Journal of
APPLIED PACKAGING RESEARCH

RESEARCH ARTICLE

Decision Making Framework Using Probabilistic Pareto for Sustainable Packaging Life Cycle Assessment

Euihark Lee
Rutgers, The State University of New Jersey
euihark@rci.rutgers.edu

Huihui Qi
Grand Valley State University
qih@gvsu.edu

Hae Chang Gea
Rutgers, The State University of New Jersey
gea@rci.rutgers.edu

ABSTRACT

The Packaging industry is one of the largest industries in the world and is associated with many environmental concerns. To reduce its environmental impacts, designing sustainable packaging has been one of the top priorities in packaging industries. A common tools for evaluating the environmental impact of a package design is the Life Cycle Assessment (LCA) which provides information on environmental impacts for different indicators. However, making decisions based on the LCA results leaves us with major challenges. First, the LCA tools should consider various uncertainties such as measurement and data quality. Second, the LCA may give conflicting results on different environmental impact factors. To address these issues, a ranking based decision making framework is proposed in this paper. Within this framework a Probabilistic Pareto Selection method is introduced to select the Pareto Front with uncertainty first. Then, the Ranking based Rate of Substitution is implemented in the decision making process in order to select the best design options based on the trade-off of each Pareto design. Tow case studies are presented to demonstrate the functionality of this framework.

Key Words:

LCA, sustainable packaging, probabilistic pareto

INTRODUCTION

The Packaging industry is one of the largest industries in the world since virtually every consumer and industrial product needs a package [1]-[4]. However, the packaging industry also causes numerous environmental issues such as waste, natural resource consumption, pollution and toxicants [5], [6]. In order to reduce the various environmental impacts, packaging industries are focusing on enhancing packaging sustainability [7] and Life Cycle Assessment (LCA) has widely been used to conduct comprehensive evaluations of the environmental impacts[8]-[14]. Theoretically, the LCA provides information on the environmental performance of the packaging designs. Based on the LCA results, the designer can measure the environmental impacts from amongst the various packaging options and choose the most sustainable design. However, straight forward decision making based solely on the LCA results is challenging [15], [16].

First, the Life Cycle Assessment of a packaging system should include uncertainties from measurement, data quality and modeling uncertainty [17]-[19]. However, many current commercial LCA tools do not take these uncertainties into account. Those that do still need the designer's input to optimize the unit processes. Therefore, simple decision making based on the current LCA tools without involving in uncertainty would not be able to identify the true optimal packaging design solution.

Second, LCA often provides multiple environmental impacts such as CO_2 emission, toxicant, and water depletion. This multiple environmental impacts can be considered as multi objective problems such as an evolutionary algorithm [20], [21], Pareto Front multi-objective optimization [22], [23] and a sorting based algorithm [24]. Each packaging system has environmental advantages and disadvantages. For each design a trade-off must be made from amongst the numerous indicators which makes the decision making not only difficult but shows that there is no one dominate design [25]-[27].

Third, the decision making for the sustainable packaging design could be different due to the designer's preference based on locations, regulations and the goals of the companies. Unfortunately, the LCA results alone cannot differentiate between the different preferences of the designer's. To solve this issue, the decision making process should incorporate the designer's knowledge, experience and data; however, this would become a very time/cost-consuming trial and error process.

To address these problems, a Ranking Based Decision Making Framework is proposed in this paper. Probabilistic Dominance is implemented to select the Pareto Front with uncertainty which is introduced as the Probabilistic Pareto Selection method. The Ranking based Rate of Substitution is also developed to guide the proper decision making for the trade-off of Pareto Front designs. The designer's preference will be included into both the Probabilistic Pareto Selection and the Ranking Based Rate of Substitution to make the systemic decision making process efficient.

The paper is organized as follows: First, the current Difficulties of the decision making process for sustainable design selection are described. Next, a probabilistic Pareto decision making framework is proposed to address the current problems of the decision making process. Finally, two case studies are presented and discussed.

PROBLEM STATEMENT

Although the LCA tools have been used widely in the packaging industries for evaluating packaging design options, decision making with LCA still has major challenges as we described in the previous section.

First, the environmental impact results from the LCA may not be able to represent an accurate measurement of each design option. It is obvious that there are many different types of uncertainties during the LCA of the packaging systems. For example, the data in LCA may not represent the exact situations of the life cycle of packaging systems. At the same time, the packaging system model for LCA may only be simplified models. Furthermore, it is possible that the data has measurement error [28]. Therefore, without consideration of uncertainties, the decision for a sustainable packaging design can be very misleading.

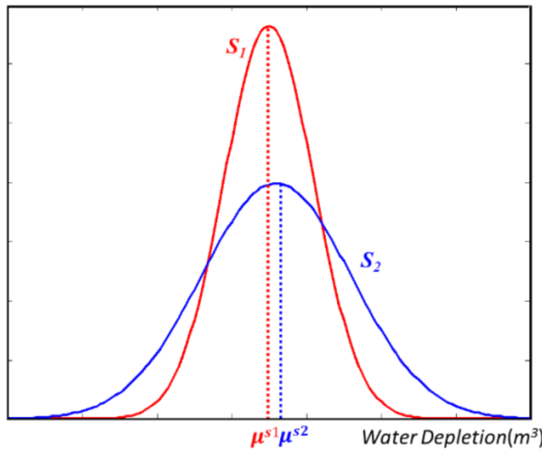

Figure 1 Distribution Curves of Two Different Designs

In Figure 1, normal distributions of two different designs (S_1 and S_2) for water depletion are plotted as an example. The mean value (μ^{s1}) of S_1 has a lower water depletion value than the mean value (μ^{s2}) of S_2. However, one cannot simply conclude that design S_1 is always better than S_2 since the variances of both options need to be considered.

The second challenge for LCA decision making is that these tools always generates multiple output design indicators associated with different environmental impacts, such as climate change, human health, ecosystems, water depletion and energy demand. It is very common that one packaging design may work well on one indicator but not as well on others. Therefore, different packaging designs will have different advantages and disadvantages which are represented as trade-offs among different environmental impacts which make the decision making process very challenging.

For example, as shown in Figure 2 four packaging system designs are analyzed by the LCA tool whose results include six environmental impact indicators: climate change (f_1), energy demand (f_2), ecosystems (f_3), human health (f_4), resources (f_5), and water depletion (f_6). The lower value of an indicator represents less environmental impact and can be considered a better option. Based on the plot, selecting the best packaging design among the design options (S_1, S_2 and S_3) is challenging. For the design S_1, all environmental impact values are lower than other designs except the indicator f_1. Similar situations happen in other design options as well and there is no clear winner among these three design options. Therefore, it is obviously necessary to find a way to properly deal with these trade-offs for the decision making process.

Third, the decision making process highly depends on the designer's preferences which could be determined by various factors such as the facility locations, government regulations, and/or the company's goals. For example, if a company is located in a region with very strict CO_2 emission regulations then the designer may have to take this into account. However, if the company is under slightly relaxed CO_2 emission regulations, then the designer could pay attention to all environmental impacts equally. Furthermore, the decision making based on the LCA results to improve sustainability of the packaging design may result in a time/cost-consuming trial and error process. Therefore, it is necessary to develop the systemic decision making framework to address all of the issues above.

Based on a survey of LCA in 2006 [29], it is mostly used to define business strategies within R & D fields and potentially will be applied to more fields in the future. However, as we discussed in previous

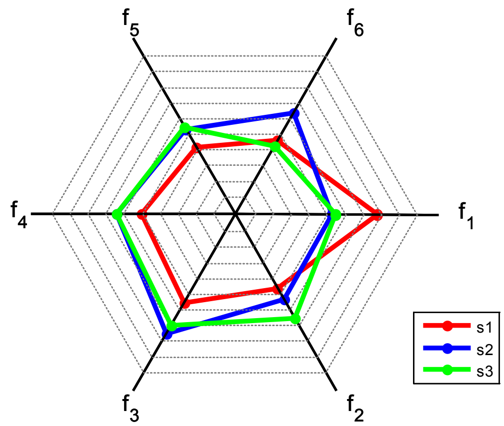

Figure 2 Radar Plot from the LCA Analysis

section, LCA tools have limitations to guide proper decision making for sustainable packaging design. To overcome these disadvantages, we propose a decision making framework using the LCA results.

Methodology

In the previous section, we discussed the major challenges of LCA based decision making. To overcome these challenges, a Ranking Based Decision Making Framework is proposed as illustrated in Figure 3. Two building blocks, Probabilistic Pareto Selection (PPS) and Ranking based Rate of Substitution (RRS) are discussed in this section, and the designer's preference is implemented into the each process.

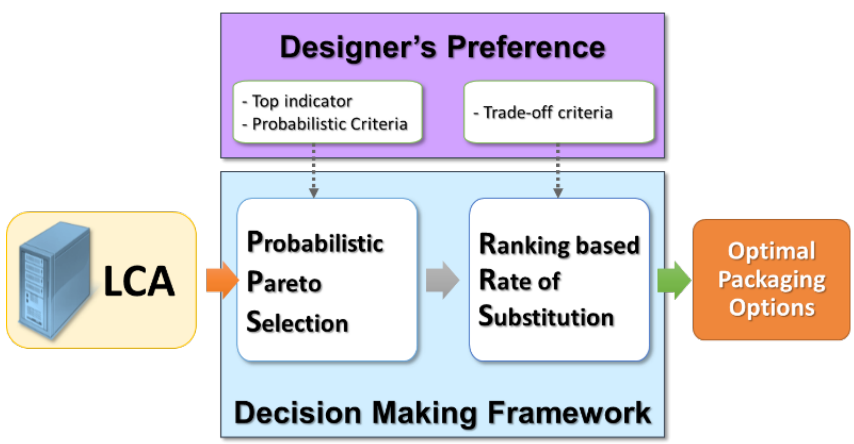

Figure 3 Diagram for Decision Making Process

Probabilistic Pareto Selection (PPS) Method

The Pareto front is a set of solutions for multi-objective problem. Each solution will have a trade-off with other but it will be a best solution for at least one objective. To identify the Pareto Front with uncertainty from the design candidate set, a Probabilistic Pareto Selection (PPS) method is presented. The PPS is composed of two main parts. The first is an algorithm to identify the Pareto Front and the second compares the different packaging designs with uncertainty.

A conventional method to identify the Pareto Front from a data set is the exhaustive search method. This method is very simple but not efficient enough because some non Pareto Fronts are kept in the comparing process until all Pareto Fronts are found. To improve the efficiency of generating the Pareto Front, a new method is proposed in this paper. In this proposed method, the designer first chooses and ranks one of the LCA environmental impact indicator results from minimum to maximum. This indicator can be selected by the designer's preference or based on other criteria. After the ranking is completed, the best design (the one with the lowest value of the selected impact indicator) is automatically one of the Pareto solutions because any other design option would be outside the boundaries of the optimal criteria for environmental impact.

To continue this process, all other design options are compared based on the second environmental impact indicator under the f_1 ranking order. For a simple example with only two indicators f_1 and f_2; if f_1 is the most important indicator and f_2 is the second indicator, then all data are ranked based on f_1 first. The best design in f_1, which is plotted as a red circle with a black outline in Figure 4, is selected as a Pareto solution. Then, all other options are compared with the Pareto solutions following the f_1 ranking order sequentially. For example, the second design option has a better f_2 impact indicator so it is marked as a red circle and included in the Pareto set.

If the new design option failed the test, it will not be included and marked grey. The remaining design options would only need to be compared with all current Pareto solutions. The design marked as a blue circle in the middle, only needs to be compared with the higher ranked Pareto designs, and three red circles to check the dominancy but not with all non-Pareto solutions and non-tested design options. This selection process has been found to be much more efficient than the exhausted search method.

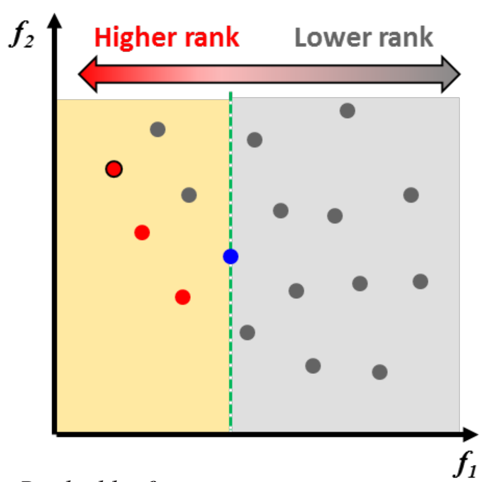

Figure 4 Pareto Front Selection: Ranked by f_1

To extend the Pareto selection process under uncertainty, the following equation is implemented for the probabilistic dominance comparison:

$$P\left(f_n\left(S_i\right)<f_n\left(S_j\right)\right)>P_c,\ \forall n=1\cdots m$$

where $P(\cdot)$ is a probability operator, f_n is an environmental impact indicator, m is the number of indicators used, and P_c is the probabilistic criteria. If the probabilistic dominancy of S_i over S_j is less than the criteria, then the design option, S_i is not considered to be a dominating design option over S_j on this indicator. If one design option has at least one dominating environmental impact indicator over any existing Pareto design, then the design can be considered as a Pareto solution and will be included in the Pareto front. By incorporating the probabilistic dominancy comparison, we will be able to include the uncertainty of the LCA results during the Pareto Front selection process. As a result, some of the designs which have larger mean values can be selected into the Pareto set if it satisfies the probabilistic criteria. This will allow the Pareto Front selection to be more flexible by means of adjusting the probabilistic criteria, P_c. Additionally, the designers preference can be implemented into the criteria as well. A comparison between the deterministic Pareto Front selection and the probabilistic Pareto Front is illustrated in Figure 5

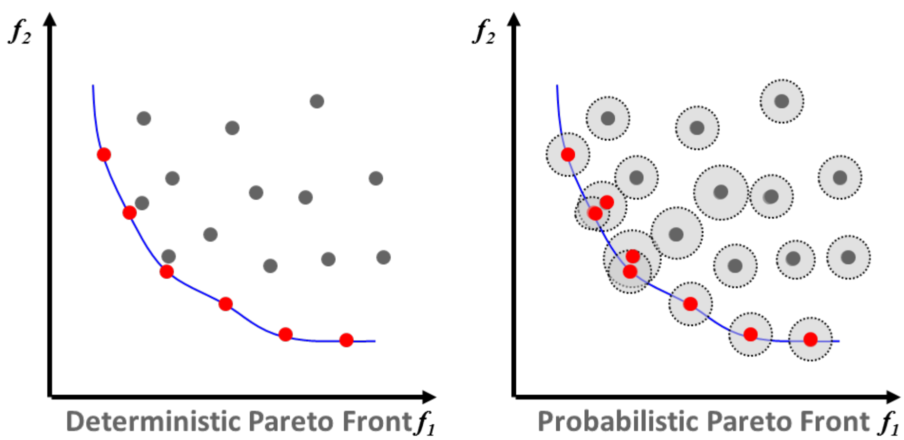

Figure 5 Conceptual illustration for PPS: Deterministic Pareto Front (Left), and Probabilistic Pareto Front (Right)

Ranking based Rate of Substitution (RRS) Method

Once the Probabilistic Pareto Front is identified, the designers may still have too many "good" design solutions that cannot be implemented in practice. To solve this issue, a Ranking based Rate of Substitution (RRS) is developed to reduce the number of possible solutions.

The basic concept of RRS is normalizing the difference of each indicator between two different designs and making a decision based on that difference. In the PPS method, the designer first chooses the most important environmental indicator and the 1st ranked design (f_p^1) is the best solution with respect to the selected indicators (p). Although all other Pareto solutions will not be better in terms of the most important indicator, it is still very likely that other Pareto solutions may have better performance based on other indicators. If one design demonstrates good improvements over the other indicators this may compensate for the deficiency of the first, and most important, indicator (p). Therefore, the design should be included in the final design set. On the other hand, if the improvement cannot compensate the deficiency, then the design will not be included in the final solutions set. By using this concept, the trade-off, R_{np}^{ij}, can be evaluated and compared in the form of equation (2).

$$R_{np}^{ij} = \frac{f_n^i / f_n^j}{f_p^j / f_p^i} \; \forall n = 1 \cdots m \wedge n \neq p$$

where f represents the values of environmental impact indicators; the subscript n represents the n^{th} environmental indicator and p is the most important indicator which is chosen based on the designer's preference; the superscripts i denotes the design options among the Pareto solution, and j is the 1st ranked design by the environmental indicator p. R_{np}^{ij} is the trade-off of a substituting design option i for the design option j in terms of the gain of f_n over the loss of f_p. The designer can define the minimum trade-off threshold for different indicators first. If the trade-off is better than the threshold then the substitution of design option i for j is acceptable and the design will be included; if not, the design is eliminated. The comparison process continues until the entire Pareto front set is evaluated and a final reduced set is obtained. To control the number of possible Pareto solutions in the final set, the designer can select a different baseline design and/or adjust the minimum trade-off threshold for each environmental impact indictor. The minimum trade-off threshold can also be defined by the designer's preference.

To enhance this process, the designer can implement priority among all environmental impact indicators to further reduce the size of a final possible solution set. It is clear that all designs that were selected by rate of substitution, can be solution but just different trade-off. In practical case, the designer has different preference for different indicator. If the design for paperboard, then the water discharge could be main concern of designer, or if it is glass packaging, then energy usage should be the major consideration. Therefore, based on the designer's

Table 1 Environmental Impact Priority Selection

	f_1	f_2	f_3	f_4	f_5	f_6	
S_1	×						f_1
S_2		×	×				f_2
S_3		×	×		×		f_2
S_4					×	×	f_5
S_5				×		×	f_4
S_6				×	×		f_4

preference, the priority of environmental impact can be determined, and using the priority, the number of final solutions can be reduced. For example, six Pareto designs are identified after the PPS and the priority of environmental impacts are ranked from high to low as f_1 to f_6. Let us use the design option S_1 as the baseline and the designs S_1 to S_6 are in the ranked order of f_1 as shown in Table 1.

The red cells represent the designs that are considered as acceptable for trade-off from the gain of f_n (corresponding column) over the loss of f_1. When the designer considers only the top two environmental impact indicators, f_1 and f_2, then only S_1, S_2 and S_3 can be added into the final possible solution set. If the designer considers two more environmental impact indicators, $f3$ and $f4$, then both S_2 and S_3 will be included in the final set. The Pareto design S_4 will not be included because of its low trade-off value found in f_1 to f_4.

CASE STUDIES

In this section, two different cases are studied using the proposed methods. PackageSmart from EarthShift Inc. is used for the LCA and six indicators are defined as follows: (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).

In the first example, soft tube packaging options are compared and discussed and the second example presents the milk packaging options. The primary, secondary and tertiary packaging are defined of all case studies, and the total number of packaging options are determined for the selections of packaging components, packaging materials, manufacturing processes and transportation methods.

Soft Tube

Soft tube is one of the commonly used packaging designs which has many applications especially in pharmaceutical and consumer products. For a soft tube package, the three packaging stages are defined as shown in Figure 6. The primary packaging is composed of a tube, tube head and a cap. The secondary packaging is a carton that could be

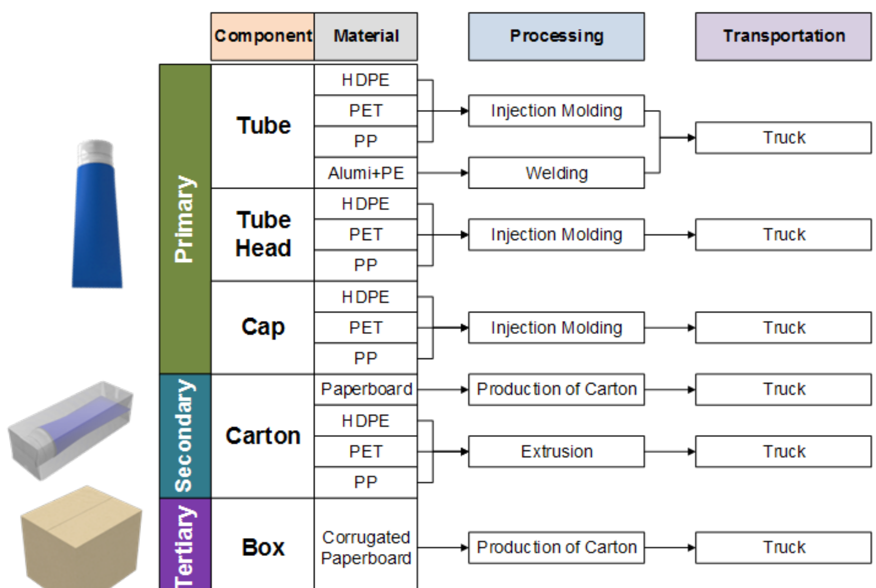

Figure 6 Soft Tube Packaging Stage and Options

made from different materials. The tertiary packaging is defined as the corrugated paperboard box. The detailed information of packaging materials, processing methods and transfortations are described in Figure 6.

For the processing method, only tube head manufacturing processings are listed since all tubes are assumed to be fabricated by simple extrution. For simplicity, we only selected trucks for the transportation method. In total, 96 packaging design options are considered by combining different materials for each packaging component in the study.

As we discussed in the previous sections, the first step is to identify the Pareto solutions set. In this process, two different types of designer preferences are used, the most important environmental indicator and probabilistic criteria. For this case study, the resource (f_5) is defined as the most important indicator among six indictors and all designs can be ranked by f_5. Once the designs were ranked, the probability dominance is checked based on the probability criteria to consider the uncertainty of the LCA results. The total number of designs in the Pareto set will be changed according to the selection of the Probabilistic criteria (P_{cr}). If the criterion is strictly defined, then the number of Pareto designs is reduced. On the other hand, if the criterion is more relaxing, then the size of the Pareto set can be increased. For example, if P_{cr} is chosen as 0.5, 24 Pareto designs are included, and if P_{cr} is 0.4999, a total of 36 Pareto design are included through the PPS process. In this study, P_{cr} = 0.5 is applied and the environmental impacts of all 96 design options are plotted in Figure 7. Red represents the Pareto Front designs and blue ones are none Pareto Front.

From Figure 7, the Pareto Front solutions can be divided into two groups, Pareto designs and non-Pareto designs. For further evaluation, only Pareto solutions are considered. As shown in Figure 8, all Pareto solutions are clearly plotted in two groups: group A (red) has high ecosystem (f_3) and water depletion impact but less resource (f_5), and group B (black) has completely reversed effects. Under further study, we found that the main difference between these two groups of the packaging system is the carton materials. The carton package for group A is made of plastic materials such as HDPE, PP and group B is paperboard. Since the most important criteria was defined as resources (f_5), the group A solutions are included in the final design selection first. If designs from group B can compensate any design in group A and pass the threshold, then it will

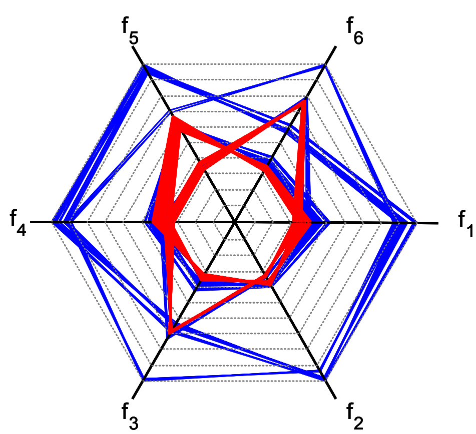

Figure 7 LCA results for Soft Tube Packaging

also be included in the final solutions. On the other hand, if designs in group B failed the test, then those designs will not be included.

To eliminate the design which cannot compensate for the disadvantage of f_5, the RRS method is implemented. Designer can implement their preference through the trade-off rate as discussed previously. Since resource (f_5) is the most important function, the trade-off rate will be compared based on the difference of f_5 and other indicators. After applying the RRS method, a total of five package design systems are selected in the final design set as shown in Figure 9. The details of the material selections for packaging components are listed in Table 2.

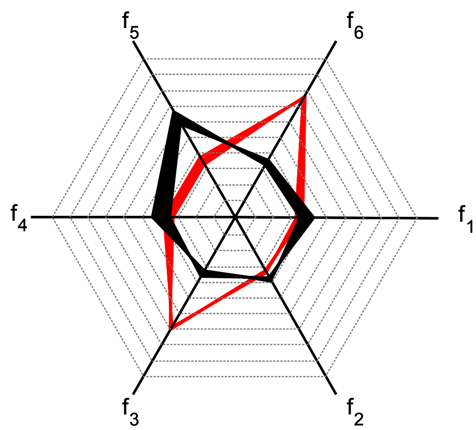

Figure 8 Pareto Fronts of the Soft Tube Packaging

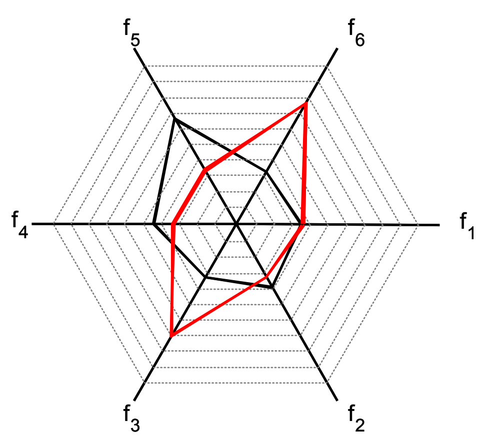

Figure 9 Final Packaging Design Set for Soft Tube

Table 2 Final Packaging design List for Soft Tube

Packaging Designs	Tube	Tube Head	Cap	Carton
Design 1	HDPE	HDPE	HDPE	Paperboard
Design 2	HDPE	PP	HDPE	Paperboard
Design 3	HDPE	HDPE	PP	Paperboard
Design 4	PP	HDPE	PP	PP
Design 5	PP	PP	PP	PP

Table 3 Environmental Impact Priority Selection for Soft Tube

Packaging Designs	f_1	f_2	f_3	f_4	f_5	f_6
Design 1					X	
Design 2				X		
Design 3				X		
Design 4						X
Design 5						X

To select the final design solution, the indicator priority can be implemented. Table 3 shows the indicators that have an advantage compared to design 1, which is chosen as the most important. The designs 2 and 3 have higher priority in Human Health (f_4), and the designs four and five are higher in Water depletion (f_5). According to the priority, the total number of final designs can be further reduced. For example, if the designer decides that water depletion is more important than human health, then the final design set would only be design 1, 4 and 5.

Milk Packaging

Milk is one of the largest consumed food products in the world, and many different packaging designs have been developed to protect the milk from recontamination and make it easier for transportation and consumption. The three packaging stages for milk packaging levels are defined as shown in Figure 10. The primary packaging is composed of two components such as jug and cap. The secondary and tertiary packaging is defined as well. The detailed packaging options for the milk packaging case study are illustrated in Figure 10. For the jug, three different types of plastic materials (HDPE, Recycled HDPE, PET), glass, and carton are implemented. For the plastic and carton jug, the HDPE, and PP materials are used for the closure, and for the glass jug an aluminum closure was chosen. 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, 44 packaging options are generated in order to find the most efficient milk packaging.

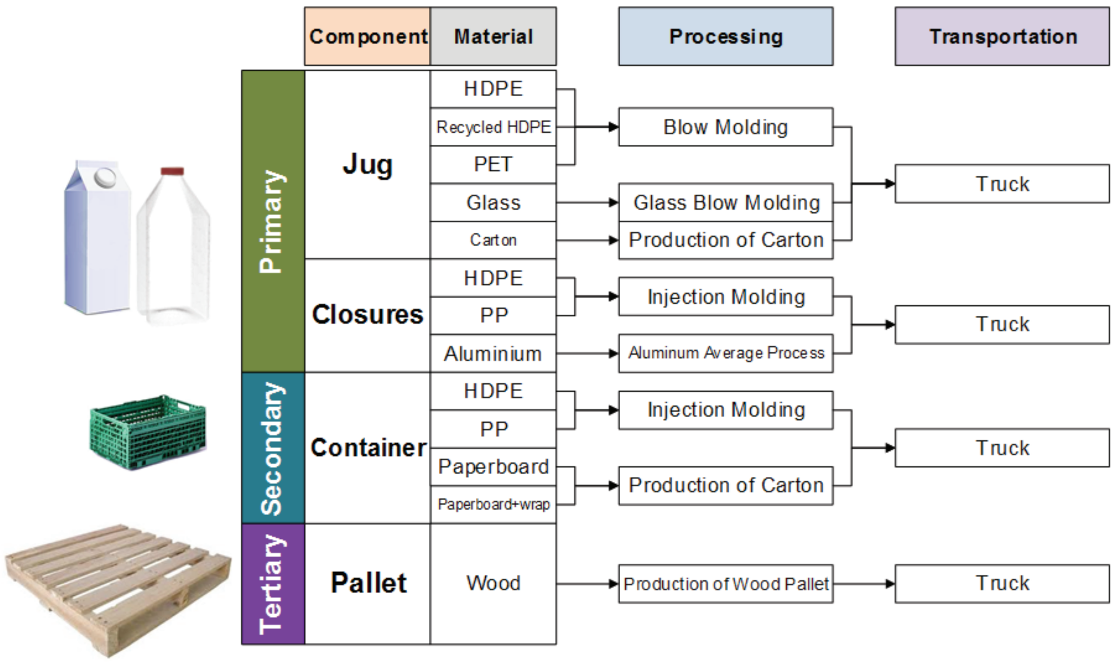

Figure 10 Milk Packaging Stage and Options

For the milk packaging option we ranked all of the designs and selected climate change (f_1) as the most important function based on impact. Through the PPS method 15 packaging options are found with P_{cr}=0.495 as Pareto Front solutions among 44 packaging options and the radar chart is illustrated in Figure 11.

After the Pareto Front is generated, the trade-off is examined and eight designs are selected as the final designs as shown in Figure 12. Then, the final designs can be ranked depending on the priority of the indicator. In this study, f_1 is selected as the most important function, the remaining priorities are 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 is listed in Table 4

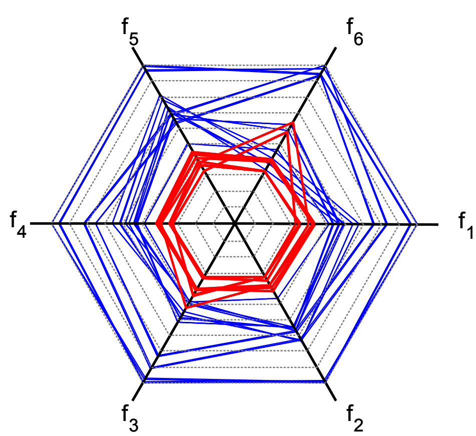

Figure 11 LCA results for Milk Packaging

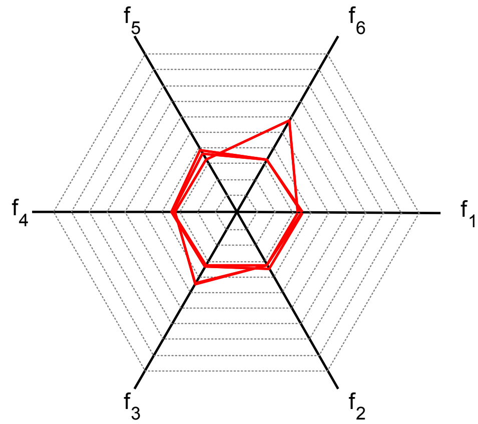

Figure 12 Final Packaging Design Set for Milk Packaging

Table 4 Final Packaging Design List for Milk Packaging

Design	Jug	Closure	Container
Design 1	Carton	PP	Paperboard
Design 2	Carton	HDPE	Paperboard
Design 3	rHDPE	PP	Paperboard
Design 4	rHDPE	PP	Paper+Wrap
Design 5	HDPE	PP	Paperboard
Design 6	HDPE	HDEP	Paperboard

Table 5 Environmental Impact Priority Selection for Milk Packaging

Packaging Designs	f_1	f_2	f_3	f_4	f_5	f_6
Design 1	X					
Design 2		X		X	X	
Design 3			X			X
Design 4			X			X
Design 5			X			X
Design 6			X			X

If the designer is only focusing on the first three environmental impacts such as f_1, f_3 and f_5, then the designs 1 through 4 will be included in the final packaging design set as highlighted in yellow color in Table 5. Of course, different indicator priorities will lead to different final design selections according to other geographical reasons or regulations.

CONCLUSIONS

In this paper, a probabilistic Pareto decision making framework is presented. Two main building blocks of the proposed framework is the Probabilistic Pareto Selection (PPS) and Ranking based Rate of Substitution (RRS) method. The PPS method can identify the Pareto Front among all packaging options by considering uncertainty. The RRS method can take into account the trade-offs for each design. The two case studies further demonstrated how the proposed method can guide the decision making for sustainable packaging options.

REFERENCES

[1] W. McDonough, and M. Braungart. "Design for the Triple Top Line: New Tools for Sustainable Commerce." Corporate Environmental Strategy, Vol. 9, no. 3, pp. 251-258, 2002

[2] R. Holdway, D. Walker, and M. Hilton. "Eco-Design and Successful Packaging." Design Management Journal (Former Series), Vol. 13, no. 4, pp. 45-53, 2002

[3] H. Lewis, "Defining Product Stewardship and Sustainability in the Australian Packaging Industry." Environmental Science & Policy, Vol. 8, no. 1, pp. 45-55, 2005

[4] S. Boylston, Designing Sustainable Packaging. Laurence King, 2009

[5] T.E. Graedel, and B.R. Allenby. Industrial Ecology and Sustainable Engineering. Prentice Hall Upper Saddle River, NJ, USA, 2010

[6] SG Lee, and X. Xu. "Design for the Environment: Life Cycle Assessment and Sustainable Packaging Issues." International Journal of Environmental Technology and Management, Vol. 5, no. 1, pp. 14-41, 2005

[7] H. Lewis, K. Verghese, and L. Fitzpatrick. "Evaluating the Sustainability Impacts of Packaging: The Plastic Carry Bag Dilemma." Packaging Technology and Science, Vol. 23, no. 3, pp. 145-60, 2010

[8] M. Duda, and J.S. Shaw. "Life Cycle Assessment." Society, Vol. 35, no. 1 , pp. 38-43, 1997

[9] W. Klöpffer, "Life Cycle Assessment." Environmental Science and Pollution Research, Vol. 4, no. 4, pp. 223-28, 1997

[10] J.B. Guinée, M. Gorrée, R. Heijungs, G. Huppes, and R. Kleijn. "Handbook on Life Cycle Assessment." Operational guide to the ISO standards, pp. 1-708, 2002

[11] G. Rebitzer, T. Ekvall, R. Frischknecht, D. Hunkeler, G. Norris, T. Rydberg, W.P. Schmidt, et al. "Life Cycle Assessment: Part 1: Framework, Goal and Scope Definition, Inventory Analysis, and Applications." Environment international , Vol. 30, no. 5, pp. 701-720, 2004

[12] M. Finkbeiner, Towards Life Cycle Sustainability Management. Springer, 2011

[13] J.B. Guinee, R. Heijungs, G. Huppes, A.Zamagni, P, Masoni, R. Buonamici, T. Ekvall, and T. Rydberg, "Life Cycle Assessment: Past, Present, and Future," The International Journal of Life Cycle Assessment,45 (1), pp.90-96, 2011

[14] G. M. Bohlmann, "Biodegradable Packaging Life-Cycle Assessment", Environmental Progress, Vol. 23, Issue 4, pp. 342-346, December, 2004

[15] P. Frankl, F. Rubick,"Life Cycle Assessment in in Industry and Business, Adoption Patterns, Applications and Implication, Berlin, Heidelberg, New York, Springer, 2000

[16] N. H. Wrisberg, de Haes, and U. A. Helias (eds.), Analytical Tools for Environmental Design and Management in a Systems Perspective, Dordrecht, Kluwer Academic Publishers

[17] J.E. Fieldsend and M. E. Richard, “Multi-objective optimization in the Presence of Uncertainty”, The 2005 IEEE Congress on, Vol. 1, pp.243-250, 2005\

[18] D.A. DeLaurentis and D.N. Mavris, “Uncertainty Modeling and Management in Multidisciplinary Analysis and Synthesis”, AIAA Aerospace Science Meeting and Exhibit, 38th, Reno, NV, 2000

[19] H. Li and S. Azarm, “ Product Design Selection Under Uncertainty and with Competitive Advantage”, Transactions of the ASME, Journal of Mechanical Design, Vol.122, no.4, pp.4111-418

[20] E. Zitzler, and L. Thiele, “An Evolutionary Algorithm for Multiobjective Optimization: The Strength Pareto Approach ” TIK Tech. Report No. 43, Swiss Federal Institute of Technology, 1998

[21] A. Zhou, B.Y. Qu, H. Li, P.N. Suganthan, Q. Zhang, “Multiobjective evolutionary algorithms: A Survey of the State of the Art”, Swarm and Evolutionary Computation, Vol.1, no. 1, pp. 32-49, 2011

[22] P. Ngatchou, A. Zarei, and M. A. El-Sharkawi, “Pareto Multi Objective Optimization” Intelligent Systems Application to Power System. Proceeding of the 13th International Conference, pp. 84-91 Nov. 2005

[23] L. Ding, S. Zeng and L. Kang, “A fast algorithm on finding the non-dominated set in multi-objective optimization”, International Journal of Computer Applications, Vol.1, no. 24, pp. 35-39,2010

[24] J. Du, Z. Cai, and Y. Chen, “A sorting based algorithm for finding non-dominated set in multi-objective optimization”, Third International Conference on Natural Computation, IEEE, Vol. 4, pp.436-440, 2007

[25] M. Ben-Akiva and S. Lerman, Discrete Choice Analysis: Theory and Application to Travel Demand, MIT Press, Cambridge, 1985

[26] B. Besharati, S. Azarm and P.K. Kannan, “A Decision Support System for Product Design Selection: A Generalized Purchase Modeling Approach”, Decision Support System, Vol.42, no. 1, pp. 333-350, 2006

[27] H. Qi, E. Lee and H. C. Gea, “Decision Making Tool in Life in Life Cycle Assessment for Packaging Sustrainability”, Proceeding of ASME IDETC/CIE 2013, DETC2013-1368

[28] J. W. Baker, and M. D. Lepech. “Treatment of uncertainties in life cycle assessment.” Intl. Congress on Structural Safety and Reliability. 2009

[29] J.S. Cooper; J. Fava. “Life Cycle Assessment Practitioner Survey: Summary of Results”. Journal of Industrial Ecology 2006