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LIFE CYCLE ASSESSMENT AND OPTIMIZATION MODEL FOR EARTH EXTRACTIVE SYSTEMS, BASED ON MULTIPLE CRITERIA DECISION MAKING PROBLEM

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by

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ABSTRACT

Life Cycle Assessment (LCA) is a comprehensive method to evaluate all attributes or aspects of potential environmental impacts (and economic benefits) throughout a product's lifecycle. However, LCA is typically not able to provide effective guidance in the design/production process and forecast potential impacts without obtaining a complete data set needed (e.g. yield, electricity consumed, and CO_2 released etc.). Such kind of large data query not only consumes a large amount of time, but limits this method application in new technologies and projects. This is because in practice, it is usually difficult to gain all the specified data in the design phase due to many new technologies or projects that are yet in production with many variables undecided.

This report describes a life cycle assessment optimization model (LCAO). This specific model is based on the life cycle inventory (LCI) hybrid method, combining with a modified multiple criteria decision making (MCDM) approach. It requires data but can conduct in the condition of incomplete data set. This helps managers to determine some unknown variables to minimize environmental impact while maximizing economic benefits. In many cases, a number of possibilities for improvements exist and it is not always obvious which one of them results the optimum solution. There could also be more than one optimum solution. In this case, LCAO is also able to find the "best" alternative with multiple and conflicting objectives to provide guidance to managers. It is important to note that LCAO is an iterative process to obtain more and more data determined by the guidance provided by LCAO until the data set is completed. The LCAO model is tested on a crude oil product system as an example.

Key words: Life cycle assessment, Optimization, Multiple criteria

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1 Introduction

Life Cycle Assessment (LCA) is a comprehensive method to evaluate all attributes or aspect of potential environmental impacts, human health and resources consumed throughout a product's lifecycle. For example, a product goes from raw material, to production, to usage, and to waste disposal (ISO, 2006a). The most unique characteristic of LCA is the life cycle perspective.

The study in LCA developed rapidly during the 1990s, after the first LCA publications emerged (e.g., Guinee et al., 1993a,b). During that time LCA was given a great expectation but its results were usually criticized (e.g., Udo de Haes, 1993; Ayres, 1995; Krozer and Viz,1998; Ehrenfeld, 1998; Finnveden, 2000). After that a strong development has occurred and resulted in an international standard (ISO, 2006a,b), including guidelines (e.g., Guinee et al., 2002) and a number of textbooks (Wenzel et al., 1997; Baumann and Tillman, 2004). This has led to the prosperity of LCA.

Although the traditional applications of LCA are oriented towards reducing the environmental impacts (Tillman, Baumann, Eriksson & Rydberg, 1991; Fava et al., 1991; Pedersen & Christiansen, 1992; Heijungs et al., 1992; Boustead, 1992; Fava, Consoli, Dennison, Keoleian, 1993; Weidema & Kru¨ ger, 1993; Guine´e, Heijungs, Udo de Haes & Huppes, 1993; Pedersen, 1993; Vigon et al., 1993; Dickson, Mohin & Vigon, 1993; Fleischer & Schmidt, 1997; Azapagic, 1997), a number of authors have recently applied LCA as a tool for process design (Pesso, 1993; Stefanis, Livingston & Pistikopoulos, 1995; Stewart & Petrie, 1996; Pistikopoulos, Stefanis & Livingston, 1996; Kniel, Delmarco & Petrie, 1996; Stefanis, Livingston & Pistikopoulos, 1997), and process selection (Golonka & Brennan, 1996; Rice, 1997; Yates, 1998; Clift & Azapagic, 1998).

Many applications of LCA are also combined with multiple criteria decision making problem (MCDM), since attributes and impact categories in LCA are usually conflicting (Azapagic & Clift, 1995a,b; Azapagic, 1996; Azapagic, Clift & Lamb, 1996a,b; Azapagic & Clift, 1997; Azapagic & Clift, 1999a,b). (Pauli & Raimo, 1997) indicates that tools and approaches coupled with decision analysis could be beneficial both in the understanding and interpretation the results and in planning an LCA study. (Azapagic, 1999; Azapagic, 1999) suggest that LCA combined with multi-objective optimization provides a strong framework for process design by optimizing economic, environmental and other criteria, because process selection is usually based on considerations of the whole environment, including consumption of raw materials, indirect releases and waste disposal. (Patrick & Laurence, 1999; Robert & Steven, 2002) show the application of the Analytical Hierarchy Process (AHP) as a support decision model to help managers make trade-offs between several environmental dimensions.

One of the main potential applications of life cycle assessment (LCA) is to identify options for environmental and even economic improvements of a system. However, a main problem of traditional LCA lies in finding the best alternative with multiple, and often conflicting, objectives. Additionally, for a new technology or some project, which is not in the real production when LCA starts, it is usually difficult to gain all the specified data, and there still are many variables that should be decided. Therefore, LCA cannot provide meaningful guides for projects without some important data.

To make LCA useful for projects from the beginning when it is difficult to obtain all the data needed, this paper proposes a new LCA optimization model (LCAO), which can conduct in the condition of lack of sufficient data, help managers to determine variables to minimize environmental impact and maximize economic benefits, and finally find the “best” alternative with multiple and conflicting objectives. This model is based on the life cycle inventory (LCI) hybrid method, combining with a modified MCDM approach for this specific problem. There are five main features of this model: 1) can conduct both optimization process and LCA simultaneously; 2) able to be applied to new technologies in the condition of incomplete data set; 3) is an iterative process to obtain more and more data determined by the guidance provided by LCAO until the data set is completed; 4) formulates the multi-objective problem based on hybrid method; 4) modifies MCDM method for this LCAO model; 5) formulates a single objective problem for entire system, from which the optimal solution can be solved according to the decision maker’s preference.

It is important to note that A. Azapagic developed a similar optimization methodology, optimum LCA performance (OLCAP), which is based on the results of LCA and still requires a complete data set and therefore cannot provide guidance in the designing phase. This method can optimize an existing system but waiting to optimize a new system until it is complete can lead to unnecessary cost. However, LCAO can provide guidance in the design phase, so that both the optimization process and the assessment will finish simultaneously. In this way, it not only saves time but also saves money. Additionally, OLCAP formulates a general multi-objective problem which can be solved by MCDM software and finally get the efficient set of solutions. But OLCAP does not specify which MCDM software should be used. LCAO provides specific function to the OLCAP general formula. Many other papers provide ideas to combine LCA and MCDM, but they do not describe how to do it in detail. However, this report shows an effective way to combine them.

The general framework of this model consists of 9 steps:

1. Scope and goal definition
2. Determination of independent variables in the system studied.
3. Completion of LCA with variables.
4. Formulation of constraints for variables.
5. Formulation of MCDM in term of LCA.
6. Optimization and gaining the efficient set of solutions.
7. Assigning weights for categories by paired comparison method.
8. Scaling and formulation of single objective problem for the entire system.
9. Iteration.

The first six steps will be discussed in part 3, and the last three parts will be illustrated in part 4.

2 Life Cycle Assessment

Measuring and reducing the environment impacts is necessary for sustainable development in human activities for providing goods and services, both of which could be summarized under the term ‘‘products’’. Environment impacts are caused by harmful substances released into the environment and interventions (e.g., land use) when producing materials, extracting resources, manufacturing the products, reusing or recycling waste and waste disposal. These emissions, interventions and consumptions lead to a wide range of environment impacts, such as climate change, acidification, stratospheric ozone depletion, eutrophication, tropospheric ozone creation, and depletion of resources, toxicological stress on human health and ecosystems, as well as noise.

Therefore, a clear need of methodology exists to provide complimentary insights, besides current regulatory, to help measure and reduce such environment impacts. Life Cycle Assessment (LCA) is a comprehensive method to evaluate all attributes or aspect of potential environmental impacts, human health and resources consumed throughout a product’s lifecycle, for example, from raw material obtaining, via production and use, to waste disposal (ISO, 2006a). It is “conducted by defining product systems as models that describe the key elements of physical systems.” (ISO, 2006a)

The LCA is still under development. At present, the LCA methodological framework consists of four phases depicted in figure 1-1 (ISO, 2006):

1) Goal and scope definition: describing the reason of study, determining the functional unit and selecting the system boundaries;

2) Inventory analysis (LCI): quantifying relevant inputs and outputs of the system defined in the goal and scope definition phase, including data collection and calculation.

3) Impact assessment (LCIA): aggregating the environmental burdens quantified in the Inventory Analysis into a limited set of recognized environmental impact categories, such as global warming, acidification, Ozone Depletion, etc.;

4) Interpretation: using the results to reduce the environmental impacts associated with the product or process.

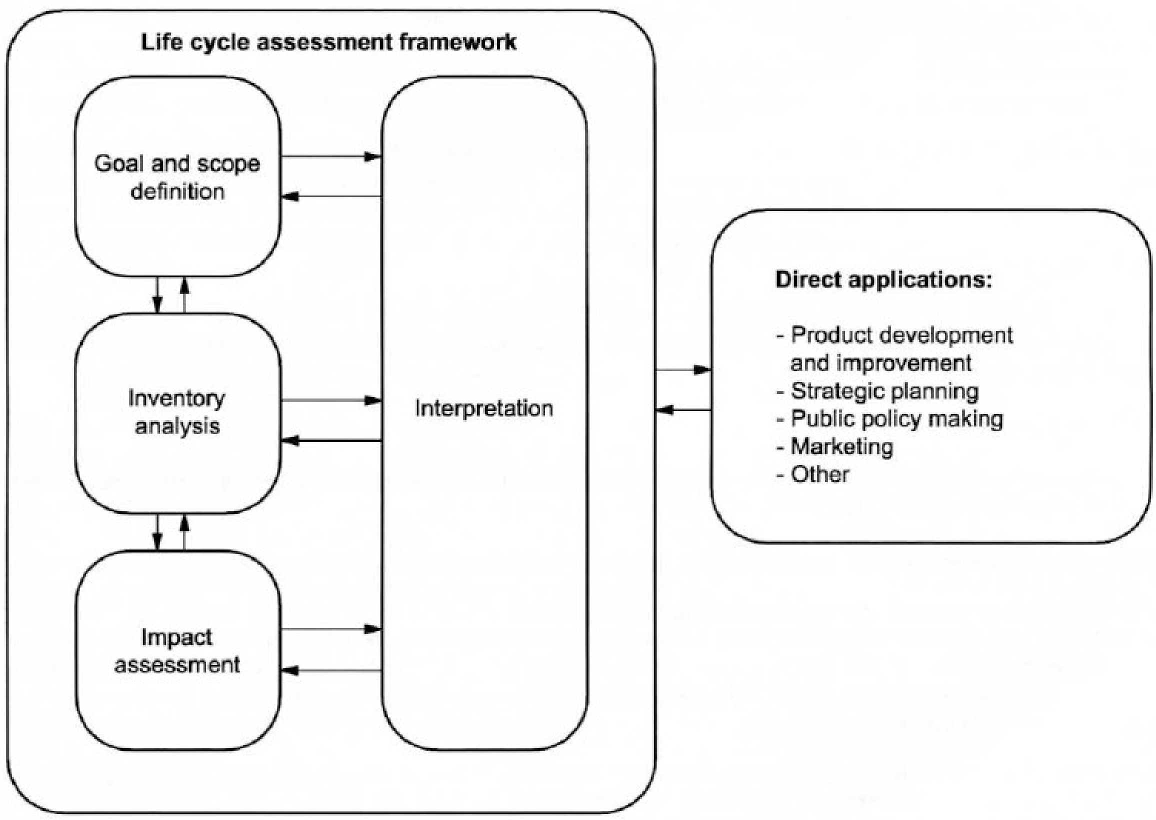

Figure 2-1 Life cycle assessment framework (ISO 14040, 2006)

2.1 The Goal and Scope Definition phase

The goal and scope definition phase of LCA descripts reasons of the study, the system boundary and the functional unit. The main goal of an LCA is to quantifying the overall environmental impacts from a product or service, so that the decision makers are able to choose the best product or service with the least environmental impacts (and highest economic benefits). There may also be other goals for conducting an LCA, which depends on the project. For example, performing an LCA could also help decision makers develop new products or service with less resource requirements.

The system boundary of an LCA defines processes need to be included in the system being studied. The system boundary and level of details depend on the goal of the study. Therefore, the depth and the breadth of LCA can be different considerably depending on the subject and the intended use of a particular LCA. Figure 2-1 illustrates the boundary of a Rare Earth Elements (REE) production system and its life cycle stages in an LCA and the typical inputs/outputs will be measured.

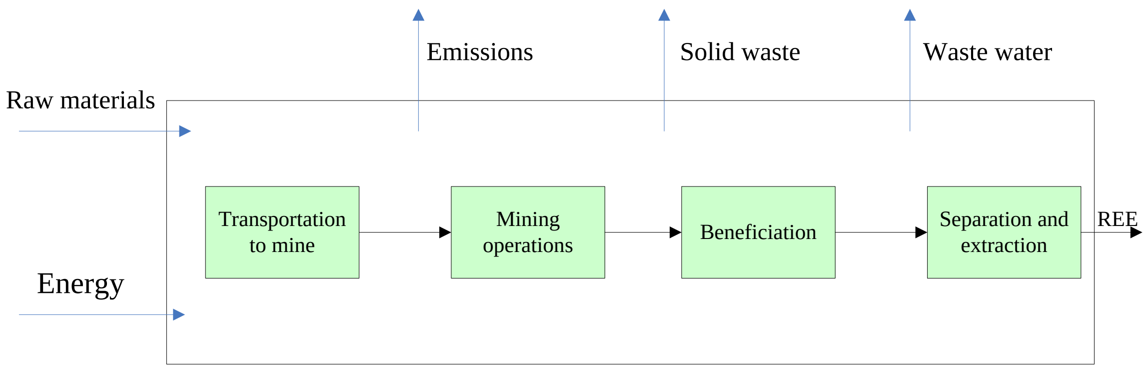

Figure 2-2 System boundary of a REE production system

The functional unit is the basis of LCA, which provides a quantitative description of the product or service of the investigated system. It enables alternative goods and services to be comparable. The functional unit can be a quantity of product, or the service provided. For example, alternative types of packaging can be compared on the basis of one cubic meter of packed and delivered goods. For refrigerators, the functional unit could be defined as one cubic meter year of cooling to 20 ℃ below room temperature.

2.2 The Inventory Analysis phase

The life cycle inventory analysis phase is an inventory of input and output data in relation to the system being studied. It involves data collection and calculation procedures to quantify all the energy and material inputs, as well as outputs from the system, i.e. wastes and emissions. De Beaufort-Langeveld et al. (1997, p. 19) believes that "streamlining efforts should focus on the life cycle inventory analysis, which is typically the most time consuming phase, with the greatest potential for savings.'' Therefore, different cut-offs are usually applied to reduce the effort for the LCI (i.e., exclude processes from the inventory analysis deliberately). The cut-off criteria for choosing key processes and input/output data to be modeled depends on the goal of the study, the intended application, data and cost constraints, and the assumptions made.

In the following sections, three different approaches of life cycle inventory analysis will be illustrated:

1) The simplification of process-LCI modeling,

2) LCI based on economic input–output tables,

3) The hybrid method, which combines simplification of process-LCI with input–output LCI approaches.

2.2.1 Simplification of Process-LCI

Simplification of process-LCI modeling, the basic method of LCI, is to collect all information needed for decision makers from each process in the system boundary. In order to reduce the effort for the LCI, different cut-offs (i.e., exclude processes from the inventory analysis deliberately) are usually applied to reduce the effort for the LCI. There are four broad traditional cut-offs methods, including removal of upstream components, removal of partial upstream components, removal of downstream components, and removal of up-and downstream components. For removal of upstream components, all processes prior to the production of primary materials are excluded. In removal of downstream components, all processes after the production of primary materials are ignored, and the fourth method only analyzes the production of primary materials. However, the universal criteria for horizontal cut-offs does not exist (based on the flow chart where flows start with raw materials extraction at the top and end with the waste disposal at the bottom). It depends on the goal of the study, the intended application, data and cost constraints, and the assumptions made.

2.2.2 I/O-LCI

An alternative to LCAs based on simplification of LCI is industry/commodity level input/output (I/O) modeling (e.g., Hall et al., 1992). I/O table is a quantitative economic table that represents the interdependencies between different industries or commodities. Wassily Leontief (1905–1999) developed this type of economic analysis and took the Nobel Prize in economics for his development of this model. Input/output modeling has been applied as a tool for LCA since 1990s. Moriguchi et al.(1993) analyzed the life cycle CO_2 emissions from an automobile, applying both the process analysis and Japanese input/output table. In the input/output modeling, economic flow databases (tables) are used to model the product system, which consists of supply chains. These databases (tables) are collected and published by the statistical departments of governments. The amount of goods and services, that produced by each industrial sector, consumed by another sector is described financially in these databases. Environmental burdens are then assigned to the output from different sectors. On the other hand, process modeling relies directly on inventory databases that quantify requirements for energy generation processes, transportation, and manufacturing, etc.

Both I/O modeling and process-LCA have their weaknesses and strengths. I/O modeling provides a whole picture of the modeled supply chain by usually considering broader system boundaries. However, the level of detail and the difference between similar systems (e.g., when comparing two different designs for coal production) is very limited. Therefore, specific comparisons between similar systems cannot usually be answered by the I/O modeling approach. I/O modeling is mathematically same as process-LCA: both of them are linear, constant coefficient models. The “unit processes” in the I/O modeling usually represent industrial sectors, rather than product entities as in the process-LCA.

$$a_{11}x_1 + a_{12}x_2 + a_{13}x_3 + \cdots + a_{1j}x_j + \cdots + a_{1m}x_m - y_1 = 0$$

$$a_{21}x_1 + a_{22}x_2 + a_{23}x_3 + \cdots + a_{2j}x_j + \cdots + a_{2m}x_m - y_2 = 0$$

$$a_{31}x_1 + a_{32}x_2 + a_{33}x_3 + \cdots + a_{3j}x_j + \cdots + a_{3m}x_m - y_3 = 0$$

$$\cdots\cdots \tag{1}$$

$$a_{i1}x_1 + a_{i2}x_2 + a_{i3}x_3 + \cdots + a_{ij}x_j + \cdots + a_{im}x_m - y_i = 0$$

$$\cdots\cdots$$

$$ax_1 + a_{m2}x_2 + a_{m3}x_3 + \cdots + a_{mj}x_j + \cdots + a_{mm}x_m - y_m = 0$$

x_i is the total output produced by the i^{th} industry, y_i is the demand of the i^{th} industry's output (consumed by non-industry consumers). Non-diagonal elements are always non-positive, which represent the i^{th} industry's output consumed to produce j^{th} industry's output. The diagonal elements denote the net productions of these industries. Equation 1 means that the total output of each industry equals the total output consumed by other industries and final consumers.

For example, suppose there are only three industries in the economy, the I/O table could be:

Table 2-1 An example of I/O table ($)

	coal	electricity	construction
coal	1	-0.6	-0.1
electricity	-0.2	1	-0.3
construction	-0.4	-0.5	1

Table 2-1 shows that 0.6 dollar's coal is needed to produce 1 dollar's electricity, and 0.1 dollar's coal is consumed for 1 dollar's construction. In the second row, 0.2 dollar's electricity will be consumed by coal production and 0.3 dollar's electricity is necessary for 1 dollar's construction.

Equation 1 can also be written as:

$$Ax - y = 0 \tag{2}$$

For non-singular A, assuming further that the elements of A does not change when its scale is changed, meaning that input coefficients are constant. Rewrite equation 2 as:

$$x = A^{-1}y \tag{3}$$

A^{-1} is the Leontief multiplier, which means the amount of output needed from all other industrial sectors to produce a unit of each industrial sector's output.

Finally, the environmental intervention (e.g., CO_2, SO_2, waste water, solid waste) for the society generated by an arbitrary final demand y can be calculated by:

$$E = Bx = BA^{-1}y \tag{4}$$

E represents the total environmental intervention vector due to an arbitrary demand vector y. Matrix B gives environmental interventions for each dollar of output in each industry, and b_{ij} represents how much intervention i produced by industry j.

The computation of I/O modeling described above is based on the assumption that each industrial sector produces one distinct output. However, in practice, each industrial sector not only produces primary products but also secondary products. Moreover, the output produced by each industrial sector does not have to be unique, so that the output produced by an industrial sector could also be produced by another industrial sector. Therefore, by improving the basic accounting scheme known as supply and use framework (Stone et al., 1963), the commodity-based accounting (input–output accounts based on commodity instead of industry output) has been developed to improve I/O modeling.

2.2.3 Hybrid Model

A process-LCI is generally detailed and specific, but based on incomplete system boundaries because of the effort for collecting ‘‘all’’ data of processes. On the other hand, I/O modeling is more complete in relation to system boundaries but lack details and specificity. Furthermore, the input-output databases are usually published with a several years’ time lag. One widely accepted method to overcome the disadvantages of both process-LCA and I/O modeling, while combining the advantages of them, is hybrid approaches (Suh and Huppes, 2002), which can maintain the quality of results with a complete system boundaries.

One available tool for hybrid approach is the Missing Inventory Estimation Tool (MIET) (Suh, 2001; Suh and Huppes, 2002). The general strategy of MIET is to minimize the use of input-output data for main processes, by restricting its use only to the processes located at the margin of the system boundary, so that the specific data of processes can be used as much as possible while the system boundary keeps complete at the same time.

The commodity-based input-output table is used in this paper, since the industry-based format, currently, is less applicable, because of the aggregation of commodities in industry sectors. Additionally, the industrial sector that produces an input material for downstream processes is generally less fully known than commodity itself. In order to distinguish commodity-based matrix from the industry-based matrix A in (2), A' denote the commodity-by-commodity matrix. The environmental burden by industry matrix B in (4) should also be adjusted to an environmental intervention by commodity matrix, B', see (Sangwon Suh, 2004).

The total environmental intervention due to an arbitrary final demand is then given by:

$$\mathrm{E}' = \mathrm{B}'\mathrm{A}'^{-1}\mathrm{y} \tag{5}$$

To form the hybrid model, it is significant to define the upstream cut-off matrix and the downstream cut-off matrix firstly. The upstream cut-off matrix D^u is formed in such a way that $(D^u)_{ij}$ shows the amount of commodity i consumed by process j during one unit of operation time, in monetary terms. On the other hand, the downstream cut-off matrix D^d is formed in such a way that $(D^d)_{ij}$ presents the amount of cut-off functional flow i needed for one unit monetary value of commodity j, in relevant physical units, find more details in (Sangwon Suh, 2004).

Now the basic balancing equation for hybrid model is given by:

$$\begin{bmatrix} A^* & -\mathrm{D}^d \\ -\mathrm{D}^u & A' \end{bmatrix} \begin{bmatrix} x^* \\ x' \end{bmatrix} = \begin{bmatrix} y^* \\ y' \end{bmatrix} \tag{6}$$

where A’ denotes the commodity-by-commodity input–output technology coefficient matrix that includes domestic and imported current products and capital, with prices updated to current levels, and excluding the portion of commodity flows already covered by the process-based system and x’and y’stand for the total production and the final demand for domestic and imported current products and capital, respectively, with prices updated and with commodity flows already covered by the process-based system subtracted. Eq. (6) shows that the amount of functional flow and input–output commodity produced, minus the amount used in the process-based system and in the input–output based system is equal to the amount delivered to the final consumers. Attention must be paid to the units of the coefficient matrix shown in (6), since all the sub-matrices differ from each other in terms of units. The LCA technical coefficient matrix A* is expressed in various physical units per unit operation time for each process, refer to (Sangwon Suh, 2004), while the input–output technical coefficient matrix A’ is in monetary units per unit output for each input– output commodity in monetary terms, D^u is in monetary units per unit operation time for each process, and D^d is in various physical units per unit of output for each input–output commodity in monetary terms. Rearranging (6) gives

$$\begin{bmatrix} x^* \\ x' \end{bmatrix} = \begin{bmatrix} A^* & -\mathrm{D}^d \\ -\mathrm{D}^u & A' \end{bmatrix}^{-1} \begin{bmatrix} y^* \\ y' \end{bmatrix} \tag{7}$$

for a non-singular square matrix

$$A^{**} = \begin{bmatrix} A^* & -\mathrm{D}^d \\ -\mathrm{D}^u & A' \end{bmatrix} \tag{8}$$

The amount of environmental intervention produced during the required unit operation time and the production of input–output commodities is calculated by

$$\bar{E} = [B^* \quad B'] \begin{bmatrix} x^* \\ x' \end{bmatrix} \tag{9}$$

Where B* is the environmental intervention by processes matrix and B' is the environmental intervention by input–output commodities matrix.

Combining (7) and (9):

$$\bar{E} = \begin{bmatrix} B^* & B' \end{bmatrix} \begin{bmatrix} A^* & -\mathrm{D}^d \\ -\mathrm{D}^u & A' \end{bmatrix}^{-1} \begin{bmatrix} y^* \\ y' \end{bmatrix} \quad (10)$$

2.3 The Impact Assessment phase

The life cycle impact assessment phase (LCIA) provides further information to help evaluate LCI results from a product system, in order to get a better understanding of its environmental impacts, by providing factors for calculating and cross-comparing environmental intervention indicators of the potential environmental impacts in relation to the emissions, the wastes, and the resources consumed which are attributable to the provision of goods and services. LCIA consists of both mandatory and optional procedures (elements), as illustrated in (ISO 14040, 2006):

1) Selection of the impact categories, impact category indicators and, the characterization models, which should be also considered in the goal and scope phase.
2) Assignment of LCI results to the chosen impact categories (classification).
3) Calculation of impact category indicators results utilizing characterization factors (characterization).
4) Calculation of the magnitude of category indicator results relative to reference information (normalization, optional).
5) Grouping and weighting the results (optional, weighting is not allowed when following ISO14042).

6) Data quality analysis (mandatory, according to ISO 14040, but little attention in current practice).

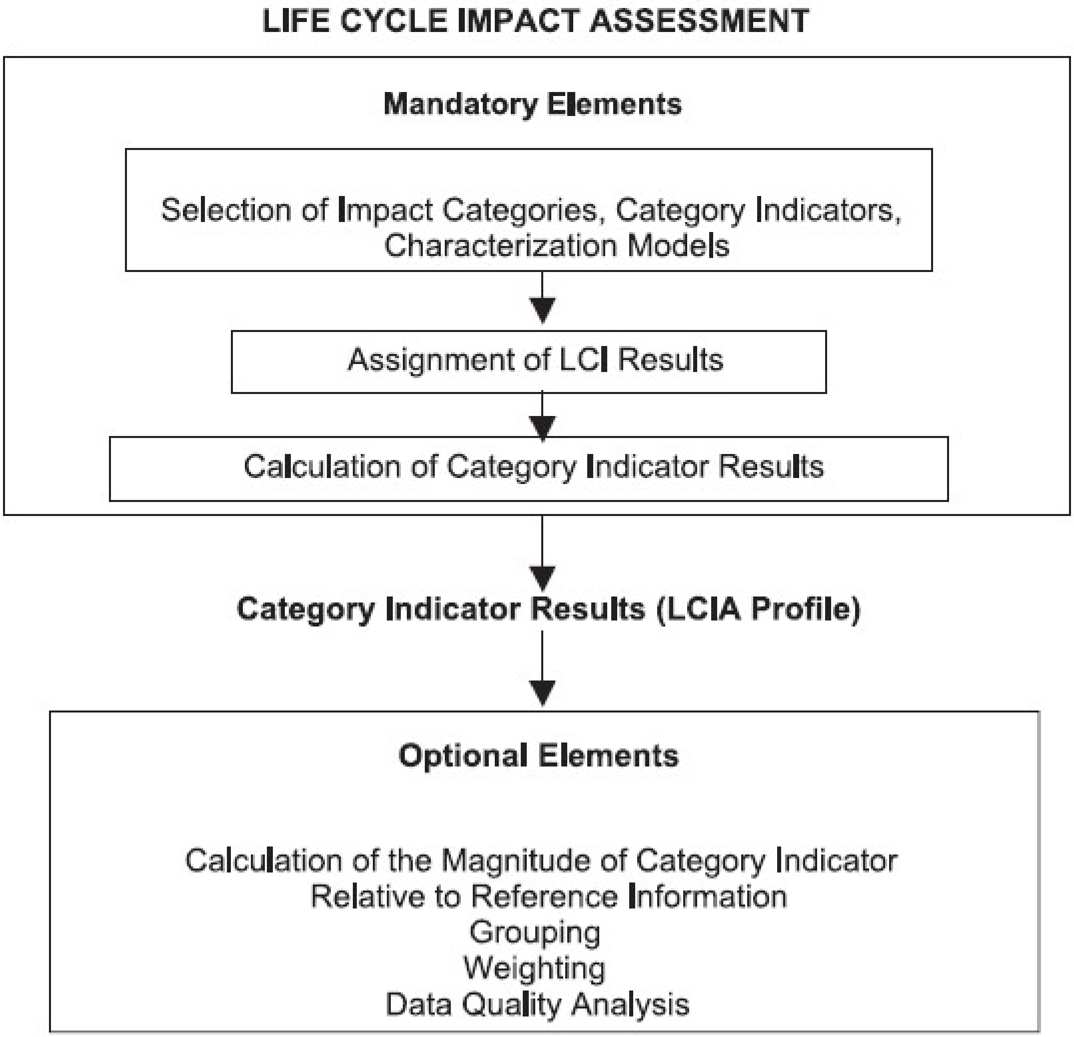

Figure 2-3 Life cycle impact assessment elements (ISO 14040, 2006)

According to ISO 14040, there are three broad groups of environmental impact categories which should be considered when defining the goal and scope of an LCA. Impact categories consist of climate change, eutrophication, acidification, stratospheric ozone depletion, water use, photo oxidant formation (smog), noise, etc. These three broad groups of impact categories are commonly referred to as AoPs (Udo de Haes etal., 1999):

1) Resource use

2) Human health consequences

3) Ecological consequences

Eq. (11) provides an example of how indicator for each environmental impact category can be calculated from the LCI results utilizing generic characterization factors, which are the output of characterization models. These factors, in the form of databases, are available to practitioners in LCA support tools and literature.

$$z_i = \sum f_j \times e_j \tag{11}$$

where z denotes the category indicator (e.g., climate change, eutrophication, acidification or resource use, human health consequences and ecological consequences), f represents the characterization factor and e is the environmental intervention. Equation (11) can also rewrite as:

$$Z = FE \tag{12}$$

$$F = \begin{pmatrix} f_{11} & f_{12} & \cdots & f_{1,n-1} & f_{1n} \\ f_{21} & f_{22} & & f_{2,n-1} & f_{22} \\ & & \ddots & & \\ \vdots & & f_{ij} & \vdots & \\ & & & \ddots & \\ f_{m-1,1} & f_{m-1,2} & & f_{m-1,n-1} & f_{m-1,n} \\ f_{m1} & f_{m2} & \cdots & f_{m,n-1} & f_{mn} \end{pmatrix} \tag{13}$$

Where Z denotes the category indicator vector, F represents the characterization factor matrix, f_{ij} means the amount of indicator i caused by environmental intervention j.

2.4 The Interpretation phase

The life cycle interpretation phase is the final procedure of the LCA, in which the results of an LCI and(or) an LCIA, are summarized and discussed in order to make conclusions, recommendations and decisions in relation to the goal and scope definition.

Life cycle interpretation phase is intended to form a readily understandable, complete report of the results of an LCA, which is consistent with the goal and scope definition. The interpretation phase may also include the iterative process of reviewing and revising the scope of the LCA, as well as the quality of the data collected and the calculation of environmental impacts, in accordance with the goal and scope definition.

3 The Multiple Criteria Problem in Life Cycle Assessment

One of the main potential applications of life cycle assessment (LCA) is to identify options for environmental and even economic improvements of a system. However, a main problem lies in finding the best alternative with multiple, and often conflicting, objectives. Additionally, for a new technology or some project, which is not in the real production when LCA starts, it is usually difficult to gain all the specified data, and there still are many variables that should be decided. Therefore, LCA cannot provide meaningful guides for projects without some important data.

To make LCA useful for projects from the beginning when it is impossible to get all the data needed, this paper proposes an life cycle assessment and optimization model (LCAO), which can conduct in the condition of lack of sufficient data, help managers to determine variables to minimize environmental impact and maximize economic benefits from the designing phase, and finally find the “best” alternative from multiple and conflicting objectives for the decision maker.

3.1 Scope and Goal Definition

The first step of this model is also the scope and goal definition. It is same as the first phase of traditional LCA. When LCAO is combined with the simplification of process-LCI, the system boundary is incomplete, and less effort is needed. This simple model can be applied to small systems which will cause little impact to the society, or for decision makers who only need to consider their systems with specific purpose. When hybrid LCI is utilized in LCAO, a whole picture can be seen in this model, including the total environmental impact to the entire society and the economic effects for the whole economy. Additionally, the goal of hybrid-LCAO is to optimize the affect for the overall society by changing controllable variables.

3.2 Data Collection and Variables Definition

Data collection is the most time consuming step of LCA, The more data is collected, the more precise the result is.

However, it is very difficult to gain all data needed at the beginning in practice, and some of them also have not decided. For example, the decision variables could be the amount of production and the way of transportation need to be decided in order to optimize the system. Therefore, in LCAO model, after gaining all available data, the unknown data and the data need to be decided can be substituted by variables, called decision variables. Moreover, the decision variable, which is determined by other variables, could be substituted by the mathematic relation formula between them.

Furthermore, it is important to give constraints for each defined decision variables. Constraints could be: continuous or integer (discrete) variables, the range of variables which could be a conservative empirical estimation, or following restrictions of other variables $g(x) \leq 0$, where x is an n-vector of decision variables.

It is important to note that, LCAO is an iterative process. As more and more data and constraints for decision variables can be gain, the result tends to correspond to the real situation.

3.3 LCIA Model Choosing

In order to understand the significance of potential environmental impacts and thereby minimize these potential environmental impacts, it is important, in general, to select appropriate LCIA model which associate the result of LCI with specific environmental impact categories and category indicators, as illustrated in section 2.3.

According to the selected LCIA model, a characterization factor matrix could be formulated:

$$F = \begin{pmatrix} f_{11} & f_{12} & & \cdots & & f_{1,n-1} & f_{1n} \\ f_{21} & f_{22} & & & & f_{2,n-1} & f_{22} \\ & & \ddots & & & & \\ \vdots & & & f_{ij} & & \vdots & \\ & & & & \ddots & & \\ f_{m-1,1} & f_{m-1,2} & & & & f_{m-1,n-1} & f_{m-1,n} \\ f_{m1} & f_{m2} & & \cdots & & f_{m,n-1} & f_{mn} \end{pmatrix} \tag{13}$$

where f_{ij} represents the characterization factor of j^{th} environmental intervention for i^{th} category indicator.

3.4 Formulation of MCDM

Because a number of distinct environmental impacts are considered in LCA, optimization problems associated with LCA are inevitably multiple criteria decision making problem (MCDM). Therefore, LCAO is formulated to optimize the system with multiple conflicting criteria (usually economic and environmental). The vector of environmental impact category indictors Z can be calculated by:

$$\mathrm{Z} = \mathrm{FE} \tag{12}$$

Combined with hybrid LCI, (12) becomes:

$$\mathrm{Z} = \mathrm{F}\overline{\mathrm{E}} \tag{14}$$

Combined (10) and (12):

$$Z = F\begin{bmatrix} B^* & B' \end{bmatrix} \begin{bmatrix} A^* & -\mathrm{D}^d \\ -\mathrm{D}^u & A' \end{bmatrix}^{-1} \begin{bmatrix} y^* \\ y' \end{bmatrix} \tag{15}$$

The economic benefits could be represented by:

$$\mathrm{P} = \mathrm{R} - \mathrm{C} \tag{16}$$

Where P is the present value of the system, R represents the revenue and C donates the cost.

Considering the sequence problem, the economic profits could be represents as:

$$\mathrm{P} = \sum_{t=0}^{T-1} \delta^t (R - C) \tag{17}$$

Where T is the total time periods considered, δ is the discount rate.

A LCAO problem is looking to minimize the various environmental impacts while maximizing the economic benefits. It takes the following form:

$$\mathrm{Min}\ z_1(\mathrm{x}, \mathrm{x}') \tag{18}$$

$$\mathrm{Min}\ z_2(\mathrm{x}, \mathrm{x}')$$

$$\cdots\cdots$$

$$\mathrm{Min}\ z_m(\mathrm{x}, \mathrm{x}')$$

$$\mathrm{Max}\ \mathrm{P}(\mathrm{x}, \mathrm{x}')$$

s.t.

$$g_k(\mathrm{x}, \mathrm{x}') \leq 0, \mathrm{k} = 1,2,3 \ldots$$

$$q_s(\mathrm{x}, \mathrm{x}') = 0, \mathrm{s} = 1,2,3 \dots$$

$$\mathrm{x} \in R^n$$

$$\mathrm{x}' \in Z^q$$

where z_i and P are impact category indicator (e.g. resources use, human health consequences or ecological consequences) function and economic profit function. $g_k(\mathrm{x}, \mathrm{x}')$, $q_s(\mathrm{x}, \mathrm{x}')$ represent inequality (e.g., the capacity: the yield should less than a certain amount) and equality constraints (e.g., the production efficiency limited by technology: put 1 dollar's coal will get 1.2 dollar's electricity), and *x* and *x'* denote the vectors of continuous and integer decision variables.

In a broader context, LCAO problem could be formulated as:

$$\text{Min } Z(x, x') = \{z_1(x, x'), z_2(x, x'), \dots, z_m(x, x')\} \tag{19}$$

$$\text{Max } \mathrm{P}(\mathrm{x}, \mathrm{x}') = \{p_1(x, x'), p_2(x, x'), \dots, p_l(x, x')\}$$

$$\text{Max } \mathrm{O}(\mathrm{x}, \mathrm{x}') = \{o_1(x, x'), o_2(x, x'), \dots, o_q(x, x')\}$$

s.t.

$$g_k(\mathrm{x}, \mathrm{x}') \le 0, \mathrm{k} = 1,2,3 \dots$$

$$q_s(\mathrm{x}, \mathrm{x}') = 0, \mathrm{s} = 1,2,3 \dots$$

$$\mathrm{x} \in R^n$$

$$\mathrm{x}' \in Z^q$$

where the economic criteria vector P may contain short term profits and long term profits etc. the vector O represents other criteria to be considered (e.g., the energy efficiency and profitability per capita).

The equality constraints include energy and material balances; the inequality constraints could represent material availabilities, emissions standards and production requirements, ranges of capacities etc.

Continuous variables maybe mass, energy and material flows, yield, pressures, compositions, sizes of units etc., while integer variables may be represented by the quantity of equipment, factories or transportation times, processing routes in the system.

If the discount rate is considered or nonlinear terms exist, (18) and (19) is a Mixed-Integer Nonlinear Programming (MINLP) problem.

The MCDM problem (18) and (19) can be solved by Excel or Lindo, and the result is usually a set of efficient solutions instead of a "best" solution. By definition, the efficient solution means that an objective is able to be improved only at the loss of at least one other objective.

For example, consider a bi-criteria LP model:

$$\text{Maximize} \; z_1 = 5x_1 + x_2 \tag{20}$$

$$\text{Minimize} \quad z_2 = x_1 + x_2$$

$$\text{Subject to:} \quad x_1 + x_2 \leq 6$$

$$x_1 \leq 5$$

$$x_2 \leq 3$$

$$x_1, x_2 \geq 0$$

The decision space is ABCDE:

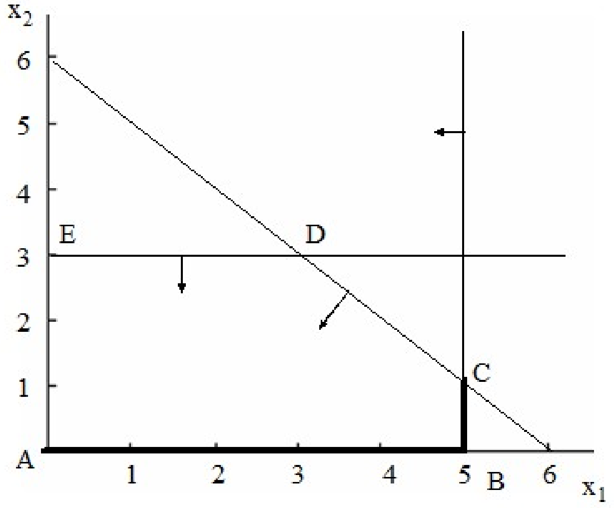

Figure 3-1 Decision space

The extreme points are

A: (0,0) with $z_1 = 0$, $z_2 = 0$

B: (5,0) with $z_1 = 25$, $z_2 = 5$

C: (5,1) with $z_1 = 26$, $z_2 = 6$

D: (3,3) with $z_1 = 18$, $z_2 = 6$

E: (0,3) with $z_1 = 3$, $z_2 = 3$

The set of efficient solutions ABC is indicated by the bold face lines in Figure 3-1 and Figure 3-2. A, B, and C are three non-dominated solutions. E and D are examples of dominated solutions, which are able to be improved without losing any other objectives. The ideal solution is $z_1 = 26$ and $z_2 = 0$ given as point I in the objective space graph. It is not achievable. Therefore, the bounds of these two objectives are $0 \leq z_1 \leq 26$ and $0 \leq z_2 \leq 6$.

The objective space is:

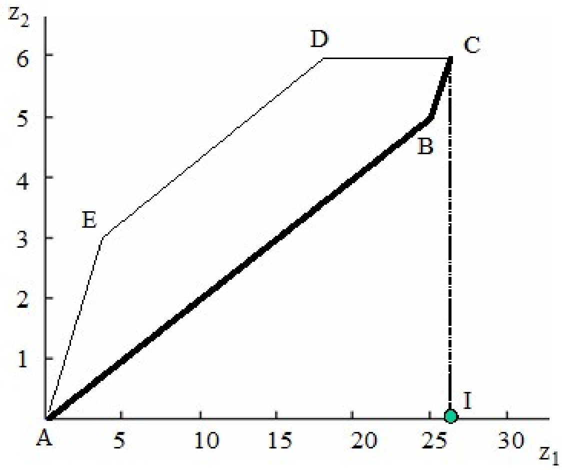

Figure 3-2 Objective space

In the real production, it is necessary to find the best solution rather than a set of alternatives. Therefore, in the next part, a modified MCDM approach is introduced to help decision makers to identify the best solution.

4 Life Cycle Optimization

The main propose of this part is to find the best solution for the decision maker from the efficient set of solutions. As already pointed out, it is impossible to improve an objective without losing others for a solution in the efficient set. Therefore, trade-offs between the objectives are inevitable to find the best compromise solution according to the goal and scope of the study.

One possible methodology to identify the best solution in the context of multiple criteria would be to assign weights to environmental and economic objectives indicating their significance, so that the problem is aggregated to a single objective optimization. There are two main groups of methods to assign weighting:

1) Monetization (use a monetary measure for all weighting factors to express the relative importance of economic profits and impact category indicators in financial terms.)
2) Panel (the relative importance of economic profits and impact category indicators are determined by a group of people)

However, one of the main drawbacks of this approach is that it requires a priori articulation of preference.

Cost-benefit analysis (CBA) is one of the monetization approaches in the decision-making process, particularly in the area of social welfare. The main idea of CBA is to maximize net gain. However, CBA is difficult to keep intergenerational equity and sustainability and evaluate the natural environment.

A widely applied, and even more criticized, approach, which combines both of monetization and panel model, is the contingent valuation (CV). In CV, decision makers are asked how much they would like to pay to avoid an environmental impact (willingness to pay) or how much they would be prepared to accept for that impact (willingness to accept) (Pearce et al., 1989).

Over the past years, a number of MCDM methods for quantifying and ranking preferences have been developed with the aid for providing guidance to decision makers to identify the "best" solution (their most desired solution), including multi-attribute utility theory (Keeney & Raiffa, 1976), simple additive weighting and median ranking method (Hwang, Paidy & Yoon, 1980), the analytic hierarchy process (HAP) (Saaty, 1980), and simple multi-attribute rating technique (von Winterfeldt & Edwards, 1987). More MCDM techniques can be found in (Stewart, 1992) and (Yoon and Ching, 1995). Software for various MCDM methods with the aim of providing guidance for decision making process is introduced in (Hamalainen & Lauri, 1995).

4.1 Weights Determination

In this paper, the approach for identifying the best solution is based on the efficient set of solutions. Although to identify the best compromise solution among infinite efficient solutions, some articulation of preferences is still inevitable, these preferences are expressed by decision makers after the elimination of all dominated solutions which can be improved without worsening any objectives, as distinct from articulating preferences and aggregating the multiple objectives into a single objective problem prior to eliminating all dominated solutions.

It is important to note that the preferences of criteria are usually expressed case by case in the specific decision making situation, and that they only can be applied in that particular context. This avoids the problem often voiced, in both LCA and CBA, of trying to find general weights to reflect the relative importance of criteria in different contexts.

Rating method, Borda Count method and paired comparison method are all widely applied to assigning weights for criteria. Rating method is to rate criteria in a scale of 1 to 10, and then normalize them to obtain weights. However, it is not always easy for decision makers to keep the same standard for each criterion. The Borda Count is named after Jean Charles de Borda, a French Physicist in 18th Century. The P criteria are ranked from P (least important) to 1(most important). Criterion ranked 1 gets P points, 2nd rank gets P-1 points and last place gets 1 point. Let S is equal to the sum of all points, S = P(P+1)/2. Then weights can be obtained by:

$$\begin{gathered}\text{criterion 1} = P/S \\ \text{criterion 2} = (P-1)/S \\ \ldots\ldots \\ \text{last criterion} = 1/S\end{gathered} \tag{21}$$

A main drawback of Borda Count is inconsistent response, because of the ranking criteria subjectively, for example, the decision may say A>B, B>C, but C>A. Another problem is the assumption that differences between weights are always equal to 1/S.

In this paper, a modified method will be developed based on rating method, Borda Count and paired comparison method, to assign weights for objectives and then find the best solution for decision makers as the target in the designing phase.

4.1.1 Paired Comparison

The main strategy of paired comparison is to ask decision maker for their preference between pairs of criteria, for example, decision maker can respond between criteria A and B: 1) A is preferred to B; 2) B is preferred to A; or 3) Indifferent. Therefore, there are N(N-1)/2 comparisons between pairs of criteria need to be made, then a (N*N) preference matrix can be formed. Finally, rank criteria and obtain weights by Borda count.

For example: there are 5 criteria A, B, C, D, E, thus10 paired comparisons will be made:

A>B; A>C; A>D; A>E

B<C; B>D; B<E

C>D; C<E

D<E

Then assign values for preferences: if not preferred assign 0, otherwise assign 1. In this example the final values for criteria are: A is 5; B is 2; C is 3; D is 1; E is 4. Therefore the ranking is: A, E, C, B, D. By applying Borda Count, weights are:

$$w_A = 0.333$$

$$w_B = 0.133$$

$$w_C = 0.2$$

$$w_D = 0.067$$

$$w_E = 0.267$$

4.1.2 Range

The problem of paired comparison method is comparing criteria without any reference. For example, in the case that the range of the waste water is from 10t to 1000t and the range of economic profit is from $100,000 to $100,100, the decision maker may believe that the waste water is more important, while if the range of the waste water is from 990t to 1000t and the range of economic profit is from $100,000 to $200,000, the decision maker must believe that the economic benefit is far more important.

In this study, the focus is on the range of choices from the set of efficient solutions, rather than the whole decision making space (the entire range of variables). Therefore, the range of each variable in the set of efficient solutions will be treated as reference for decision makers. It is also important to note that the final single objective function in section 4.2 should be scaled by range, since it used as reference here.

4.1.3 Modified Paired Comparison

In the modified paired comparison method, it is necessary to gain the bound (range) of each criterion from the efficient set of solutions first. These bounds can be calculated from (14) or (15) by excel. The next step is to conduct paired comparison and assign strength of preference with the reference of the bounds, using a ratio. For example, in the case that the range of the waste water is from 10t to 1000t and the range of economic profit is from \$100,000 to \$100,100, the question for decision makers could be that how many \$100 you want to pay for reducing 990t waste water. The final step of this modified paired comparison method is to determine the normalized criteria weights W= (W_1, W_2, …, W_n) using n by n paired comparison matrix in step 2.

For example, for criteria C_1, C_2, C_3, C_4, the paired comparison matrix can be obtained according to the bounds of them:

$$A = \begin{array}{c} \\ C_1 \\ C_2 \\ C_3 \\ C_4 \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & C_3 & C_4 \end{array} \\ \begin{bmatrix} 1 & 5 & 2 & 4 \\ 1/5 & 1 & 1/2 & 1/2 \\ 1/2 & 2 & 1 & 2 \\ 1/4 & 2 & 1/2 & 1 \end{bmatrix} \end{array} \tag{22}$$

Where a_{ij} means the weight of criteria i divided by the weight of criteria j.

Normalize matrix A:

$$A_{Norm} = \begin{array}{c} \\ C_1 \\ C_2 \\ C_3 \\ C_4 \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & C_3 & C_4 \end{array} \\ \begin{bmatrix} 0.5128 & 0.5 & 0.5 & 0.5333 \\ 0.1026 & 0.1 & 0.125 & 0.0667 \\ 0.2564 & 02 & 0.25 & 0.2667 \\ 0.1282 & 0.2 & 0.125 & 0.1333 \end{bmatrix} \end{array} \tag{23}$$

Finally, weights can be calculated:

$$W_1 = \frac{0.5128 + 0.5 + 0.5 + 0.5333}{4} = 0.5115$$

$$W_2 = \frac{0.1026 + 0.1 + 0.125 + 0.0667}{4} = 0.0986$$

$$W_3 = \frac{0.2564 + 0.2 + 0.25 + 0.2667}{4} = 0.2433$$

$$W_4 = \frac{0.1282 + 0.2 + 0.125 + 0.1333}{4} = 0.1466$$

4.2 Single Objective Optimization

After assigning weights to environmental and economic objectives indicating their significance, the multiple criteria decision making problem can be aggregated to a single objective optimization. In his way, the “best” solution, which is in accordance with the decision makers’ preference, could be calculated for the design guidance.

4.2.1 Scaling

It is important to note that scaling is necessary in this method, because the weights for environmental and economic objectives are all based on the bounds of criteria (objectives). Several approaches are widely applied to scaling, including simple scaling, scaling by ideal values, linear normalization, vector scaling. In this study, linear normalization is used to keep consistent, since bounds are used as reference to gain weights. The criteria values are scaled as follows:

$$\mathrm{r} = \begin{cases} \frac{f-L}{H-L} & for \max criterion \\ \frac{H-f}{H-L} & for \min criterion \end{cases} \tag{24}$$

where L represents the lowest bound of the criteria, H means the highest bound of the criteria and f is the actual value function of the criteria. Here all the scaled criteria values will be between 0 and 1 and all the criteria are to maximize after scaling.

4.2.2 Formulation

For (18), the final single objective function is:

$$\max \sum_{i=1}^{m} W_i \frac{H_i - z_i(x, x\prime)}{H_i - L_i} + W_P \frac{P(x, x\prime) - L_P}{H_P - L_P} \tag{25}$$

s.t.

$$g_k\left(\mathrm{x}, \mathrm{x}^{'}\right) \leq 0, \mathrm{k} = 1,2,3 \dots$$

$$q_s(\mathrm{x}, \mathrm{x}') = 0, \mathrm{s} = 1,2,3 \dots$$

$$\mathrm{x} \in R^n$$

$$\mathrm{x}' \in Z^q$$

where z_i and P are impact category indicators (environmental criteria) function and economic profit function. $g_k\left(\mathrm{x}, \mathrm{x}^{'}\right)$, $q_s(\mathrm{x}, \mathrm{x}')$ represent inequality and equality constraints, and *x* and *x'* denote the vectors of continuous and integer decision variables. W_i is the weight for the ith impact category indicators (environmental criteria), H_i and L_i are the highest and lowest bounds of z_i, W_P is the weight for the economic profit, H_i and L_i are the highest and lowest bounds of P.

For the general formula (19), the single objective function could be formulated as:

$$\max \sum_{i=1}^{m} W_i r_i + \sum_{j=1}^{l} W_j r'_j + \sum_{t=1}^{q} W_t r''_t \tag{26}$$

s.t.

$$g_k(\mathrm{x}, \mathrm{x}') \leq 0, \mathrm{k} = 1,2,3 \ldots$$

$$q_s(\mathrm{x}, \mathrm{x}') = 0, \mathrm{s} = 1,2,3 \ldots$$

$$\mathrm{x} \in R^n$$

$$\mathrm{x}' \in Z^q$$

where W_i is the weight for scaled impact category indicators (environmental criteria) r_i.

$$r_i = \frac{H_i - z_i(x, x')}{H_i - L_i} \tag{27}$$

W_j is the weight for scaled economic profit r'_j

$$r'_j = \frac{P_j(x, x') - L_j}{H_j - L_j} \tag{28}$$

W_t is the weight for scaled other criteria r''_t

$$r''_t = \begin{cases} \dfrac{O_t(x, x') - L_t}{H_t - L_t} & for \max criterion \\ \dfrac{H_t - O_t(x, x')}{H_t - L_t} & for \min criterion \end{cases} \tag{29}$$

The problem (25), (26) could be linear programming (LP) or nonlinear programming (NLP), depending on the relationship among variables. The approach for solving such problems is well developed in (Dantzig, 1963; Floudas, 1995) and several commercial software packages are also available online for the large scale LP or NLP problem, for example, XPRESS-MP (Dash Associates, 1993) and (GAMS, 1998) which are often applied in chemical engineering.

5 Application

The computational structure of LCAO will be further illustrated here by a simple example. The process chosen for illustrating the LCAO approach is a crude oil extraction. The environmental impacts and economic benefits of the system can be optimized, subjecting to market constraints, by varying variables. It is important to note that only one month oil production is studied in this example, so that the time horizon is not being considered.

5.1 Scope and Goal Definition

A crude oil production system is shown in Fig 5-1.

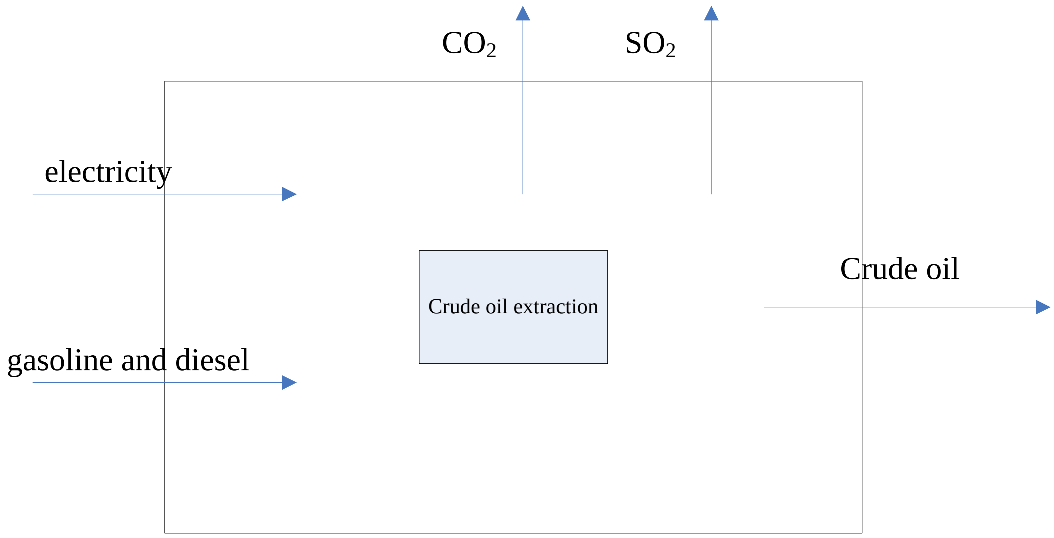

Figure 5-1 Crude oil extraction system boundary

This system is a commodity-by-commodity input-output table in monetary terms ($). Data are from U.S. Life Cycle Inventory Database, U.S. Energy Information Administration Database, and Bureau of Economic Analysis Database.

Table 5-1 Input and output of crude oil product system in monetary terms ($)

	crude oil	electricity	gasoline and diesel
crude oil	1.117	0.133	0.762
electricity	0.5942	1.0097	0.0193
gasoline and diesel	0.0035	0.0287	1.1072

In the crude oil product system shown in Fig 5-1 and Table 5-1, $1.117 of crude oil is produced using $0.5942 of electricity and $0.0035 of gasoline and diesel.

Note that this system shown in Fig. 1 and Table 1 is difficult to analyze using the process approach, since it has internal loops among these three sectors. Table 1 can be summarized in matrix:

$$A^* = \begin{bmatrix} 1.117 & -0.133 & -0.762 \\ -0.5942 & 1.0097 & -0.0193 \\ -0.0035 & -0.0287 & 1.1072 \end{bmatrix} \qquad (30)$$

5.2 Completion of LCA with Variables

Let us suppose that the only thing need to be determined in this system is the production of crude oil which is controlled by the amount of water injected into ground. Additionally, the CO_2 emission from oil production is unknown, and the price of crude is another independent variable.

Assuming that only transportation, construction, primary metals, machinery, fabricated metal products and chemical products are related to this system. According to the US annual input-output (I-O) table 2011, the upstream cutoffs, the downstream cutoffs and the input–output technical coefficients are shown in Table 5-2, Table 5-3 and Table5-4.

Table 5-2 Upstream cutoffs in monetary terms ($)

	crude oil	electricity	gasoline and diesel
transportation	0.0058	0.0099	0.0121
construction	0.0576	0.0363	0.043
primary metals	0.0348	0.0127	0.0272
Machinery	0.0134	0.0058	0.0105
Fabricated metal products	0.0293	0.0131	0.0235
chemical products	0.0398	0.0136	0.05

Table 5-3 Downstream cutoffs in monetary terms ($)

	transportation	construction	primary metals	machinery	fabricated metal products	chemical products
crude oil	0.5321	0.0545	0.0524	0.0258	0.0282	0.1243
electricity	0.0327	0.0148	0.085	0.0283	0.0403	0.0385
gasoline and diesel	0.7654	0.0743	0.0461	0.0273	0.0274	0.0976

Table 5-4 Input–output technical coefficient in monetary terms ($)

	transportation	construction	primary metals	machinery	fabricated metal products	chemical products
transportation	1.0034	0.0091	0.055	0.0161	0.022	0.0218

construction	0.0965	1.0082	0.0232	0.0115	0.0143	0.0158
primary metals	0.0959	0.0527	1.7119	0.263	0.4239	0.029
Machinery	0.0194	0.0267	0.0275	1.098	0.023	0.0141
Fabricated metals	0.0779	0.0652	0.0611	0.1416	1.1398	0.0265
chemical products	0.0634	0.0391	0.0511	0.0587	0.0669	1.4771

C^u, C^d, A' are then given by:

$$C^u = \begin{bmatrix} 0.0058 & 0.0099 & 0.0121 \\ 0.0576 & 0.0363 & 0.0430 \\ 0.0348 & 0.0127 & 0.0272 \\ 0.0134 & 0.0058 & 0.0105 \\ 0.0293 & 0.0131 & 0.0235 \\ 0.0398 & 0.0136 & 0.0500 \end{bmatrix} \quad (31)$$

$$C^d = \begin{bmatrix} 0.5321 & 0.0545 & 0.0524 & 0.0258 & 0.0282 & 0.1243 \\ 0.0327 & 0.0148 & 0.0850 & 0.0283 & 0.0403 & 0.0385 \\ 0.7654 & 0.0743 & 0.0461 & 0.0273 & 0.0274 & 0.0976 \end{bmatrix} \quad (32)$$

and

$$A' = \begin{bmatrix} 1.0034 & -0.0091 & -0.0550 & -0.0161 & -0.022 & -0.0218 \\ -0.0965 & 1.0082 & -0.0232 & -0.0115 & -0.0143 & -0.0158 \\ -0.0959 & -0.0527 & 1.7119 & -0.2630 & -0.4239 & -0.0290 \\ -0.0194 & -0.0267 & -0.0275 & 1.0980 & -0.0230 & -0.0141 \\ -0.0779 & -0.0652 & -0.0611 & -0.1416 & 1.1398 & -0.0265 \\ -0.0634 & -0.0391 & -0.0511 & -0.0587 & -0.0669 & 1.4771 \end{bmatrix} \quad (33)$$

Suppose that only CO_2, SO_2, NO_x are released to the environment, and crude oil is the only resource needed for these 9 sectors, and the environmental intervention matrix $[B^* \quad B'] =$

$$\begin{bmatrix} x & 0.1358 & 0.0117 & 0.0189 & 0.0121 & 0.0036 & 0.0084 & 0.3880 & 0.4237 \\ 0.0000 & 0.0009 & 0.0021 & 0.0000 & 0.0000 & 0.0005 & 0.0000 & 0.0032 & 0.0075 \\ 0.0000 & 0.0004 & 0.0000 & 0.0005 & 0.0000 & 0.0003 & 0.0000 & 0.0001 & 0.0013 \\ 166.67/p & 21.95/p & 114.70/p & 88.38/p & 9.01/p & 5.10/p & 3.92/p & 4.12/p & 14.03/p \end{bmatrix}$$

(34)

Where p represents the price of crude oil, x represents the amount of CO_2 released from the production of one dollar's crude oil.

The environmental intervention matrix shows that 166.67/p kg oil is needed to produce 1 dollar's crude oil. For 1 dollar's electricity, 0.1358 kg CO_2, 0.0009 kg SO_2, 0.0004 kg NO_x will emit to air, and 21.95/p kg crude oil will be consumed.

According to (ReCiPe, 2008), There are three environmental impact categories, including damage to human health, damage to ecosystem diversity, and damage to resource availability. Life cycle assessments commonly evaluate damage to human health by using the concept of "disability-adjusted life years" (DALY). The DALY is derived from health statistics on both years of life lost and disabled. In this paper, equal weightings are used to the importance of them for all ages, and DALY is equal to the sum of life year lost and life year disabled. Ecosystems are very complex to monitor, and the unit used in this paper is loss of species during a year. For damage to resource availability, the ReCiPe model is based on how the use of these resources leads to marginal changes in relation to the efforts to extract future resources.

The characterization factor matrix is:

$$F = \begin{bmatrix} 1.19 \times 10^{-6} & 0 & 0 & 0 \\ 8.73 \times 10^{-6} & 1.52 \times 10^{-9} & 0 & 0 \\ 0 & 0 & 0 & 0.052 \end{bmatrix} \tag{35}$$

The characterization factor matrix shows that 1 kg CO_2 emitted to air causes 1.19×10^{-6} years of life lost, 8.73×10^{-6} of species loss during a year, and nothing for the resource availability. 1 kg SO_2 emitted to air leads to 1.52×10^{-9} of species loss during a year. 1kg oil extracted causes 0.052 dollars' cost increase for the future resources extraction.

If
$$\begin{bmatrix} y^* \\ y' \end{bmatrix} = \begin{bmatrix} y \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \tag{36}$$

Where y represents the production of crude oil

Then, according to (15), the vector of environmental impact category indictors Z can be calculated:

$$Z = F[B^* \quad B'] \begin{bmatrix} A^* & -C^d \\ -C^u & A' \end{bmatrix}^{-1} \begin{bmatrix} y^* \\ y' \end{bmatrix} \tag{15}$$

$$Z = \begin{bmatrix} (1.43991 \times 10^{-7} + 1.21 \times 10^{-6} x) y/p \\ (1.05634 \times 10^{-6} + 8.9 \times 10^{-6} x) y/p \\ 9.979231394 y/p \end{bmatrix} \tag{37}$$

5.3 Formulation of MCDM

Suppose that the production of crude oil depends on the amount of water injected, and the limitation for the injection is 6000 barrels per day, that is 180000 barrels per month.

$$0 \le v \le 180000 \tag{38}$$

Where v represents the amount of water injected. The relationship between the production of crude oil and the injection follows the equation below:

$$0.02vp = y \tag{39}$$

The economic benefits could be represented by:

$$\mathrm{P} = \mathrm{R} - \mathrm{C} \tag{16}$$

In this case, it is given as:

$$\mathrm{P} = y - 10000 - 0.1y \tag{40}$$

\$100000 is the fixed cost per month, and 0.1y is the variable cost.

The CO_2 released from oil production should be positive:

$$x \geq 0 \tag{41}$$

The crude oil price will vary between \$40 and \$150:

$$40 \leq p \leq 150 \tag{42}$$

According (18), this LCAO problem takes the following form:

$$\text{Min } z_1 = (1.43991 \times 10^{-7} + 1.21 \times 10^{-6}x)y/p \tag{43}$$

$$\text{Min } z_2 = (1.05634 \times 10^{-6} + 8.9 \times 10^{-6}x)y/p$$

$$\text{Min } z_3 = 9.979231394y/p$$

$$\text{Max P} = y - 10000 - 0.1y$$

s.t.

$$0 \leq v \leq 180000$$

$$0.02vp = y$$

$$x \geq 0$$

$$40 \leq p \leq 150$$

When x=0 and v=0, z_1, z_2, z_3 attain the minimum value. When v=180000, P achieve the maximum value. Therefore, the efficient set of solutions is (x=0, p=40, v) and (x=0, p, v=0).

The range of z_1, z_2, z_3, and p are: (0, 0.000518368), (0, 0.003802824) (0, 35925.23302) (-10000, 476000).

5.4 Formulation of Single Objective Problem

For criteria z_1, z_2, z_3, P, the paired comparison matrix can be obtained according to the bounds of them:

$$A = \begin{array}{c} \\ z_1 \\ z_2 \\ z_3 \\ \mathrm{P} \end{array} \begin{array}{c} \begin{array}{cccc} z_1 & z_2 & z_3 & \mathrm{P} \end{array} \\ \begin{bmatrix} 1 & 1/2 & 1/10 & 1/100 \\ 2 & 1 & 1/5 & 1/50 \\ 1/10 & 5 & 1 & 1/10 \\ 1/100 & 50 & 10 & 1 \end{bmatrix} \end{array} \tag{44}$$

Normalize matrix A:

$$A_{Norm} = \begin{array}{c} \\ z_1 \\ z_2 \\ z_3 \\ \mathrm{P} \end{array} \begin{array}{c} \begin{array}{cccc} z_1 & z_2 & z_3 & \mathrm{P} \end{array} \\ \begin{bmatrix} 0.0089 & 0.0089 & 0.0089 & 0.0089 \\ 0.0177 & 0.0177 & 0.0177 & 0.0177 \\ 0.0885 & 0.0885 & 0.0885 & 0.0885 \\ 0.8850 & 0.8850 & 0.8850 & 0.8850 \end{bmatrix} \end{array} \tag{45}$$

Finally, weights can be calculated:

$$W_1 = \frac{0.0089 + 0.0089 + 0.0089 + 0.0089}{4} = 0.0089$$

$$W_2 = \frac{0.0177 + 0.0177 + 0.0177 + 0.0177}{4} = 0.0177$$

$$W_3 = \frac{0.0885 + 0.0885 + 0.0885 + 0.0885}{4} = 0.0885$$

$$W_4 = \frac{0.885 + 0.885 + 0.885 + 0.885}{4} = 0.885$$

According to (25):

$$\max \sum_{i=1}^{m} W_i \frac{H_i - z_i(x, x')}{H_i - L_i} + W_P \frac{P(x, x') - L_P}{H_P - L_P} \tag{46}$$

The single objective problem can be formulated:

$$\max 0.0089\frac{0.000518368-(1.43991\times10^{-7}+1.21\times10^{-6}x)y/p}{0.000518368}$$
$$+0.0177\frac{0.003802824-(1.05634\times10^{-6}+8.9\times10^{-6}x)y/p}{0.003802824}$$
$$+0.0885\frac{35925.23302-9.979231394y/p}{35925.23302}$$
$$+0.885\frac{y-10000-0.1y+10000}{486000} \tag{47}$$

By calculation, the optimum solution is: x=0, y=540000, p=150, v=180000. That means that the best result can be achieved when 180000 barrels water injected into ground, the crude oil price is $150 and no CO_2 released in the oil production process.

5.5 Iteration

As the process goes on, more data will be obtained, and fewer variables need to be determined. For example, if it is finally known that the CO_2 emission of oil production is 0, there are only three variables left in this model. According to the results from previous section, the optimum solution of CO_2 emission from oil production is 0 as well. Therefore, there is no change in the results.

However, in practice, the oil price varies independently, so that the relationship among these three variables can be drawn as the oil price change. In this case, the optimum value of v is always 180000 barrels, and does not change with the oil price. The relationship graph between crude oil price (p) and the production of oil (y) is shown below:

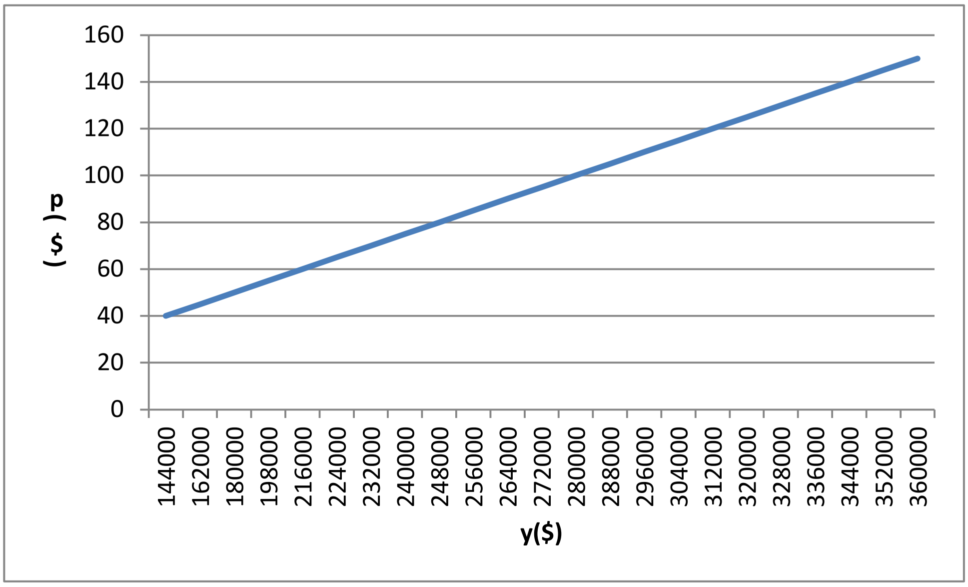

Figure 5-2 Relationship between crude oil price (p) and the production of oil (y)

6 Conclusions

In addition to the function of evaluating environmental impacts and economic benefits of a process in a life cycle view to help decision-makers to choose the best project among alternatives, another function of improvement developed by LCAO is to provide guidance throughout the design and product process in the condition of data set that is incomplete. These guidance include the target value of each variable to achieve the optimum performance and the relationship among variables for “what if” analysis. LCAO is an iterative process that eventually completes a data set.

In many cases, a number of possibilities for improvements exist and it is not always obvious which one of them results the optimum solution. There could also be more than one optimum solution. In this case a method of choosing the best compromised solution from the optimum solution set is necessary. Therefore, combining LCAO with a modified multiple criteria decision making (MCDM) approach helps decision-maker find the optimum solution set and the best compromised solution for every specific case. It should be noted that this combination may not be the best option in some cases, but it is another approach in MCDM to find the solution.

The future work of LCAO will include testing the risk and variance as it applies to new technology, and performing sensitive analysis on variables.

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