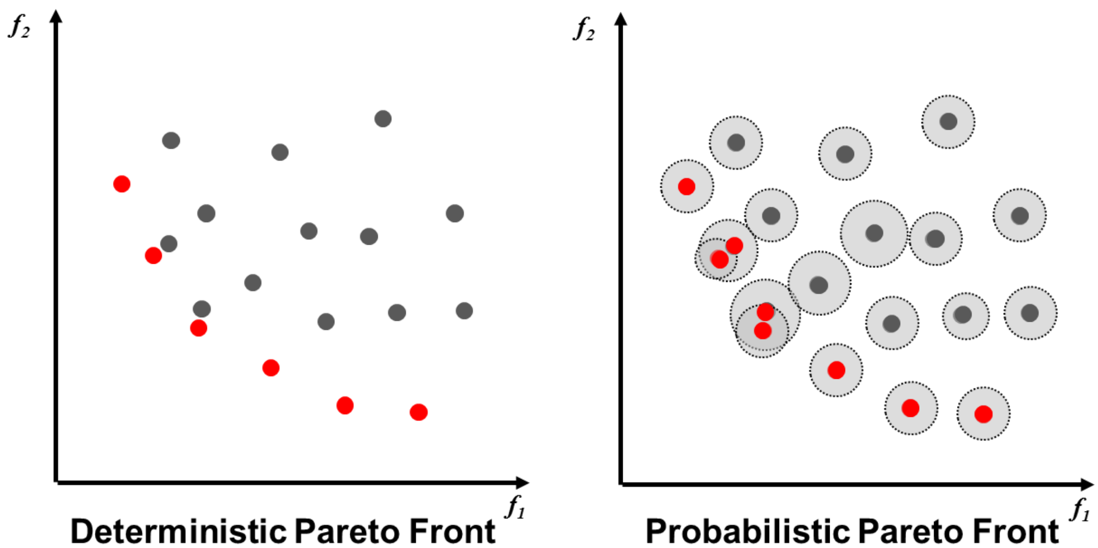


Figure 4.3. Conceptual illustration for PPS: Deterministic Pareto Front (Left), and Probabilistic Pareto Front (Right)

4.4. Calculation of the Probabilistic Dominance Factor

The previous sessions have introduced the definition of Probabilistic Dominance, Probabilistic Dominance Factor and Probabilistic Pareto Optimum, in order to obtain the Probabilistic Front, the calculation of Probabilistic Dominance Factor between each pair of designs is critical, which will be introduced in this session from the statistics theory. In this session, normal distributed environmental impact indicators are discussed are an example.

The environmental impact indicator values may follow the symmetrical, bell-shaped curve of the normal distribution, or Gaussian frequency distribution. Assume on one environmental impact indicator f_i, for design A, the environmental impact indicator value x_i^A is normally distributed, with the mean value μ_i^A and standard deviation σ_i^A, then the distribution can be expressed as:

$$f(x_i^A) = \frac{1}{\sigma_i^A \sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x_i^A - \mu_i^A}{\sigma_i^A})^2} \qquad (4.2)$$

Where $f(x_i^A)$ is the height of the frequency curve corresponding to an assigned value x_i^A, μ_i^A is the mean value of the environment impact indicator f_i for design A, and σ_i^A is the standard deviation of the environmental impact indicator f_i .

In order to demonstrate how the Probabilistic Dominance Factor, consider there are two designs A and B as shown in Figure 4.4. For one environmental impact indicator, for example f_1, which are normally distributed, environmental impact indicator value of design A is x_1^A has the mean value μ_1^A=30 and standard deviation is σ_1^A=6; similarly, for design B, the environment impact indicator x_1^B has the mean value μ_1^B=32 and standard deviation is σ_1^B=10. The probability of $x_1^A < x_1^B$ is given by

$$P_1^{AB} = P(x_1^A < x_1^B) \qquad (4.3)$$

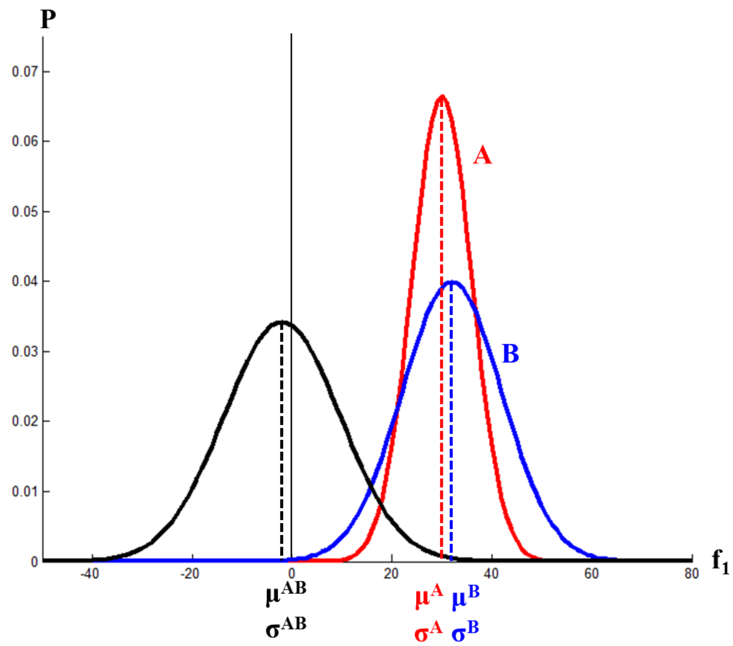


Figure 4.4. Distributions of Two designs on One Environmental Impact Indicator

If we subtract x_1^A from x_1^B, then the distribution $x_1^{AB}= x_1^A - x_1^B$, so we want to get P (x_1^{AB} <0).

The mean and standard deviation of the distribution of the destruction x_1^{AB} needs to be determined. Without going into the statistical details, we know that since the environmental impact indicators of the two designs A and B can be considered as independent, the result distribution of x_1^A and x_1^B can be obtained by performing algebraic operations on the two independent variables x_1^A and x_1^B. Then we can get $\mu_1^{AB} = \mu_1^A - \mu_1^B = 30 - 32 = -2$, $\sigma_1^{AB} = \sqrt{(\sigma_1^A)^2 + (\sigma_1^B)^2} = \sqrt{(6)^2 + (10)^2} = 11.66$.

The part of the distribution to the left of x_1^{AB} represents the area for which $\mu_1^A - \mu_1^B < 0$, which means $\mu_1^A < \mu_1^B$, and x_1^A is smaller than x_1^B occurs. If we transfer to standard normal variable, $z=(x-\mu)/\sigma$, then at $x_1^{AB}=0$,

$$z = \frac{0-\mu_1^{AB}}{\sigma_1^{AB}} = \frac{0-(-2)}{11.66} = 0.17 \tag{4.4}$$

From Appendix, the area to the left of z for the cumulative normal distribution function, we can see that P (x_1^{AB} <0)=0.5657. If in this case, Pc=0.55, then on f1, the Probabilistic Dominance Factor of A over B satisfies the criteria, then other environmental impact indicators needs to be checked, to determine that if A probabilistically dominates B on all environmental impact indicators or not; If Pc=0.6, then the Probabilistic Dominance Factor of A over B does not satisfy the criteria, this mean A must not dominate B.

4.5. Probabilistic Dominance and Probabilistic Pareto Optima

In Chapter 2, the Ranking Based Pareto Filter Algorithm was proposed to improve the efficiency of the process of finding Pareto Optima. When uncertainty exists in the environmental impact indicators, the dominance check criteria need to be changed to the probabilistic dominance in the algorithm. As a result, the flow chart for the Probabilistic Pareto Selection algorithm has been changed into the as shown in Figure 4.5 below.

The Probabilistic Pareto Filter algorithm is summered below step by step, for finding the whole Probabilistic Pareto Front case, and followed with the flow chart in Figure 4.4.

Step-1: Set the most prioritized design attribute fq, q is any number from 1 to n, n=number of design decision attribute.

Rank all designs with respect to the mean value of fq, to get the design's ID D_i,

$i=[1,\ldots,m]$, m=number of designs.

Step-2: Initialize the algorithm indices and variables:

$i=1$, $j=1$, $k=1$, $l=1$

$P=[D_1]$,

l is the number of Pareto Optima

Step-3: Set $i=i+1$; $j=1$

Step-4: Set $j=j+1$

Step-5: Check one design is dominated by the current Pareto Optima set or not by checking:

If $Di \neq Pk$

And $P((Di-Pj)s \geq 0) \geqslant P_c, \forall s$

Then Di is dominated by P^k

Go to step-6

Else if k=l

Update Pareto Set P, P ={D1, Di}

Else go to step-4

Step-6: If i=m, go to step-3, else end.

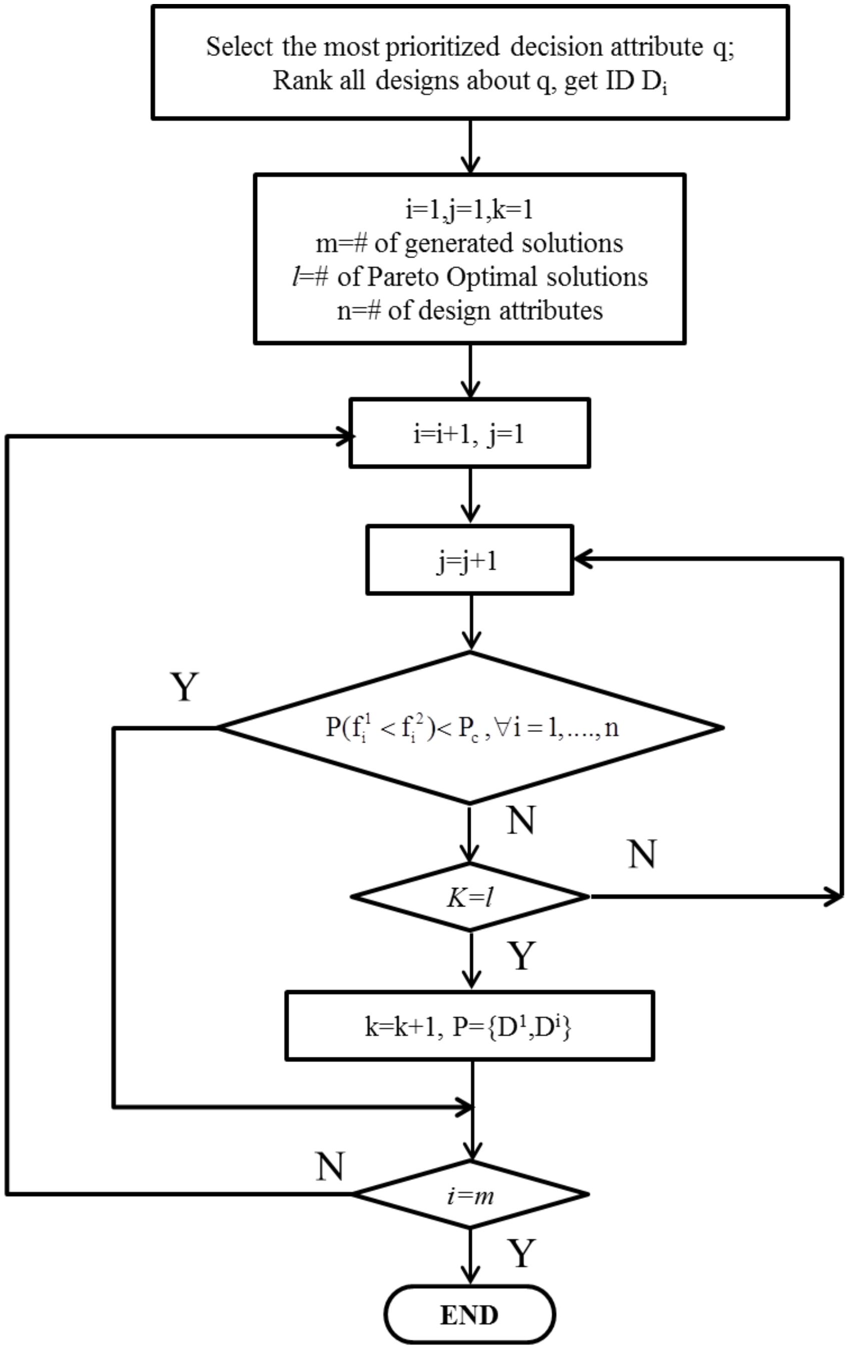


Figure 4.5. Flow Chart for Probabilistic Pareto Selection Algorithm

Because of the adoption of probabilistic dominance criteria, uncertainty in the environmental impact indicators has been taken into consideration while filtering the Pareto Optima successfully.

4.6. Example

In this session, an example will be shown to illustrate Probabilistic Pareto Selection algorithm.

In this example, assume there are 6 designs, each with six environmental impact indicators, which assumed to be normally distributed. In Figure 4.6, for easier visualization, the uncertainty was plotted as $\pm 3\sigma$ around the mean value.

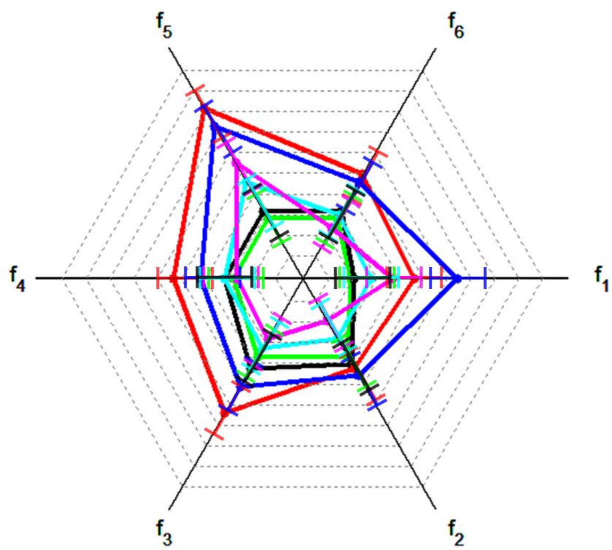


Figure 4.6. Whole Set of Design Alternatives with Uncertainty

First, one environmental impact indicator will be chosen as the top prioritized, according to the decision maker's preference. Here we assume f_1 is the most important indicator, and then all 6 designs will be ranked with respect to $f_{1,}$ as shown in Figure 4.7.

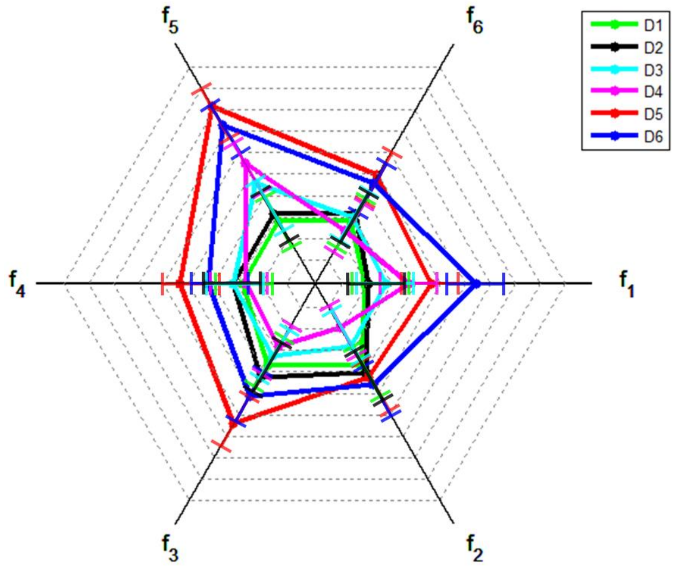


Figure 4.7. Whole Set of Design Alternatives with Uncertainty after Ranking

Then D1 is automatically a Pareto because it has the smallest mean value. Next, the Probabilistic Dominance will be checked for the next design option D2, against D1. D2 is not dominated on all indicators by D1, and then D2 is included in the Pareto Set. This dominance check continues to D3, D4, D5 and D6, and finally found that D5 and D6 are dominated, and other four designs, D1, D2, D3 and D4 are not probabilistically dominated, thus are to be probabilistic Pareto Optima, as shown in Figure 4.8.

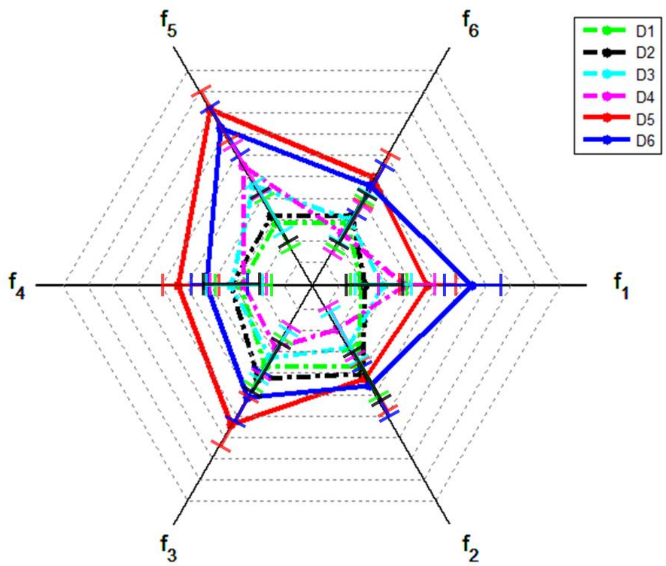


Figure 4.8. Whole Set of Pareto Design Alternatives

4.7. Conclusion and Remarks

In this chapter, Probabilistic Pareto Front Filter algorithm was introduced in order to cope with the uncertainty in the environmental impact indicators. As the first phase of the decision making process for sustainable packaging, the algorithm facilitate to select the all designs that have a high probability not dominated by other designs. The Probabilistic Pareto Front Filter algorithm includes different designs as Probabilistic Pareto Optimal design by adjusting the probabilistic criteria. The uncertainty in the environmental impact indicators has been successfully incorporated by this method.

Chapter 5.

Sustainable Packaging Design Selection Decision Case Studies

In this chapter, two case studies will be shown to demonstrate the function of the decision making framework proposed in previous chapters. In the first case study, the environmental impacts indicators are assumed to be deterministic, so the deterministic decision making framework will be used, which contains Ranking Based Pareto Filter Algorithm, Design Preference Function, and Ranking Based Rate of Substitution. In the second case study, the environmental impact indicators are assumed to be normally distributed. So in the first phase of the decision making process, Probabilistic Pareto Front Filter Algorithm will be utilized to deal with the uncertainty. Then the preferred sustainable designs are found by adopting the second phase of the decision making framework. The environmental impact indicator values were obtained from PackageSmart (EarthShift Inc.) by conducting the Life Cycle Assessment, which are (1) Climate Change (*kg* CO_2eq), (2) Energy Demand (*MJ*), (3) Ecosystems (*species/yr*.) (4) Human Health (*DALY*), (5) Resources (*$/kg*) (6) Water depletion (m^3) [29]. The primary, secondary and tertiary packaging are defined respectively for both case studies, and number of packaging options are determined by a number of packaging components, materials, processes and transportations manners.

5.1. Deterministic Case Study-Soft Tube

In the deterministic decision making scenario, the soft tube packaging design is studied as an example. Soft tube is one of the most useful packaging types which have many applications especially in cosmetic, pharmaceutical and consumer products [22]. In order to utilize the Life Cycle Assessment to analyze the environmental impacts of the soft tube package, the three stages of packaging - primary, secondary and tertiary packaging are defined. The three stages of packaging may vary for different product. In this case, the primary packaging is composed of a tube, tube head and a cap. The secondary packaging is a carton that could be made from different materials. The tertiary packaging is defined as the corrugated paperboard box.

As we mentioned before, the process of the sustainable packaging design selection decision making process is as follows: First, all the feasible designs needs to be found, which can be obtained by feasibly combine different design input options, such as materials options, manufacturing processing and transportation manner. Secondly, all the design alternatives will be input into the Life Cycle Assessment software, so the environmental impact indicators can be evaluated. Thirdly, the deterministic decision making method for sustainable packaging selection, which is proposed in this dissertation will be applied to the environmental impact indicator data, so that the sustainable designs can be selected.

5.1.1. Designs Inputs

- **Design Variables**

In this part, design input variables will be briefly described for the soft tube packaging, including material options, manufacturing processing options, and transportation manners.

1. Materials Options:

HDPE

HDPE (high-density polyethylene) is widely used as the materials for tube packaging and carton， because of it significant features such as low cost, easy processibility and good moisture barrier [22].

PET

PET （polyethylene terephthalate), the high melting point of 249 ℃ makes it one of the highest of the common packaging plastics, including soft tube and carton. PET also has good heat resistance, excellent grease/oil barrier properties, high tensile strength, good printing characteristics, high impact strength, high scuff resistance and excellent dimensional stability [22].

PP

PP (polypropylene), is widely used for soft tubes and carton, for its easy processibility, good dimensional stability, good water vapor barrier properties, and good heal-seal strength.

Aluminum +PE

Composite materials is also very often used for soft tubes, one example is aluminum and PE. Aluminum and PE has a wide application on soft tube because its good elongation.

Paperboard

Paperboard is the most important materials for folding carton packaging. One significant advantage is the low tooling cost comparing with that for other materials such as plastics.

Corrugated Paperboard

Corrugated paperboard is mostly often used to produce the shipping boxes for its durability, easy processibility.

2. Manufacturing Processing Options:

Injection molding

Injection molding uses a powerful extruder with the capability to inject a precise amount of resin into a fully enclosed mold, and it is the leading method of manufacturing for soft tube.

Profile Extrusion

Profile extrusion processing could produce a shape of constant cross section profile, such a hollow pipe or tube.

Welding Process

Welding is the process to connect the tube and the tube head.

Production of Carton

The production of carton in the Life Cycle Assessment database refers to a serious of production sequence, such as one-up die, machine test, production die, finishing operations and production printing.

3. Transportation Manner Options:

Truck

Among many of the transportation manners to choose from, the transportation is selected as the diesel truck, because of diesel truck‘s advantages such as durability, less maintenance.

- **Design Alternatives**

The feasible combination of the previously introduced design variables forms a design alternative. Based on the design variables mentioned in the previous session, totally of 96 feasible packaging design options are generated by combining different feasible materials of each packaging components, which is shown in Figure 5.1. All these design alternatives were input into the Life Cycle Assessment Software, and the environmental impact indicators are obtained.

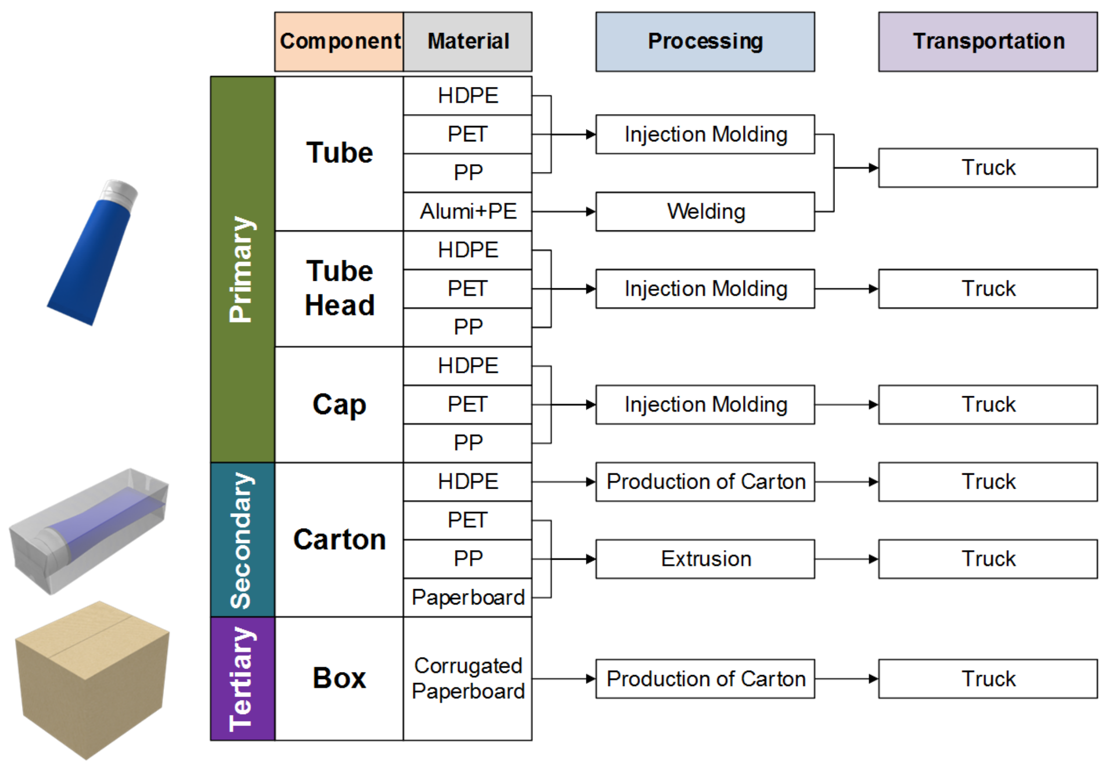


Figure 5.1. Design Inputs for Soft Tube Packaging

5.1.2. Decision Making for Sustainable Packaging

This session of the case study present the application of the deterministic decision making framework for sustainable packaging design, which is the focus of this dissertation. As introduced in previous chapters, the first phase of the decision making process is to find all, or part of the "good designs"-Pareto Optimal Designs, using the Ranking Based Pareto Filter Algorithm. In order to do so, one most prioritized environmental impact indicators needs to be selected. For this case study, assume resource (f_5) is defined as the most important indicator among six indicators; the priority about the indicators is $f_5 \rightarrow f_1 \rightarrow f_2 \rightarrow f_4 \rightarrow f_3 \rightarrow f_6$. All of the design will be ranked with respect to f_5. By implementing Ranking Based Pareto Filter algorithm, all the 24 Pareto Optimal designs can be found, as shown in Figure 5.2. All Pareto Optimal designs are represented by the Red color, and non-Pareto Optimal designs are represented the environmental impacts of the Pareto Front designs are plotted in blue.

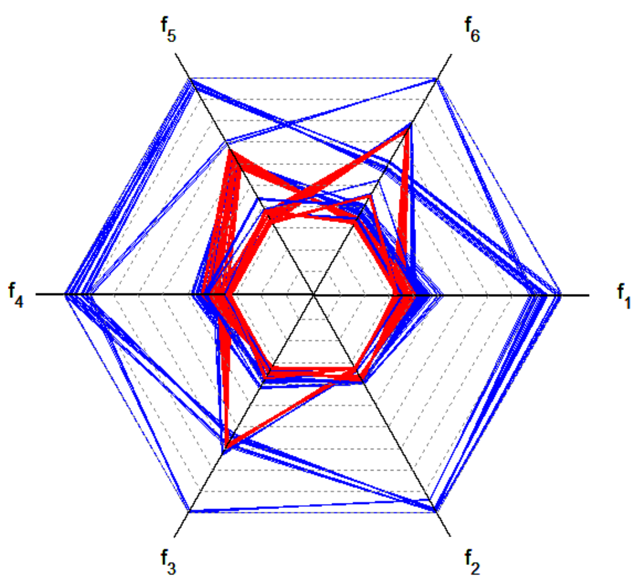


Figure 5.2. Radar Chart of Environmental Impact Indicator of All Designs

The Pareto Optimal designs are the “good designs” from the original set of design alternatives. Further decision aid is needed to select the most decision maker’s preferred designs. At this stage of the decision making, decision maker’s preference, including threshold values and Marginal Rate of Substation needs to be implemented. The first step of the preference implementation is the classification of the Pareto Designs according to the satisfactory value for each of the environmental impact indicator, which is, Design Preference Function. For different cases, the Design Preference Function for each indicator may vary, since these preferences come from regulation, policy, local resource availability and so on. The Design Preference Function for this soft tube case study has been plotted in Figure 5.3.

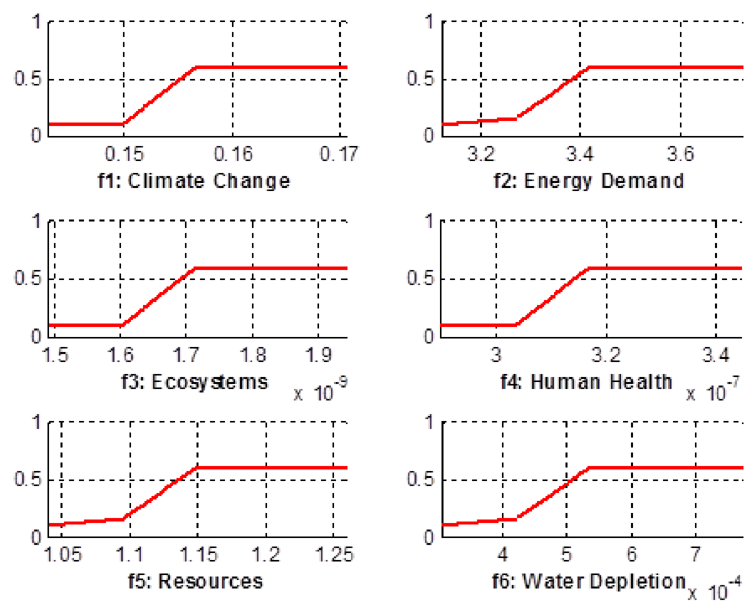


Figure 5.3. Design Preference Function for Soft Tube

After the utilization of Design Preference Function, all the Pareto Designs' environmental impact indicators will be converted into the preferred value, in this dissertation which is 0 to 1, which is plotted in Figure 5.4.

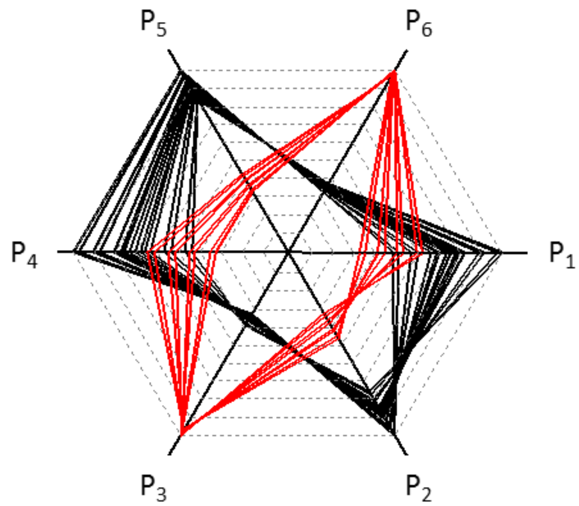


Figure 5.4. Pareto Optimal Designs of The Soft Tube

After the environmental impact indicators have been converted into the preferred values, the trade-off between each Pareto Optimal Designs needs to be differentiated, thus find out the decision maker's preferred designs. Since f_5 is the most prioritized design attribute, all Pareto Optimal Designs will be ranked with respect to f_5 value. Then all the Pareto Designs will get a new ID, form D_1 to D_P, P is the total number of Pareto Optima. D_1, who has the best performance on f_5, is the "Most Preferred Design" among all the Pareto Optima. Next, Ranking Based Rate of Substitution will help to selected all the designs that have a good compensation on other environmental impact indicator, comparing with the value of D_1 on f_5.

Finally, all of the designs that have a good compensation comparing with the "most preferred design" are selected. The final selected designs have been plotted in Figure 5.5, and listed in Table 5.1.

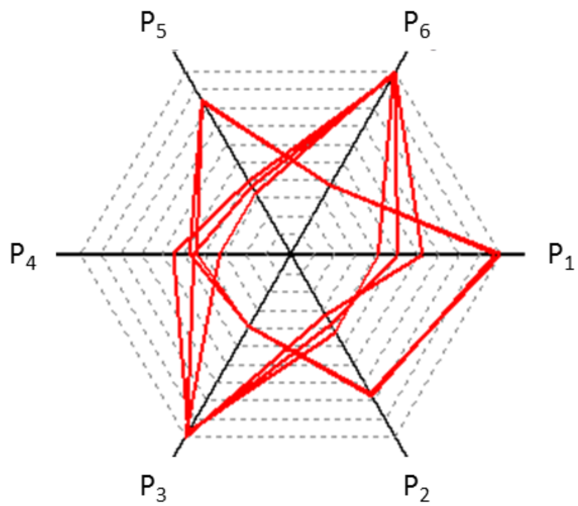


Figure 5.5. Radar Chart of all Pareto Optimal Designs after Design Preference Function

Design	Tube	Tube Head	Cap	Carton	Rate of Substitution: All
Design 1	HDPE	HDPE	HDPE	PP	
Design 2	HDPE	PP	Carton	Paperboard	f_2, f_4, f_3
Design 3	PP	PP	HDPE	Paperboard	f_4
Design 4	HDPE	HDPE	HDPE	HDPE	f_3, f_6
Design 5	HDPE	PP	HDPE	HDPE	f_6

Table 5.1. List of Optimal Selection for Sustainable Milk Packaging Designs Considering All Decision Attributes

If a smaller set is needed for the decision maker, we could reduce the decision attributes. By reducing f_3 and f_6, Design 4 and Design 5 will be eliminated. Thus only Design 1, Design and Design 3 are selected, which is in Table 5.2.

Design	Tube	Tube Head	Cap	Carton	Rate of Substitution: Reduce f_3, f_6
Design 1	**HDPE**	**HDPE**	**HDPE**	**PP**	
Design 2	**HDPE**	**PP**	**Carton**	**Paperboard**	f_2, f_4, f_3
Design 3	**PP**	**PP**	**HDPE**	**Paperboard**	f_4
Design 4	**HDPE**	**HDPE**	**HDPE**	**HDPE**	f_3, f_6
Design 5	**HDPE**	**PP**	**HDPE**	**HDPE**	f_6

Table 5.2. List of Final Selection for Sustainable Milk Packaging Designs after Reducing f_3 and f_6

5.2. Non-deterministic Case Study -Milk Packaging

In the non-deterministic decision making scenario, milk packaging design is shown as a case study. Milk is one of the largest consumed food products in the world, and many different packaging designs are developed to protect the milk product from recontamination. Therefore, in this example, the milk packaging system is studied to demonstrate the non-deterministic decision making tool.

5.2.1. Design Inputs

As the first step, a set of design options needs to be generated by considering different design input options, which will be introduced below.

- **Design Variables**

1. Materials Options:

The features of many of the materials that will be used for milk packaging, such as HDPE, PET and PP, have been introduced in the case study for soft tube, so will not be repeated here again. And some materials special for milk packaging are introduced as follows:

Glass

Glass is used for milk packaging because it is easy to bed recycled, and evern reused. Glass is also provides good moisture barrier.

Carton

Carton with a thin layer of PE film is also a widely used milk packaging for its advantages such as light weight, easy shaping and so on.

Aluminum

Aluminum is used to produce for glass milk packaging closure, for it easy shaping and elongation.

Wood

Wood is a very important material for tertiary packaging, or shipping unit, because it is low cost, renewable, green, clean, light weight, also has very good strength and durability.

2. Manufacturing Processing Options

Blow molding

Blow molding is moderate in cost, and allows users to customize the design mold. So it could satisfy the user to create a variety of milk packaging bottles.

Production of Wood Pallet

Wood pallets are extruded using special dies. High temperature and high pressure are generated in this process, which soften the components of the wood and bind the materials in the pallet together.

3. Transportation Manner Options

In this case study, the transportation manner is also selected as truck, same as the first case study.

- **Design Alternatives**

By combining the compatible design variables, the design alternatives are generated. The three packaging stages for milk packaging levels are defined as shown in Figure 5.6. The primary packaging is composed of two components such as jug and cap. The secondary and tertiary packaging is defined too. The detail packaging options for the milk packaging case study are illustrated in Figure 5.6. For the jug, three different types of plastic materials (HDPE, Recycled HDPE, PET), glass, and carton are implemented. In case of plastic and carton jug, the HDPE, and PP materials are used for closure, and for glass jug, aluminum closure was used. For secondary packaging, two types of plastic material (HDPE, PP), and two types of carton packaging are considered as an example (carton box and carton container with wrap). Through these packaging combinations, totally 44 packaging options are generated in order to find the most desired packaging. All of them are input into the Life Cycle Assessment software to analyzed the environmental impact.

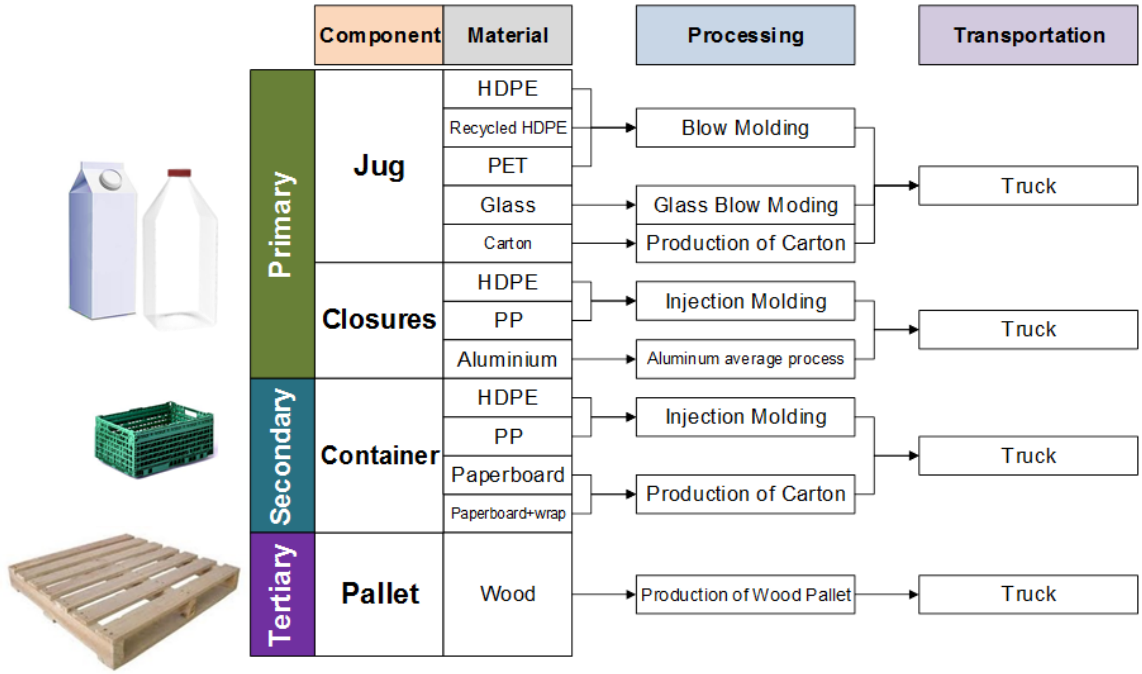


Figure 5.6.Design Inputs for Milk Packaging

5.2.2. Decision Making for Sustainable Packaging

This session of the case study present the application of the non-deterministic decision making framework for sustainable packaging design. The first phase of the decision making process is to find all, or part of the "good designs"-Pareto Optimal Designs. And in the non-deterministic case, uncertainty needs to be taken into consideration, so the Probabilistic Pareto Filter Algorithm is adopted. In this case study, probability of failure criteria is defined as lower than 0.45. In order to do so, one most prioritized environmental impact indicators needs to be selected. For this case study, assume resource (f_1) is defined as the most important indicator among six indicators; the priority is defined from high to low as: $f_1 \rightarrow f_3 \rightarrow f_5 \rightarrow f_4 \rightarrow f_2 \rightarrow f_6$. All of the design will be ranked with respect to f_1. By implementing Probabilistic Based Pareto Filter algorithm, all the 6 Pareto Optimal designs can be found, as shown in Figure 5.7. All Pareto Optimal designs are represented by the Red color, and non-Pareto Optimal designs are represented the environmental impacts of the Pareto Front designs are plotted in random colors. The uncertainty was represented by short bar, which is 3 times of the standard deviation.

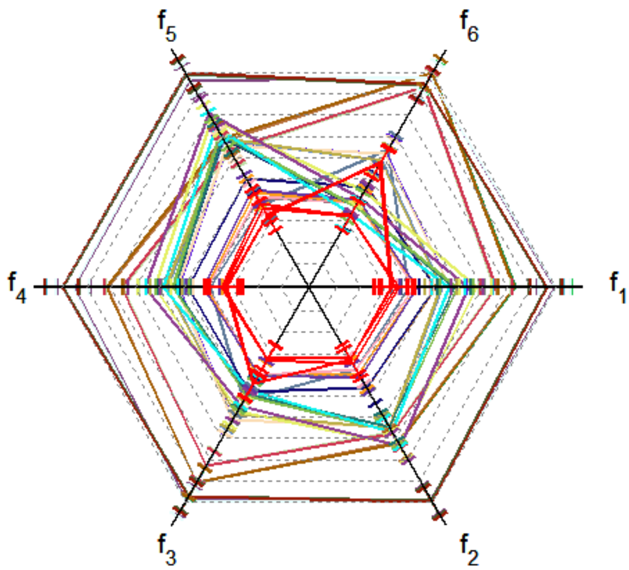


Figure 5.7. Radar Chart for Environmental Impact Indicators for All Milk Packaging Designs with Uncertainty

Next, similarly to the soft tube case study, Design Preference Function needs to be defined to implement the decision maker’s preference. The mean value was utilized of the environmental impact indicator in the Design Preference Function. The Design Preference Function for this milk packaging case study has been plotted in Figure 5.8.

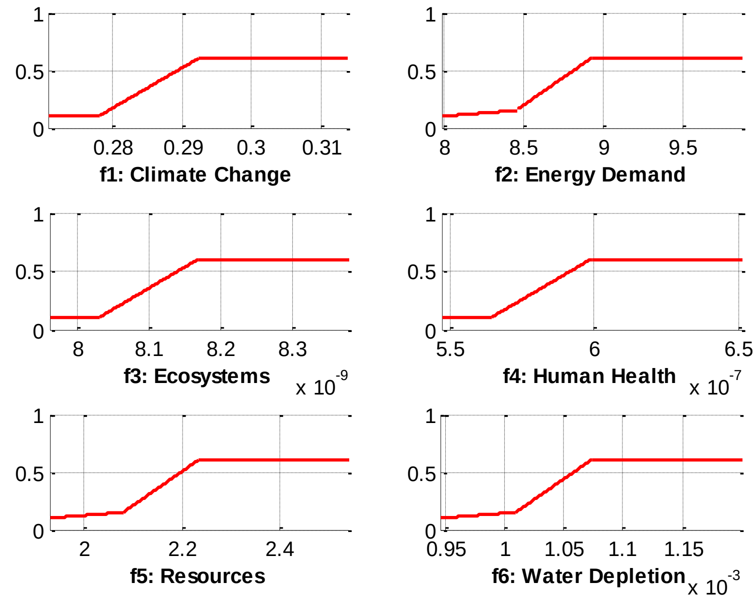


Figure 5.8. Design Preference Function for Milk Packaging

After Design Preference Function is applied, the advantages of trade off are examined and eight designs are founded as final designs as shown in Figure 5.9. Once final designs are founded, it is also known that which environmental impact indicators are giving advantages for each design during Pareto Selections and rate of substitution. Therefore, the final design can also be ranked as group of design depending on the priority of the indicator. Since f_1 is the most important function, the priority is defined from high to low as: $f_1 \rightarrow f_3 \rightarrow f_5 \rightarrow f_4 \rightarrow f_2 \rightarrow f_6$ and the final design and advantage functions of trade-off is list in Table 5.2.

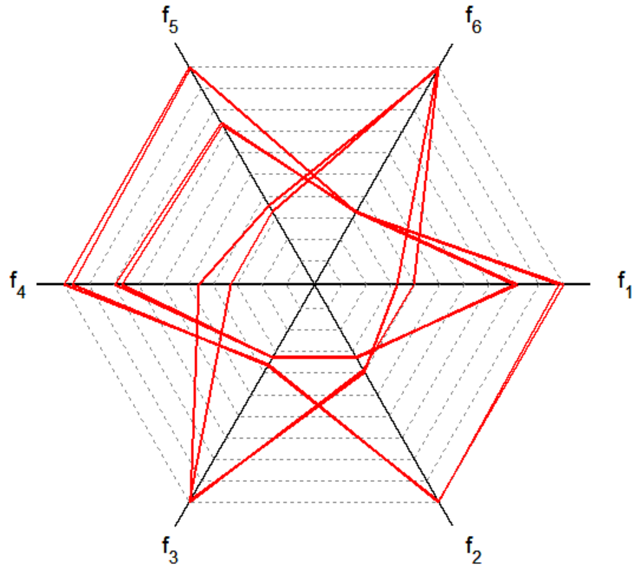


Figure 5.9. Radar Plot for all Pareto Selections for Sustainable Milk Packaging Selections

Design	Jug	Closure	Container	Rate of Substitution: All
Design 1	Carton	PP	Paperboard	
Design 2	rHDPE	PP	Carton	$f_{5,}$ f_4,f_2
Design 3	rHDPE	PP	PP	f_5
Design 4	Carton	PP	Paper+Wrap	f_4,f_2
Design 5	rHDPE	HDPE	Carton	f_2
Design 6	rHDPE	HDEP	PP	f_2

Table 5.3. List of All Pareto Selections for Sustainable Milk Packaging Designs

If designer only focusing on first three environmental impacts such as f_1, f_3 and f_5, and f_4, then design 1 to 4 can be selected as final packaging design set as highlighted with green color. Moreover, different indicator priority can lead different final design selection which can implement different situations such as geological reasons or regulations.

Design	Jug	Closure	Container	Rate of Substitution: Reducing f_2,f_6
Design 1	Carton	PP	Paperboard	
Design 2	rHDPE	PP	Carton	f_5, f_4,f_2
Design 3	rHDPE	PP	PP	f_5
Design 4	Carton	PP	Paper+Wrap	f_4,f_2
Design 5	rHDPE	HDPE	Carton	f_2
Design 6	rHDPE	HDEP	PP	f_2

Table 5.4. List of Final Selection for Sustainable Milk Packaging Designs after Reducing f_2 and f_6

5.3. Conclusion and Remarks

In this chapter, two case studies were shown, to illustrate the procedure and effectiveness of both the deterministic and non-deterministic decision making framework for sustainable packaging design.

In the deterministic case, based on the environmental impact indicators from Life Cycle Assessment, Ranking Based Rate of Substitution can find the Pareto Optimal designs of the packaging options. Furthermore, by using the Design Preference Function and Ranking Based Rate of Substitution, the trade-off between environmental impact indicators for each design can be handled.

In the non-deterministic case, the first phase of the decision making framework has been revised to Probabilistic Pareto Selection finds the Pareto Optimal designs, based on the environmental impact indicators that have variation.

The two case studies demonstrate how the proposed decision making framework can guide the decision for sustainable packaging options.

Chapter 6.

Conclusion and Future Work

6.1. Summary

A systematic decision making framework to choose sustainable packaging designs from a set of design alternatives has been proposed in this research work. There are two phase in this decision making framework, first is to find the Pareto Optimal Designs efficiently, using Ranking Based Pareto Filter algorithm, eliminate the bad designs, which are the dominated design; secondly, the decision maker's preference are corporate to select the most sustainable packaging design solution among the non-dominated designs by using Design Preference Function and Ranking Based Rate of Substitution.

In order to find the more sustainable packaging designs, a set of design alternatives were generated which serve the same function, from which the more sustainable packaging design was selected. The Life Cycle Assessment is conducted for the packaging designs, using the Life Cycle Assessment software, to evaluate the environmental impacts. Then the design decision making for the sustainable packaging based on the Life Cycle Assessment results was formulated as Multi-Criteria Decision Making Problem. In the decision making framework, the Pareto Optimum Concept was adopted to differentiate good designs and bad designs; and the Marginal Rate of Substitution concept was adopted to deal with the trade-off between Pareto Optimal Designs. Ranking Based Pareto Front Filter algorithm was proposed to improve the efficiency of the process of find the Pareto Optimal designs, Design Preference Function and Ranking Based Rate of Substitution was proposed to integrate the decision maker's preference to find the decision maker's preferred designs, and narrow the final solutions. Probabilistic Pareto Filter algorithm was proposed to find the Probabilistic Pareto Optima when the environmental impact indicator values is involved with uncertainty.

Soft tube packaging for the deterministic case and milk packaging for the non-deterministic case have been selected as case study, because of their wide application, and large number of packaging options. The sustainable packaging designs were found through the proposed decision making process, in each case study, for deterministic and non-deterministic case, respectively. As a result, not only the proposed decision making framework can be utilized to aid the soft tube and milk packaging design decision, but also it can be applied other packaging system.

6.2. Future Work

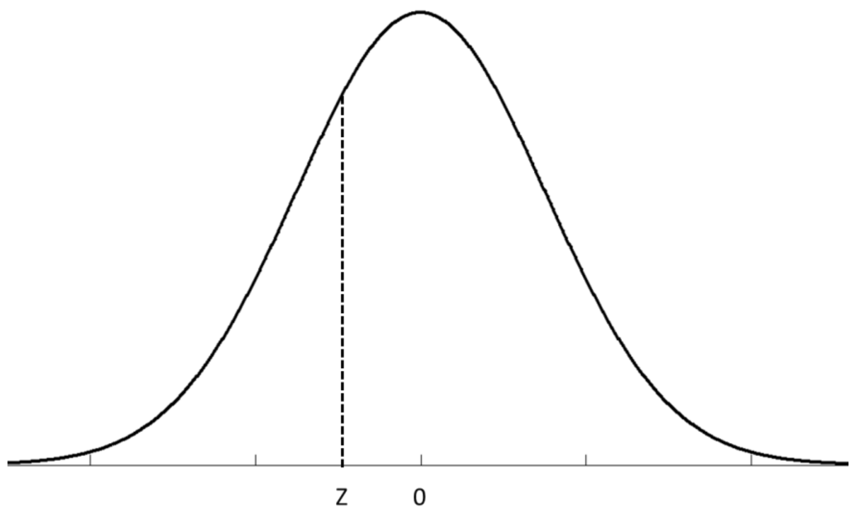
The proposed framework of decision making for sustainable packaging based on Life Cycle Assessment can be applied to many packaging design decision problems. In the future study, the proposed decision making framework can be applied to find the sustainable packaging design for other many other packaging systems. Different design input of the packaging also can be considered with different materials selections, manufacturing process, and transportation manners.

Another focus for the future work could be devoted to the uncertainty. Especially in the viewpoint of non-deterministic Pareto filter process; there are many different kinds of statistical distributions for the environmental impact indicators besides the distribution mentioned in the dissertation. In the Future study, the Pareto filter process should be studied for other distractions, such as Weibull and Gumbel distributions.

Also, in the non-deterministic decision making framework, uncertainty has been addressed only in the first phrase-Pareto Optima Selection, more research should be done to the next step, such as in the Design Preference Function and Ranking Based Rate of Substitution.

Appendices

Cumulative Distribution Function Value for Standard Normal Distribution



Cumulative Distribution Function Value for Standard Normal Distribution

(Continued)

Z	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
-3.9	.00005	.00005	.00004	.00004	.00004	.00004	.00004	.00004	.00003	.00003
-3.8	.00007	.00007	.00007	.00006	.00006	.00006	.00006	.00005	.00005	.00005
-3.7	.00011	.00010	.00010	.00010	.00009	.00009	.00008	.00008	.00008	.00008
-3.6	.00016	.00015	.00015	.00014	.00014	.00013	.00013	.00012	.00012	.00011
-3.5	.00023	.00022	.00022	.00021	.00020	.00019	.00019	.00018	.00017	.00017
-3.4	.00034	.00032	.00031	.00030	.00029	.00028	.00027	.00026	.00025	.00024
-3.3	.00048	.00047	.00045	.00043	.00042	.00040	.00039	.00038	.00036	.00035
-3.2	.00069	.00066	.00064	.00062	.00060	.00058	.00056	.00054	.00052	.00050
-3.1	.00097	.00094	.00090	.00087	.00084	.00082	.00079	.00076	.00074	.00071
-3.0	.00135	.00131	.00126	.00122	.00118	.00114	.00111	.00107	.00104	.00100
-2.9	.00187	.00181	.00175	.00169	.00164	.00159	.00154	.00149	.00144	.00139
-2.8	.00256	.00248	.00240	.00233	.00226	.00219	.00212	.00205	.00199	.00193
-2.7	.00347	.00336	.00326	.00317	.00307	.00298	.00289	.00280	.00272	.00264
-2.6	.00466	.00453	.00440	.00427	.00415	.00402	.00391	.00379	.00368	.00357
-2.5	.00621	.00604	.00587	.00570	.00554	.00539	.00523	.00508	.00494	.00480
-2.4	.00820	.00798	.00776	.00755	.00734	.00714	.00695	.00676	.00657	.00639
-2.3	.01072	.01044	.01017	.00990	.00964	.00939	.00914	.00889	.00866	.00842
-2.2	.01390	.01355	.01321	.01287	.01255	.01222	.01191	.01160	.01130	.01101
-2.1	.01786	.01743	.01700	.01659	.01618	.01578	.01539	.01500	.01463	.01426
-2.0	.02275	.02222	.02169	.02118	.02068	.02018	.01970	.01923	.01876	.01831
-1.9	.02872	.02807	.02743	.02680	.02619	.02559	.02500	.02442	.02385	.02330
-1.8	.03593	.03515	.03438	.03362	.03288	.03216	.03144	.03074	.03005	.02938
-1.7	.04457	.04363	.04272	.04182	.04093	.04006	.03920	.03836	.03754	.03673
-1.6	.05480	.05370	.05262	.05155	.05050	.04947	.04846	.04746	.04648	.04551
-1.5	.06681	.06552	.06426	.06301	.06178	.06057	.05938	.05821	.05705	.05592
-1.4	.08076	.07927	.07780	.07636	.07493	.07353	.07215	.07078	.06944	.06811
-1.3	.09680	.09510	.09342	.09176	.09012	.08851	.08691	.08534	.08379	.08226
-1.2	.11507	.11314	.11123	.10935	.10749	.10565	.10383	.10204	.10027	.9853
-1.1	.13567	.13350	.13136	.12924	.12714	.12507	.12302	.12100	.11900	.11702
-1.0	.15866	.15625	.15386	.15151	.14917	.14686	.14457	.14231	.14007	.13786
-0.9	.18406	.18414	.17879	.17619	.17361	.17106	.16853	.16602	.16354	.16109
-0.8	.21186	.20897	.20611	.20327	.20045	.19766	.19489	.19215	.18943	.18673
-0.7	.24196	.23885	.23576	.23270	.22965	.22663	.22363	.22065	.21770	.21476
-0.6	.27425	.27093	.26763	.26435	.26109	.25785	.25463	.25143	.24825	.24510
-0.5	.30854	.30503	.30153	.29806	.29460	.29116	.28774	.28434	.28096	.27760
-0.4	.34458	.34090	.33724	.33360	.32997	.32636	.32276	.31918	.31561	.31207
-0.3	.38209	.37828	.37448	.37070	.36693	.36317	.35942	.35569	.35197	.34827
-0.2	.42074	.41683	.41294	.40905	.40517	.40129	.39743	.39358	.38974	.38591
-0.1	.46017	.45620	.45224	.44828	.44433	.44038	.43644	.43251	.42858	.42465
0.0	.50000	.49601	.49202	.48803	.48405	.48006	.47608	.47210	.46812	.46414

Cumulative Distribution Function Value for Standard Normal Distribution

(Continued)

Z	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
0.0	.50000	.50399	.50798	.51197	.51595	.51994	.52392	.52790	.53188	.53586
0.1	.53983	.54380	.54776	.55172	.55567	.55962	.56356	.56749	.57142	.57535
0.2	.57926	.58317	.58706	.59095	.59483	.59871	.60257	.60642	.61026	.61409
0.3	.61791	.62172	.62552	.62930	.63307	.63683	.64058	.64431	.64803	.65173
0.4	.65542	.65910	.66276	.66640	.67003	.67364	.67724	.68082	.68439	.68793
0.5	.69146	.69497	.69847	.70194	.70540	.70884	.71226	.71566	.71904	.72240
0.6	.72575	.72907	.73237	.73565	.73891	.74215	.74537	.74857	.75175	.75490
0.7	.75804	.76115	.76424	.76730	.77035	.77337	.77637	.77935	.78230	.78524
0.8	.78814	.79103	.79389	.79673	.79955	.80234	.80511	.80785	.81057	.81327
0.9	.81594	.81859	.82121	.82381	.82639	.82894	.83147	.83398	.83646	.83891
1.0	.84134	.84375	.84614	.84849	.85083	.85314	.85543	.85769	.85993	.86214
1.1	.86433	.86650	.86864	.87076	.87286	.87493	.87698	.87900	.88100	.88298
1.2	.88493	.88686	.88877	.89065	.89251	.89435	.89617	.89796	.89973	.90147
1.3	.90320	.90490	.90654	.90824	.90988	.91149	.91309	.91466	.91621	.91774
1.4	.91924	.92073	.92220	.92364	.92507	.92647	.92785	.92922	.93056	.93189
1.5	.93319	.93448	.93574	.93699	.93822	.93943	.94062	.94179	.94295	.94408
1.6	.94520	.94630	.94738	.94845	.94950	.95053	.95154	.95254	.95352	.95449
1.7	.95543	.95637	.95728	.95818	.95907	.95994	.96080	.96164	.96246	.96327
1.8	.96407	.96485	.96562	.96638	.96712	.96784	.96856	.96926	.96995	.97062
1.9	.97128	.97193	.97257	.97320	.97381	.97441	.97500	.97558	.97615	.91670
2.0	.97725	.97778	.97831	.97882	.97932	.97982	.98030	.98077	.98124	.98169
2.1	.98214	.98257	.98300	.98341	.98382	.98422	.98461	.98500	.98537	.98574
2.2	.98610	.98645	.98679	.98713	.98745	.98778	.98809	.98840	.98870	.98899
2.3	.98928	.98956	.98983	.99010	.99036	.99061	.99086	.99111	.99134	.99158
2.4	.99180	.99202	.99224	.99245	.99266	.99286	.99305	.99324	.99343	.99361
2.5	.99379	.99396	.99413	.99430	.99446	.99461	.99477	.99492	.99506	.99520
2.6	.99534	.99547	.99560	.99573	.99585	.99598	.99609	.99621	.99632	.99643
2.7	.99653	.99664	.99674	.99683	.99693	.99702	.99711	.99720	.99728	.99736
2.8	.99744	.99752	.99760	.99767	.99774	.99781	.99788	.99795	.99801	.99807
2.9	.99813	.99819	.99825	.99831	.99836	.99841	.99846	.99851	.99856	.99861
3.0	.99865	.99869	.99874	.99878	.999882	.99886	.99889	.99893	.99898	.99900
3.1	.99903	.99906	.99910	.99913	.99916	.99918	.99921	.99924	.99926	.99929
3.2	.99931	.99934	.99936	.99938	.99940	.99942	.99944	.99946	.99948	.99950
3.3	.99952	.99953	.99955	.99957	.99958	.99960	.99961	.99962	.99964	.99965
3.4	.99966	.99968	.99969	.99970	.99971	.99972	.99973	.99974	.99975	.99976
3.5	.99977	.99978	.99978	.99979	.99980	.99981	.99981	.99982	.99983	.99983
3.6	.99984	.99985	.99985	.99986	.99986	.99987	.99987	.99988	.99988	.99989
3.7	.99989	.99990	.99990	.99990	.99991	.99991	.99992	.99992	.99992	.99992
3.8	.99993	.99993	.99993	.99994	.99994	.99994	.99994	.99995	.99995	.99995
3.9	.99995	.99995	.99996	.99996	.99996	.99996	.99996	.99996	.99997	.99997

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