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Sustainable design of complex industrial and energy systems under uncertainty

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DEDICATION

To my wife Liyuan,

my daughter Melissa,

and my parents

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For the motivation and desire that I receive to pursue my dreams and become the best I can be, thank you all.

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CHAPTER 1

INTRODUCTION

Increased human activities combined with new economic, environmental and social constrains shows that energy consumption, raw materials depletion and environmental impacts are receiving increased attention by modern society (Carvalho *et al.*, 2008). Due to those factors, sustainability is being pursued by the whole world to achieve a short- to long-term harmonious development for various types of systems.

The word "sustainability" is derived from the Latin "sustinere". It has been used since the 1980s in the sense of human sustainability on planet Earth, which finally resulted in the most widely quoted definition of sustainability and sustainable development, given by the Brundtland Commission of the United Nations on March 20, 1987: “sustainable development is development that meets the needs of the present without compromising the ability of future generations to meet their own needs” (Brundtland, 1987). It was noted at the 2005 World Summit that sustainability requires the reconciliation of environmental, social and economic demands (United Nations General Assembly, 2005), which is so called the "three pillars" of sustainability until now. This view has been expressed later as an illustration using three overlapping ellipses indicating that the three pillars of sustainability are not mutually exclusive and can be mutually reinforcing (Forestry Commission of Great Britain, 2009), see Fig. 1.1.

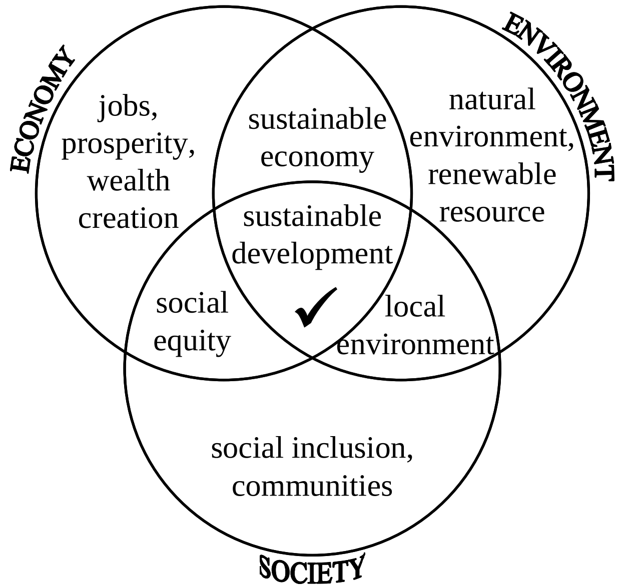


Figure 1.1. Illustration of the three pillars of sustainability.

1.1 Sustainability of Industrial and Energy Systems

As a broad subject, sustainability is studied and managed over many scales of time and space – from planet Earth to ecosystems, countries, economic sectors, individual lives, occupations, lifestyles, behavior patterns and so on (Millennium Ecosystem Assessment, 2003). Among those, a major branch is industrial sustainability, which focuses on how to pursue the short- to long-term sustainable development of industrial systems, such as a plant, corporation, geographic region, industrial zone, or beyond, where material and energy efficiencies, waste reduction, safety, synergies among the systems, etc., are among the major concerns (Piluso *et al.*, 2010).

Industrial sustainability has been well recognized as a multi-scale (in terms of both the time and space) research area, which covers micro-scale issues such as sustainable nano-paint design, the topics in meso-scale level related to sustainable process manufacturing, and in macro-scale level the sustainable development decision-making for industrial zones. This work mainly focuses on the issues of sustainable process manufacturing and the sustainable development decision-making for industrial zones, which are addressed on the meso- to macro-scale levels.

Among the three pillars of sustainability, economy is definitely the most critical one due to the intrinsic nature of industrial activities in creating wealth and reducing costs. Sustainability interfaces with economics through the social and ecological consequences of economic activity (Daly and Cobb, 1989). However, comparing with the conventional economics that historically demonstrated a close correlation between economic growth and environmental degradation, a sustainable economics represents "A broad interpretation of ecological economics where environmental and ecological variables and issues are basic but part of a multidimensional perspective. Social, cultural, health-related and monetary/financial aspects have to be integrated into the analysis" (Soederbaum, 2008). Note that integrating economics with environmental and social concerns can provide opportunities for creating new benefits and business. For example, industrial waste can be treated as an "economic resource in the wrong place". In this sense, the economic benefits of a sustainable waste reuse include savings from disposal costs, fewer environmental penalties, and reduced liability insurance. Moreover, it may lead to increased market share due to an improved social public image (Jackson, 2008). As another instance for energy systems, the improvement on energy efficiency can also increase profits by reducing costs.

Environment must be protected during any types of industrial activities since all types of vital goods and services required by humans and other organisms are provided by healthy ecosystems. However, human activities of industrial and energy systems most likely have negative impacts to the environment due to inherent resource depleting and waste generation. There are two major ways of reducing negative human impacts on the environment. The first one is the environmental management, or in other word, pollution prevention, which dominated industrial practices through the 1980-90's. This direct approach is based largely on information gained from environmental science, earth science, and conservation biology. However, environmental management is only at the end of a long series of causal factors that are initiated by human consumption. Therefore, this approach is passive and reactive, and more importantly, may not provide the best possible results. The second way is the management of human consumption of resources, which is extended from Green Engineering (developed and acted in 2000's) to Sustainable Engineering (developing and acting recently). This approach emphasizes that the consumption of goods and services should be analyzed and managed at all scales through the chain of the product lifecycle for industrial and energy systems, where energy, materials and water are key resource categories under investigation. As a positive and active approach compared with the first one, the implementation of it has resulted in three broad criteria for environmental sustainability (Daly and Farley, 2004): (i) renewable resources should provide a sustainable yield (the rate of harvest should not exceed the rate of regeneration); (ii) for non-renewable resources, there should be equivalent development of renewable substitutes; (iii) waste generation should not exceed the assimilative capacity of the environment. Note that the environmental sustainability design and analysis should be incorporated with the other two-pillars of sustainability.

Compared with the first two pillars, social sustainability is much more difficult to be addressed and analyzed. The reason is that sustainability issues are easily expressed in scientific economic and environmental terms, but social aspects are always related to non-scientific concerns such as national law, public image, local and individual lifestyles, and ethical consumerism (Janerio, 1992). In general, social sustainability is the idea that future generations should have the same or greater access to social resources as the current generation. In this regard, the most fundamental principle of social sustainability is to meet human needs fairly and efficiently, which encompasses human rights, labor rights, and corporate governance. Therefore, the following criteria are commonly used to rate the social sustainability of industrial and energy systems, namely, community, diversity, employee relations, human rights, and process and product safety. Needless to say, those criteria are still quite difficult to be quantified exactly, which brings some soft-indicator-based approaches in practical for the assessment of social performance, i.e., put a scaling system (for instance, from 0 to 10) on each social indicator to represent the relatively good or bad performance of industrial systems (Carvalho *et al.*, 2008; Othman *et al.*, 2010).

Sustainability has inherent concerns on the temporal dimension, which clearly direct to the future. Therefore, all those principles and theories about the triple-bottom-lines stated above should be discussed not only restrictively to the spatial scale for today, but also from short-term to long-term over the temporal scale of interest to meet the demands tomorrow.

1.2 Challenges in the Study of Sustainability

Sustainability problems of industrial and energy systems are always difficult to be fully investigated due to the complexity carried by the large scope and scale of the systems under study, and the multiple objectives by the sustainability essential. From the process point of view, an industrial (energy) sustainability problem always refers to a large scope containing the facts of materials, energy, water, money, service, information, etc. Note that all those facts are integrated in a large scale process-product system, which is structured by different functional sectors (or sub-industries) along the supply chain, and more thoroughly, the entities within each sector. Serving through the whole supply chain, each sector and entity connects with its upper suppliers and lower customers for the purpose of making the final products. Thus, a desired sustainability design and decision must be made by coordinating the entire process system in terms of the hierarchy of process levels (such as the zone, sector, and entity) and multiple facts (such as materials, energy, water, money, service, information, etc.). From the product point of view, sustainability of industrial (energy) systems also has a large scope since every final or intermediate product has a specific life cycle from raw material acquisition, to manufacturing and distribution, and finally to customer usage, disposal, and recycle. Therefore, a desired sustainability design and decision should also be analyzed and managed at all stages through the chain of the product lifecycle. Moreover, industrial sustainability is also being recognized as a multi-scale (in terms of both the time and space) research area. Thus, a sustainability assessment and decision-making problem has to be coordinated over all the multiple scales covered, where different demands and criteria may apply on each specific scale. Finally, sustainability is a multi-objective and interdisciplinary task due to the sustainability essential defined on the triple-bottom-line objectives. In detail, a convincing methodology for sustainability study must ensure the balance on triple-bottom-line aspects, and based on this, provide the optimal solutions of the best possible overall sustainability.

It must be pointed out that data and information uncertainty is another challenge in sustainability assessment, design and decision-making. The inherent uncertainties in the data and information needed for a study arise from the incomplete and complex nature of the structure of the industrial system. For example, the multifaceted makeup of the inter-entity dynamics, dependencies, and interrelationships, the uncertain prospect of forthcoming environmental policies (even in the short-term), and the indistinct interrelationship among the triple bottom-lines of industrial sustainability (i.e. how the environmental, economic, and societal components of the system affect each other) are frequently (very) complex and uncertain. In addition, the specific data regarding material or energy consumption, product, waste, or by-product generation, amount of recycle, and profitability of an individual plant, industry, or zone are often incomplete and imprecise. These complexities and uncertainties can be even more difficult to deal with when they appear in future planning, such as potential modifications to environmental policies, market demand, supply chain structures, etc (Piluso *et al.*, 2010). According to Parry (1996), uncertainties can be classified into two types: aleatory and epistemic. Aleatory uncertainty refers to the inherent variations associated with the physical system or the environment under consideration and it is objective and irreversible, which can be represented in stochastic terms. By contrast, epistemic uncertainty is carried by the lack of knowledge and/or information, and it is subjective and reducible, which can be represented in terms of intervals (Hemez, 2002). The uncertainties encountered in the study of large-scale industrial sustainability problems, as exemplified above, can be either aleatory or epistemic. In this regards, the sustainability assessment results and sustainability-based decision-making can be meaningful only if the involved uncertainty issues are addressed properly.

As described above, sustainability design and decision making of industrial and energy systems is a multi-objective and interdisciplinary task, which has great challenges due to the inherent complexity and uncertainty. In order to achieve a sustainable development, much progress is needed for the identification, design and implementation of appropriate products, processes, supply chains, planning strategies and even policies under various types of uncertainty. Thus, it is necessary to develop systematic methods and tools, which enable the generation of sustainable design and decisions to adapt to the short- to long-term needs into the future (Carvalho *et al.*, 2008).

1.3 System Approaches for Study of Sustainability

To deal with those challenges, the sustainability study of industrial and energy systems requires sustainable systems approaches, which should be able to not only effectively address the sustainability principles, but also systematically handle the design and decision-making under complexity and uncertainty.

A sustainable systems approach can be interpreted as a systems approach developed based on sustainability theories and principles for handling certain types of sustainability problems. A system is a group of interacting components that work together to achieve some common purposes. With that definition, the general systems approach can be characterized as the one focus on the whole group (not just a single component) of the system under study, investigates the interactions and variations between all involved components simultaneously, and achieves overall purposes in design and/or decision making (for instance, a sustainable development) on the system (Vanek and Albright, 2008). Note that the understanding of the nature of interactions and variations between components is always the key to the implementation of systems approaches for problem solving. The opposite of the systems approach is sometimes called the unit approach. The idea of a unit approach is to identify one key component of the system and one criterion as the core of a project. Then, a design solution is first generated by ensuring the components satisfies the minimum requirement for the criterion. After that, the other components are further designed to take care of all other physical and economic characteristics of the problem. In practice, the unit approach is suitable to be applied on simple and direct systems, but impossible to be applied on industrial and energy systems that carry great complexity and uncertainty (Vanek and Albright, 2008).

The systems approach emerged as scientists and philosophers identified common themes in the approach to managing and organizing complex systems. Four major concepts can be summarized: (1) Specialization: a system is divided into smaller components allowing more specialized concentration on each component; (2) Grouping: it is necessary to group related disciplines or sub-disciplines in order to avoid the generation of even greater complexity with increasing specialization; (3) Coordination: as the components of a system are grouped, it is necessary to coordinate the interactions among groups; and (4) Emergent properties: dividing a system into subsystems (groups of component parts within the system), requires recognizing and understanding the "emergent properties" of a system; that is, recognizing why the system as a whole is greater than the sum of its parts.

In the past decades, different methodologies have been proposed for applying the concepts of systems approach in the study of chemical processes with respect to improvement of the cost-efficiency (Carvalho *et al.*, 2008). For instance, Rapoport *et al.* (1994) proposed a systematic methodology for the design of process plants, which generally follows recursive steps of synthesis, analysis, and evolution. This approach is essentially based on heuristic rules from engineering experience, detailed process calculations and detailed economical evaluations are capable for the generation of optimal design alternatives. Another typical systems approach in design of chemical processes is based on mathematical concepts and optimization methods, such as mixed integer non-linear programming (MINLP), which was proposed by Ciric and Floudas (1989), and Jackson and Grossmann (2002), and had been widely accepted by the research society and continually discussed until now.

Due to the superior ability of handling complexity, those general process systems methodologies have been combined with sustainability principles to form sustainable systems approaches. For instance, Lange (2002) proposed a methodology on identifying the opportunities in pursing sustainable development of chemical manufacturing processes. This method is based on both the material and energy efficiency. As the application, nearly 50 chemical processes are evaluated by this method and those processes with low sustainability performance are identified through comparisons. However, only heuristic opportunities by the ideas of recycling and reuse are considered by the author for system development. Another mass and energy indicator-based methodology was proposed by Uerdingen *et al.* (2003 and 2005). By this methodology, several pre-defined cost-efficiency indicators are first checked for a chemical process, then the critical points in the process are determined by local sensitivity analysis and feasible design alternatives are further generated heuristically. However, these feasible alternatives are only compared with each other in terms of economic aspects for determining the best alternative. Jensen *et al*. (2003) further extended this methodology where the previously defined indicators were retained but the choice of the best alternative was obtained using new parameters related to economic, safety and environmental factors.

More recently, Carvalho *et al.* (2008) introduced a process retrofit design methodology for deriving sustainable design configurations. In detail, this methodology determines a set of mass and energy indicators from steady-state process data, establishes the operational and design targets, and through a sensitivity-based analysis, identifies the design alternatives that can match a set of design targets. However, for the sensitivity analysis conducted, this method only focused on operational parameters rather than design parameters. In addition, the methodology is limited to scenario-based decision making, and thus no design optimality can be addressed adequately. Piluso *et al.* (2008) introduced a sustainability assessment methodology through extending existing Ecological Input-Output Analysis (EIOA) approach (Bailey *et al.*, 2004). The methodology is capable of quantitatively evaluating the sustainability level of industrial systems when different system enhancement strategies are implemented. It is particularly applicable to large industrial systems, such as industrial zones. However, it offers only scenario-based assessment, where no design optimality can be addressed. Tora and El-Halwagi (2009) applied system decomposition, super-structure, and optimization methods into an optimal design and integration of solar systems and fossil fuels for sustainable and stable power outlet. By this method, an optimization model is derived, where the objective function is to seek the maximum overall sustainability of the whole process. The adjustable variables are the energy provided by fossil fuels, the energy associated with the steam from each header down to other headers, and the area of the solar collector. Constraints of the optimization are those energy balance, power generation requirement, etc. After solving this optimization problem, the optimal solution obtained is interpreted as the final decisions of the design for sustainable and stable power outlet.

Although one of the challenges in sustainability study, i.e., the complexity, can be handled by those existing methodologies, the other challenge, uncertainty, was not considered by all of them, which quite much restricts their applications. As stated before, inherent uncertainties cannot be neglected due to the essential of sustainability focusing on the future needs and the lack of data, information, and knowledge. Therefore, uncertainty issues must be addressed properly in sustainability assessment, design, and decision-making. In fact, A variety of mathematical and computational intelligence methods are available for uncertainty handling, such as those by resorting to statistical theory, fuzzy mathematics, and artificial intelligence (Ayyub and Gupta, 1997; Graham and Jones, 1988; Kanovicha and Vauzeillesb, 2007; Yang, 2001; Cawleya *et al*., 2007; Meinrath, 2000; Zimmermann, 1991; Xia *et al*., 1991). For instance, Probability Bounds Analysis (PBA) (Tucker *et al*., 2003) is a method extended from the probability theory (Moore, 1966). It expresses uncertainty using a probability-box (or p-box) approach (Ferson *et al*., 2003), where a p-box represents a range of distribution functions. The method can provide a balance between the expressiveness of imprecision and computational efficiency (Walley, 1991). Note that since the availability of distribution functions is a requirement, and modeling of uncertainty propagation is a real change, these could disqualify the PBA methods in the study of many types of sustainability problems.

In dealing with aleatory uncertainties, Monte Carlo based simulation becomes more popular in the recent research progress. This approach embodies uncertainties by checking a large number of random samples with different uncertainty combinations, and taking aggregated results from them for decision-making.

Fuzzy logic and fuzzy programming based approaches are attractive in formulating and manipulating epistemic uncertainties, where rigorous logics are used to deal with fuzzy information that are difficult to compute using conventional mathematical methods (Piluso *et al*., 2009). The solution derivation process is usually transparent, which makes solution reasoning easy to understand. Piluso *et al*. (2010) and Liu *et al*. (2009) introduced a fuzzy-logic-based decision making approach for industrial sustainability enhancement under uncertainty. Note that, however, decision quality is largely affected by the definitions of fuzzy sets and fuzzy numbers, where subjective judgments are used to a large extent because of lack of sufficient quality data. Apparently, poor judgments could be detrimental to decision quality. Sevionovic presented some general concepts surrounding fuzzy set approaches to processing types of uncertainties appeared in water sustainability problems (Sevionovic, 1997). Hersh (1999) demonstrated a need for conducting sensitivity analysis when investigating the dependence of decisions on uncertain parameters, weights, and models, but the success in problem solving is yet to be proven.

Information Gap Theory (IGT) (Ben-Haim, 2006) is a fairly new method for expressing uncertainty and making decisions when only the best guess for a specific quantity is available (Ben-Haim, 2005). An info-gap is a disparity between what is known and what needs to be known in order to make a responsible decision. It has some engineering applications (Ben-Haim, 2005; Hine *et al.*, 2010). However, the mathematics of IGT is complicated and appears to be a distraction from some important goals of modeling decision problems directly (Gelman, 2009).

Interval Parameter (IP) based uncertainty handling is an interesting approach, by which parameter uncertainties are expressed by interval numbers, each of which has the lower and upper bounds; it does not need any data distribution information (Xia *et al.*, 1997). The IP-based approaches have been used for tackling many environmental problems (Lin *et al.*, 2008; Lu *et al.*, 2008; Lv *et al.*, 2009; Li *et al.*, 2010). This type of approaches could be of great usage for various sustainability assessment and decision making tasks, where no probability function is derivable from the accessible data and no subjective judgment is extensively needed. This is particularly true for the tasks of sustainability enhancement of industrial systems via technology adoption, since the accessible data are usually limited and uncertain, data ranges of parameters are known, but not data distribution (Piluso *et al.*, 2010).

In the regards of processing complexity and uncertainty, the existing system approaches in the study of industrial sustainability can be recognized as the first generation, which demonstrate good capability for handling complexity but no uncertainty issues are being considered. To overcome this limit, there is a research need to integrate techniques and methods for handling uncertainties (such as fuzzy logic theories, interval based approaches, and Monte Carlo based simulation) with the general systems approaches and develop a new generation of sustainable systems methodologies, which can effectively and systematically handle the design and decision-making of industrial and energy systems under both the complexity and uncertainty. Those second generation methodologies should have three major features: (1) sustainability approaches that can effectively address the sustainability principles, (2) system approaches that can handle great complexity and identify optimal solutions, and (3) practical approaches that can be implemented under various types of uncertainty.

In this work, a series of methodologies showing those desired features are proposed for the study of sustainability problems of industrial and energy systems under various types of uncertainties and design purposes. The first and second methodologies are developed by using interval parameter based approaches in dealing with aleatory and epistemic uncertainties for sustainability-oriented decision-making. In specific, there is a difference in the functional design between those two methodologies, where the first one is designed for decision-making of sustainability improvement on existing industrial systems; and the second one is developed for sustainability-oriented strategic planning on new (non-existing) energy systems. The third methodology is developed for the sustainability enhancement under aleatory and epistemic uncertainties. By imbedding Fuzzy Logic theory with systems approaches, a fuzzy logic based Triple-A template was designed for deriving the optimal sustainability enhancement strategies under uncertainties. Compared with the first three methodologies, the last one is developed for the sustainability improvement under aleatory uncertainties. This methodology is featured as the function of using both system optimization for obtaining sustainable development options, and Monte Carlo based simulation for handling stochastic uncertainties.

1.4 Objectives and Significance

Incontestable evidence has shown that industrial efforts for development in the past decades have accelerated nonrenewable resource depletion and caused serious green house gas emissions as well as many other types of pollutions today. With no other option, industries must find ways to ensure all development efforts to meet the goals of sustainability.

Sustainability refers to a state of harmonious interaction among the economic, environmental, and social aspects of the systems of interest, whereas sustainable development refers to the process of continuous improvements and the path that must be followed in order to achieve an improved state of sustainability. As a major branch of sustainability, industrial sustainability focuses on how to pursue the short- to long-term sustainable development of an industrial or energy system, such as a plant, corporation, geographic region, industrial zone, or beyond, where material and energy efficiencies, waste reduction, safety, synergies among the systems, etc., are among the major concerns (Piluso *et al.*, 2010).

Sustainability design and decision-making of industrial and energy systems is a multi-objective and interdisciplinary task, which has great challenges due to the inherent complexity and uncertainty. In order to achieve a sustainable development, much progress is needed for the identification, design and implementation of appropriate products, processes, supply chains, planning strategies and even policies under various types of uncertainty. Thus, it is necessary to develop systems methods and tools, which enable the generation of sustainable design and decisions to adapt to the short- to long-term needs into the future (Carvalho *et al.*, 2008).

Although a variety of process systems methodologies have been developed to assist sustainability study, the issue of how to deal with the challenge of uncertainty issues has not been adequately discussed by those existing works. To overcome this limit, there is a research need to integrate techniques and methods for handling uncertainties with general process systems approaches and develop a new generation of sustainable systems methodologies for effectively and systematically handling the design and decision-making of industrial and energy systems.

For this objective, a series of methodologies are proposed in this work for the study of sustainability problems under various types of complexity and uncertainty. Those methodologies proposed have three major features: (1) sustainability approaches that can effectively address the sustainability principles, (2) system approaches that can handle great complexity and identify optimal solutions, and (3) practical approaches that can be implemented under various types of uncertainty. Beyond that, a computational tool was designed, which provides functions on both the industrial sustainability assessment and decision-making through several convenient and interactive steps of computer operation. By this tool, people without knowing the complex sustainability theories and calculations, can easily evaluate the sustainability status of industrial and energy systems of interest, compare different design alternatives, identify the best design for decision-making, and acquire suggestions on potential system improvements.

This research is quite valuable in its methodological contribution for sustainability assessment, design and decision-making, and solutions obtained can help decision makers to identify desired manufacturing strategies for industrial practices. Moreover, the computational tool will greatly facilitate the academic and industrial practices on the study of sustainability, which is the first one available to the public.

1.5 Dissertation Organization

As stated before, the objective of this research is to develop a series of sustainable systems methodologies and a computational tool for the study of sustainability problems of industrial and energy systems under various types of complexity and uncertainty. Since the research leading to the present dissertation covers a broad spectrum of sustainability design and decision-making problems, this dissertation is composed of two parts.

Part I, dealing with sustainability design and decision-making methodologies under various types of uncertainties, consists of five chapters: The first two chapters introduce interval parameter based sustainability decision-making methodologies. In specific, Chapter 2 deals with sustainability enhancement on existing industrial systems, and Chapter 3 focus on sustainability-oriented strategic planning of new (non-existing) energy systems. A Fuzzy Logic based Triple-A template is given in Chapter 4 for deriving the optimal sustainability enhancement strategies under subjective uncertainties, where the Fuzzy Logic theory is imbedding with systems approaches to handling both the complexity and uncertainty associated with the sustainability study. Compared to the first three chapters all dealing with epistemic uncertainties, a methodology for taking care of aleatory uncertainties is given in Chapter 5. This methodology is featured as the function of using both system optimization for obtaining sustainable development options, and Monte Carlo based simulation for handling stochastic uncertainties.

Part II contains Chapter 6 and 7, where a computational tool and an exergy based analysis method are given as a complement to the main sustainability research of Part I. Although no direct design and decision-making methodologies are developed in these two chapters, the contents of them also have great contributions to the current sustainability research and practice. In Chapter 6, a computational tool is designed for industrial sustainability assessment and decision-making. By this tool, people without knowing the complex sustainability theories and calculations, can easily evaluate the sustainability status of industrial and energy systems of interest, compare different design alternatives, identify the best design for decision-making, and acquire suggestions on potential system improvements. In Chapter 7, a brief introduction about the concept of exergy and the exergy-based process analysis is given. After that, an exergy-based IOA method is proposed for industrial sustainability analysis, and a detailed case study is given to demonstrate the efficacy of the proposed method.

Finally, Chapter 7 provides concluding remarks and future work.

CHAPTER 2

TECHNOLOGY EVALUATION AND DECISION MAKING FOR SUSTAINABILITY ENHANCEMENT UNDER INTERVAL BASED UNCERTAINTY

Depletion of natural resources, environmental pressure, economic globalization, etc., demand seriously industrial organizations to ensure that their manufacturing be sustainable (Batterham, 2003). Today, numerous advanced manufacturing technologies are available for improvement of energy/material efficiency, product development and quality assurance, zero (waste) discharge, process safety assurance, productivity increment, etc. (Sikdar *et al*., 2011). Needless to say, technology adoption by industrial organizations must be financially justified. Industries seek continuously systematic methodologies and tools that can help them identify the most suitable technologies to achieve their sustainability goal at the minimum cost. (Beloff *et al*., 2005).

Sustainability enhancement is always a very challenging task, even for a small industrial system, such as a plant or product. To identify strategies for sustainability enhancement, economic, environmental, and social sustainability assessments are always the first and critical step. In assessment, an unavoidable task is to identify an effective approach to process a variety of uncertainties that appear in system characterization, technology description, and beyond. For example, the combined economic, environmental, and social performance of technologies can be hardly determined precisely. It is usually not predictable when environmental regulations will change and how they will affect technology development and adoption. The inter-dependency of industrial systems and the relevance to sustainability are frequently difficult to model. The information about material or energy consumption, product, waste, or by-product generation, and profitability of individual systems are often incomplete and imprecise. The uncertain situation can be more severe when predicting future sustainability performance, as market demand, supply chain structures, environmental policies, etc., change along the time.

Uncertainties can be generally classified into two categories: the aleatory and the epistemic uncertainties (Parry, 1996). The aleatory uncertainty refers to the variations associated with physical systems and/or the environment; it is objective and irreversible. By contrast, the epistemic uncertainty is carried due to lack of knowledge and/or information; it is subjective and reducible. The uncertainties encountered in the study of industrial sustainability problems, as exemplified above, could be either aleatory or epistemic.

A variety of mathematical and computational intelligence methods are available for uncertainty handling, such as those by resorting to statistical theory, fuzzy mathematics, and artificial intelligence (Ayyub and Gupta, 1997; Graham and Jones, 1988; Kanovicha and Vauzeillesb, 2007; Yang, 2001; Cawleya *et al.*, 2007; Meinrath, 2000; Zimmermann, 1991; Xia *et al.*, 1991). For instance, Probability Bounds Analysis (PBA) (Tucker *et al.*, 2003) is a method extended from the probability theory (Moore, 1966). It expresses uncertainty using a probability-box (or p-box) approach

(Ferson *et al*., 2003), where a p-box represents a range of distribution functions. The method can provide a balance between the expressiveness of imprecision and computational efficiency (Walley, 1991). Note that since the availability of distribution functions is a requirement, and modeling of uncertainty propagation is a real change, these could disqualify the PBA methods in the study of many types of sustainability problems.

Fuzzy logic and fuzzy programming based approaches are attractive in formulating and manipulating epistemic uncertainties, where rigorous logics are used to deal with fuzzy information that are difficult to compute using conventional mathematical methods (Piluso *et al*., 2009). Solution derivation is usually transparent, which makes solution reasoning easy to understand. Piluso *et al*. (2010) and Liu *et al*. (2009) introduced a fuzzy-logic-based decision-making approach for industrial sustainability enhancement under uncertainty. Note that, however, decision quality is largely affected by the definition of fuzzy sets and fuzzy numbers, where subjective judgments are used to a large extent because of lack of sufficient precise data. Apparently, any poor judgment could be detrimental to decision quality. Sevionovic presented some general concepts surrounding fuzzy set approaches to process a few types of uncertainties appeared in water sustainability problems (Sevionovic, 1997). Hersh (1999) demonstrated a need for conducting sensitivity analysis when investigating the dependence of decisions on uncertain parameters, weights, and models, but the success in problem solving is yet to be proven. Recently, Conner *et al*. (2011) introduced a fuzzy-logic-based method for sustainability assessment of nations and corporations under interval-based uncertainties. By their approach, sustainability index intervals are calculated through fuzzy-logic-based operations. Again, how to define adequately a variety of fuzzy sets is a challenge.

Information Gap Theory (IGT) (Ben-Haim, 2006) is a fairly new method for expressing uncertainty and making decisions when only the best guess for a specific quantity is available (Ben-Haim, 2005). Note that information gap is defined as a disparity between what is known and what needs to be known in order to make a responsible decision. It has some engineering applications (Ben-Haim, 2005; Hine *et al*., 2010). However, the mathematics of IGT is complicated and thus the method is difficult to use in modeling decision problems (Gelman, 2009).

Interval Parameter (IP) based uncertainty handling is an interesting approach, by which parameter uncertainties are expressed by interval numbers, each of which has the lower and upper bounds and there is no data distribution information required (Xia *et al*., 1997). IP-based approaches have been used to study successfully many environmental problems (Lin *et al*., 2008; Lu *et al*., 2008; Lv *et al*., 2009; Li *et al*., 2010). This type of approaches should be suitable for various sustainability assessment and decision-making tasks, where no probability function is derivable from the accessible data. The approaches are particularly attractive for the tasks of technology-based sustainability enhancement, where the known data are usually limited and uncertain, data ranges of parameters are known, but not data distribution information is available (Piluso *et al*., 2010).

In this chapter, we introduce a simple, yet systematic interval-parameter-based methodology for sustainable technology assessment and decision making for sustainability enhancement of industrial systems under uncertainty. By this method, technology candidates can be thoroughly evaluated using suitable sustainability metrics, and optimal technology sets can be readily identified to meet the industrial organization's strategic goals under budget constraints. The developed methodology is general that can be applied to sustainability enhancement problems of any size and scope. The remainder of the chapter is organized as follows. We introduce first the basic definition of an interval number and arithmetic operation types. Then, a set of interval-parameter-based sustainability assessment formulations are introduced, and the interval-parameter-based approach is extended to the identification of sustainability enhancement needs. Next, an interval-parameter-based technology identification methodology is described in detail. The efficacy of the methodology is demonstrated through investigating a sustainable biodiesel manufacturing problem. Finally, we will discuss some application issues and conclude the significance of the introduced methodology.

2.1 Interval Parameter Based Uncertainty Handling

Let $\overline{X}$ be an interval number with known lower and upper bounds, for which parameter distribution within the interval is unknown. This interval number can be defined as:

$$\overline{X} = \left[x^L,\ x^U\right], \tag{2.1}$$

where x^L and x^U are real numbers and $x^L \le x^U$. Note that if x^L equals x^U, then $\overline{X}$ becomes a deterministic number, which means no uncertainty involved, and thus can be written as *X*. The definition in Eq. 2.1 still applies to a deterministic number as a special case.

Let symbol $* \in [+, -, \times, \div]$ be a binary operation on interval numbers. Then the algorithmic operations of interval numbers, $\overline{X}$ and $\overline{Y}$, are generalized as (Xia *et al*., 1997):

$$\overline{X} * \overline{Y} = [\min\{x * y\},\ \max\{x * y\}], \text{ where } x^L \le x \le x^U,\ y^L \le y \le y^U. \tag{2.2}$$

More specifically, we have:

$$\overline{X} + \overline{Y} = \left[x^L + y^L,\ x^U + y^U\right], \tag{2.3}$$

$$\overline{X} - \overline{Y} = \left[x^L - y^U,\ x^U - y^L\right], \tag{2.4}$$

$$\overline{X} \times \overline{Y} = [\min\{x \times y\},\ \max\{x \times y\}], \tag{2.5}$$

$$\overline{X} \div \overline{Y} = [\min\{x \div y\},\ \max\{x \div y\}]. \tag{2.6}$$

Based on the definition of multiplication in Eq. 2.5, the following operation holds:

$$\sqrt{\overline{X}} = \left[\sqrt{x^L},\ \sqrt{x^{\mathrm{U}}}\right]. \tag{2.7}$$

Note that the resulting interval ensures the lower bound not greater than the upper bound. Also note that the above definitions are applicable to the operations involving one or more deterministic numbers, since a deterministic number is a special case of an interval number. In the following text, every interval number is symbolized by a variable symbol with a bar above, and the operations of interval numbers will follow the definition in Eq. 2.2.

2.2 Sustainability Assessment

Various metrics systems are available for performing sustainability assessment, such as the IChemE (2002) and AIChE (Cobb *et al*., 2009) sustainability metrics that are widely adopted by the chemical industries. For an industrial system named *P*, we assume that a set of sustainability metrics, namely set *S*, is selected by the decision maker. The set of metrics contains three subsets, each of which can have a number of specific indices:

$$S = \{E, \ V, \ L\}, \tag{2.8}$$

where

$E = \{E_i \mid i = 1, 2, \cdots, F\}$, the set of economic sustainability indices,

$V = \{V_i \mid i = 1, 2, \cdots, G\}$, the set of environmental sustainability indices,

$L = \{L_i \mid i = 1, 2, \cdots, H\}$, the set of social sustainability indices.

Note that all the sustainability indices in this text take normalized values for the convenience of discussion. Therefore, it is required that in application, all the data be normalized first.

By using selected sustainability indices, the status quo of the sustainability of system *P* could be assessed using available data collected from the system. For those uncertain data, the corresponding parameters should be expressed as intervals with the upper and lower bounds specified. In this way, the index-specific assessment results, i.e., $\overline{E}_i(P)$'s, $\overline{V}_i(P)$'s, and $\overline{L}_i(P)$'s, are also interval numbers (see the 3rd column of Table 2.1). These data can be used to estimate the categorized sustainability of the system, i.e., $\overline{E}(P)$, $\overline{V}(P)$, and $\overline{L}(P)$, which are called the composite sustainability indices and can be evaluated using the following formulas:

$$\overline{E}(P)=\frac{\sum_{i=1}^{F} a_i \overline{E}_i(P)}{\sum_{i=1}^{F} a_i}, \tag{2.9}$$

$$\overline{V}(P)=\frac{\sum_{i=1}^{G} b_i \overline{V}_i(P)}{\sum_{i=1}^{G} b_i}, \tag{2.10}$$

$$\overline{L}(P)=\frac{\sum_{i=1}^{H} c_i \overline{L}_i(P)}{\sum_{i=1}^{H} c_i}, \tag{2.11}$$

where a_i, b_i, and $c_i \in [1, 10]$ are the weighting factors associated with the corresponding indices, reflecting the relative importance of an individual index over others in overall assessment. If all the factors are equally important, then each factor is set to 1.

It is understandable that at a higher level of a management hierarchy, decision makers may be interested in their organization's overall sustainability rather than very specific index values. In this case, the overall sustainability level of the system, denoted by $\overline{S}(P)$, can be estimated as follows:

$$\bar{S}(P) = \frac{\left\|\left(\alpha\bar{E}(P),\ \ \beta\bar{V}(P),\ \ \gamma\bar{L}(P)\right)\right\|}{\left\|(\alpha,\ \ \beta,\ \ \gamma)\right\|}, \tag{2.12}$$

where α, β, and γ each has a value of 1 (default) or greater. Naturally, $\bar{S}(P)$ is still normalized.

Table 2.1. Sustainability evaluation on the system and the technologies.

Category	Index	System (P)	Technologies			
			T_1	T_2	…	T_N
Econ. (E)	E_1	$\bar{E}_1(P)$	$\bar{E}_1(T_1)$	$\bar{E}_1(T_2)$	…	$\bar{E}_1(T_N)$
	…	…	…	…	…	…
	E_F	$\bar{E}_F(P)$	$\bar{E}_F(T_1)$	$\bar{E}_F(T_2)$	…	$\bar{E}_F(T_N)$
Environ. (V)	V_1	$\bar{V}_1(P)$	$\bar{V}_1(T_1)$	$\bar{V}_1(T_2)$	…	$\bar{V}_1(T_N)$
	…	…	…	…	…	…
	V_G	$\bar{V}_G(P)$	$\bar{V}_G(T_1)$	$\bar{V}_G(T_2)$	…	$\bar{V}_G(T_N)$
Soc. (L)	L_1	$\bar{L}_1(P)$	$\bar{L}_1(T_1)$	$\bar{L}_1(T_2)$	…	$\bar{L}_1(T_N)$
	…	…	…	…	…	…
	L_H	$\bar{L}_H(P)$	$\bar{L}_H(T_1)$	$\bar{L}_H(T_2)$	…	$\bar{L}_H(T_N)$

2.2.1 The weighting factor issue

Equations 2.9 through 2.12 contain a number of weighting factors, which reflect the relevant importance of different sustainability aspects. It is widely recognized that the weighting factors should be determined by decision makers based on their understanding of an organization's development goal. The assessment framework introduced in this work provides opportunities for them to assign preferred values to weighting factors in their applications. They can also assign different values to those weighting factors and then compare the results.

2.3 Goal Setting and Determination of the Need for Sustainability Performance Improvement

For any industrial system, sustainability improvement needs can be determined based on the organization's strategic goal.

2.3.1 Strategic goal

An industrial organization's strategic plan can be detailed by specifying its economic, environmental, and social development goals below:

$E^{sp}(P)$ = the economic sustainability goal for system P,

$V^{sp}(P)$ = the environmental sustainability goal for system P,

$L^{sp}(P)$ = the social sustainability goal for system P.

By following the same approach used in Eq. 2.12, the overall sustainable development goal can be expressed as:

$$S^{sp}(P)=\frac{\left\|\left(\alpha E^{sp}(P),\quad \beta V^{sp}(P),\quad \gamma L^{sp}(P)\right)\right\|}{\left\|(\alpha,\quad \beta,\quad \gamma)\right\|}, \tag{2.13}$$

where α, β, and γ take the same values as those used in Eq. 2.12. Obviously, $S^{sp}(P)$ is also a normalized parameter. The sustainable development goals could be achieved in one or multiple stages. In this work, we assume that this is a one-stage improvement effort. For a multiple stage improvement, the organization should specific its sustainability goals for each stage.

2.3.2 Determination of improvement need

Whether the sustainability performance of system P should be improved or not is determined firstly by measuring the difference between the system's status quo and the sustainability goals in the following way:

$$\Delta\bar{E}^{imp}(P) = E^{sp}(P) - \bar{E}(P), \tag{2.14}$$

$$\Delta\bar{V}^{imp}(P) = V^{sp}(P) - \bar{V}(P), \tag{2.15}$$

$$\Delta\bar{L}^{imp}(P) = L^{sp}(P) - \bar{L}(P). \tag{2.16}$$

The deviation of the overall sustainability of the system from the goals is:

$$\Delta\bar{S}^{imp}(P) = S^{sp}(P) - \bar{S}(P). \tag{2.17}$$

Note that $\Delta\bar{E}^{imp}(P)$, $\Delta\bar{V}^{imp}(P)$, and $\Delta\bar{L}^{imp}(P)$, and thus $\Delta\bar{S}^{imp}(P)$ are rarely zero intervals. The industrial organization should set its satisfaction level about the system performance, and then decide whether actions should be taken for performance improvement. Let η_E, η_V, and η_L be the maximum acceptable deviations of the system's sustainability performance from the pre-set goals. They can be set to, for example, 5% each. If any of the following inequalities holds, a sustainability improvement effort is needed:

$$\Delta\bar{E}^{imp,L}(P) > \eta_E E^{sp}(P), \tag{2.18}$$

$$\Delta\bar{V}^{imp,L}(P) > \eta_V V^{sp}(P), \tag{2.19}$$

$$\Delta\bar{L}^{imp,L}(P) > \eta_L L^{sp}(P), \tag{2.20}$$

where $\Delta\overline{E}^{imp,L}(P)$, $\Delta\overline{V}^{imp,L}(P)$, and $\Delta\overline{L}^{imp,L}(P)$ are the lower bounds of the improvement intervals obtained in Eqs. 2.14-2.16.

2.4 Technology Evaluation on Sustainability

In this study, sustainability enhancement of system *P* is achieved through implementation of suitable technologies. Assume that *N* candidate technologies are available. They should be evaluated by the same sustainability indices as those used for system *P*. The evaluation results expressed as interval numbers are entered in Table 2.1 (from the 4th column). It is very possible that technology inventors, providers, and users can provide some technology assessment information based on their tests and experience. The information, however, should be re-evaluated using the selected sustainability indices, through working with the industrial organization, for system *P*. In the case of missing technical data, a reliable system simulator can be used to generate reasonable performance data. Note that all the parameters in Table 2.1 have normalized values.

Based on the index-specific evaluation data for each technology, the categorized sustainability performance of each can be derived as follows:

$$\overline{E}(T_j) = \frac{\sum_{i=1}^{F} a_i \overline{E}_i(T_j)}{\sum_{i=1}^{F} a_i}; \qquad j = 1, 2, \cdots, N \tag{2.21}$$

$$\overline{V}(T_j)=\frac{\sum_{i=1}^{G} b_i \overline{V}_i(T_j)}{\sum_{i=1}^{G} b_i}; \qquad j = 1, 2, \cdots, N \qquad (2.22)$$

$$\overline{L}(T_j)=\frac{\sum_{i=1}^{H} c_i \overline{L}_i(T_j)}{\sum_{i=1}^{H} c_i}; \qquad j = 1, 2, \cdots, N \qquad (2.23)$$

where a_i, b_i, and $c_i \in [1, 10]$ are the same weighting factors as those used in Eqs. 2.9 to 2.11.

The suitability of each technology listed in Table 2.1 for the improvement of system P can be readily evaluated in the following way:

$$\Delta\overline{E}_i(T_j;P)=\overline{E}_i(T_j)-\overline{E}_i(P); \qquad i = 1, 2, \cdots, F; \qquad j = 1, 2, \cdots, N \qquad (2.24)$$

$$\Delta\overline{V}_i(T_j;P)=\overline{V}_i(T_j)-\overline{V}_i(P); \qquad i = 1, 2, \cdots, G; \qquad j = 1, 2, \cdots, N \qquad (2.25)$$

$$\Delta\overline{L}_i(T_j;P)=\overline{L}_i(T_j)-\overline{L}_i(P); \qquad i = 1, 2, \cdots, H; \qquad j = 1, 2, \cdots, N \qquad (2.26)$$

The above index-specific suitability evaluation results can then be used to calculate the categorized sustainability improvement level for system P as follows:

$$\Delta\overline{E}(T_j;P)=\frac{\sum_{i=1}^{F} a_i \Delta\overline{E}_i(T_j;P)}{\sum_{i=1}^{F} a_i}; \qquad j = 1, 2, \cdots, N \qquad (2.27)$$

$$\Delta\overline{V}(T_j;P)=\frac{\sum_{i=1}^{G} b_i \Delta\overline{V}_i(T_j;P)}{\sum_{i=1}^{G} b_i}; \qquad j = 1, 2, \cdots, N \qquad (2.28)$$

$$\Delta\bar{L}(T_j;P)=\frac{\sum_{i=1}^{H} c_i \Delta\bar{L}_i(T_j;P)}{\sum_{i=1}^{H} c_i}; \qquad j = 1, 2, \cdots, N \tag{2.29}$$

where a_i, b_i, and $c_i \in [1, 10]$ are the same weighting factors as those used in Eqs. 2.9 to 2.11. These results are summarized in Table 2.2, where the cost information for using each technology, i.e., $B(T_j;P)$, is also included.

Table 2.2. Technology specific sustainability improvement and cost data.

Sustainability category and cost for technology use	Improvement levels by individual technologies			
	T_1	T_2	⋯	T_N
Econ. sust. improvement	$\Delta\bar{E}(T_1;P)$	$\Delta\bar{E}(T_2;P)$	...	$\Delta\bar{E}(T_N;P)$
Environ. sust. improvement	$\Delta\bar{V}(T_1;P)$	$\Delta\bar{V}(T_2;P)$	...	$\Delta\bar{V}(T_N;P)$
Soc. sust. improvement	$\Delta\bar{L}(T_1;P)$	$\Delta\bar{L}(T_2;P)$	...	$\Delta\bar{L}(T_N;P)$
Overall sust. Improvement	$\Delta\bar{S}(T_1;P)$	$\Delta\bar{S}(T_2;P)$	...	$\Delta\bar{S}(T_N;P)$
Cost for technology use ($)	$B(T_1;P)$	$B(T_2;P)$	...	$B(T_N;P)$

2.5 Identification of Superior Technologies

With the assessment information derived by the method described in the preceding section, technology identification can be systematically conducted, which is to generate a complete set of information about the capacities of technology combinations for sustainability enhancement under a given budget limit. The solution superiority here is defined as follows: by the identified technologies, the industrial system's sustainability performance can meet the goals satisfactorily at the cost under the budget limit. Very likely, multiple sets of technology combinations exist under cost constraint. Those technology combinations usually show different capacities in improving different areas of sustainability, although their overall sustainability performances may be so close that their superiority levels cannot be differentiated. Therefore, it is appropriate that all those superior solutions are provided with detailed information to the decision makers, who can make their decisions on technology adoption.

To assist the industrial organization in technology selection, the methodology can generate the following types of information that are summarized in Table 2.3.

a) The technology sets numbered in column 1 and listed in column 2 of the table. Each technology set contains one or more technologies, such as $\{T_2\}$ and $\{T_3, T_5, T_{10}\}$, etc. The total number of candidate technology sets is 2^N-1, including all combinations by the *N* candidate technologies.

b) The capabilities of the technologies for economic, environmental, social, and overall sustainability improvement. This group of information shows not only the categorized sustainability improvement levels ($\Delta\overline{E}_i(T;P)$, $\Delta\overline{V}_i(T;P)$, and $\Delta\overline{L}_i(T;P)$) after implementing each technology set (in columns 4-6 of the table), but also the extent of the overall sustainability of the system ($\overline{S}_i(T;P)$)that can be reached (in column 7 of the table). Assuming that the *i*-th technology set has *m* technologies included, the improvement level by the set can be derived as follows.

$$\Delta\overline{E}_i(T;P)=\sum_{j=1}^{m}\Delta\overline{E}_i(T_j;P), \qquad (2.30)$$

$$\Delta\overline{V}_i(T;P)=\sum_{j=1}^{m}\Delta\overline{V}_i(T_j;P),(2.31)$$

$$\Delta\overline{L}_i(T;P)=\sum_{j=1}^{m}\Delta\overline{L}_i(T_j;P). \tag{2.32}$$

Table 2.3. System sustainability improvement by technology sets.

No.	Tech. set	Cost for tech. set	Achievable categorized sustainability			Overall sust. by tech. set
			Econ.	Environ.	Soc.	
1	$\{T_1\}$	$B_1(T;P)$	$\overline{E}_1(T;P)$	$\overline{V}_1(T;P)$	$\overline{L}_1(T;P)$	$\overline{S}_1(T;P)$
…	…	…	…	…	…	…
$N+1$	$\{T_1, T_2\}$	$B_{N+1}(T;P)$	$\overline{E}_{N+1}(T;P)$	$\overline{V}_{N+1}(T;P)$	$\overline{L}_{N+1}(T;P)$	$\overline{S}_{N+1}(T;P)$
…	…	…	…	…	…	…
2^N-1	$\{T_1, T_2, \cdots, T_N\}$	$B_{2^N-1}(T;P)$	$\overline{E}_{2^N-1}(T;P)$	$\overline{V}_{2^N-1}(T;P)$	$\overline{L}_{2^N-1}(T;P)$	$\overline{S}_{2^N-1}(T;P)$

The above categorized sustainability improvement results can be used to evaluate the overall sustainability, $\overline{S}_i(T;P)$, by firstly calculating the categorized sustainability that system P can achieve after implementing the i-th technology set. The formulations are given as follows:

$$\overline{E}_i(T;P)=\sum_{j=1}^{m}\Delta\overline{E}_i(T_j;P)+\overline{E}(P), \tag{2.33}$$

$$\overline{V}_i(T;P)=\sum_{j=1}^{m}\Delta\overline{V}_i(T_j;P)+\overline{V}(P), \tag{2.34}$$

$$\overline{L}_i(T;P)=\sum_{j=1}^{m}\Delta\overline{L}_i(T_j;P)+\overline{L}(P). \tag{2.35}$$

Then the overall sustainability after using a specific set of technologies becomes:

$$\bar{S}_i(T;P) = \frac{\left\|\left(\alpha \bar{E}_i(T;P),\quad \beta \bar{V}_i(T;P),\quad \gamma \bar{L}_i(T;P)\right)\right\|}{\left\|\left(\alpha,\quad \beta,\quad \gamma\right)\right\|}, \tag{2.36}$$

where α, β, and γ take the same values as those used in Eq. 2.12 for consistency. The information derived from Eqs. 2.33-2.36 should be entered in the 4th - 7th columns of Table 2.3.

c) The total cost for using the *i*-th set of *m* technologies can also be readily calculated as follows:

$$B_i(T;P) = \sum_{j=1}^{m} B\left(T_j;P\right), \tag{2.37}$$

The cost data are listed in the 3rd column of Table 2.3.

The effectiveness of technology sets in application can be further evaluated through calculating the sustainability improvement percentages in the following way:

$$\bar{E}_i^{imp}(T;P)(\%) = \frac{\bar{E}_i(T;P) - \bar{E}(P)}{\bar{E}(P)}, \tag{2.38}$$

$$\bar{V}_i^{imp}(T;P)(\%) = \frac{\bar{V}_i(T;P) - \bar{V}(P)}{\bar{V}(P)}, \tag{2.39}$$

$$\bar{L}_i^{imp}(T;P)(\%) = \frac{\bar{L}_i(T;P) - \bar{L}(P)}{\bar{L}(P)}, \tag{2.40}$$

$$\bar{S}_i^{imp}(T;P)(\%) = \frac{\bar{S}_i(T;P) - \bar{S}(P)}{\bar{S}(P)}. \tag{2.41}$$

2.5.1 Solution identification procedure

The sustainability performance of an industrial organization can be improved in many ways. For instance, a corporation may plan to introduce a number of new products, to replace existing energy systems using alternative energy, to replace some production lines to improve production rate, to reduce energy consumption and emission, or any combination of these or others. The approach for technology identification described below includes two procedures: (i) the one for a single improvement task, and (ii) the one for a multiple improvement task. Solution procedures are introduced below.

a) *Procedure for a single improvement task* (*SIT*). Assume that a total of N candidate technologies are identified, i.e., $T = \{T_1, T_2, \cdots, \text{and } T_N\}$. A five-step procedure is given below for identification of all technology sets that can be used to achieve the economic, environmental, and social sustainability goals.

Step 1. Generate a complete list of technology sets (denoted as list Q) through enumerating the combinations by N candidate technologies. The list contains 2^N-1 distinct technology sets, each of which has a size of k ($1 \leq k \leq N$) and in the form of $\{T_a, \cdots\}$. These sets are numbered in the 1st column and listed in the 2nd column of Table 2.3. In list Q, there should be $\binom{N}{1}$ sets containing one technology each, $\binom{N}{2}$ sets with two technologies each, $\cdots$, and $\binom{N}{N}$ set including all N technologies.

Step 2. Calculate the total cost required for adopting each set of technologies according to Eq. 2.37. The results should be entered in the 3rd column of Table 2.3. Note that any technology set, if the total cost exceeds the budget limit, $B^{lim}(P)$, should be removed from the table.

Step 3. For each set remained in the table, evaluate $\Delta\overline{E}_i(T;P)$'s and $\overline{E}_i(T;P)$'s, respectively, using Eqs. 2.30 and 2.33, and then enter $\overline{E}_i(T;P)$'s in the 4th column of Table 2.3. Note that any set, if the value of $\overline{E}_i^L(T;P)$ is lower than $(1-\eta_E)E^{sp}(P)$ (where η_E could be 0.05, for example), should be eliminated from the table, as it is incapable of improving the system to the level set by the economic sustainability goal.

Step 4. Calculate $\Delta\overline{V}_i(T;P)$'s and $\overline{V}_i(T;P)$'s using Eqs. 2.31 and 2.34, respectively, and enter $\overline{V}_i(T;P)$'s in the 5th column of Table 2.3. If the value of $\overline{V}_i^L(T;P)$ of the *i*-th technology set is lower than $(1-\eta_V)V^{sp}(P)$ (where η_V is 0.05, for example), the set should be deleted from the table, due to its incompetence of achieving the environmental sustainability goal.

Step 5. Calculate $\Delta\overline{L}_i(T;P)$'s and $\overline{L}_i(T;P)$'s using Eqs. 2.32 and 2.35, respectively, and enter $\overline{L}_i(T;P)$'s in the 6th column of Table 2.3. Then keep only those sets in the table whose $\overline{L}_i^L(T;P)$'s are equal or greater than $(1-\eta_L)$ (e.g., 0.95) of $L^{sp}(P)$.

Step 6. Evaluate $\overline{S}_i(T;P)$ using Eq. 2.36, and enter it in the 7th column of Table 2.3.

Note that the technology sets still remained in Table 2.3 after Step 5 are those that can be used to achieve the organization's sustainability goals under the preset budget limit.

b) ***Procedure for a multiple improvement task*** **(*MIT*).** In the case of achieving multiple objectives, the total budget limit, $B_{tot}^{lim}(P)$, should be set first. Assuming that M objectives are defined, a solution search procedure is proposed below.

Step 1. For each objective, run the above SIT procedure to identify the optimal technology set(s) that are contained in Table 2.3. For the *k*-th objective, for instance, the resulting table is named $\Omega_k = \{\omega_{k,1}, \omega_{k,2}, \cdots, \omega_{k,G_k}\}$, where $\omega_{k,i}$ is the *i*-th technology set. The total number of technology sets for it is G_k. Note that for a task of M objectives, a total of M tables are generated, namely Ω_1. Ω_2, $\cdots$, and Ω_M.

Step 2. Generate a complete list of the grouped technology sets (denoted as list Q_{tot}) through enumerating all the combinations of the identified technology sets among the M tables; the total number of such combinations is $G_{tot} = \prod_{k=1}^{M} G_k$. These combined technology sets are numbered in the 1st column and listed in the 2nd column of Table 2.4.

Step 3. Calculate the total cost for adopting each grouped technology set according to Eq. 2.37. The results should be entered in the 3rd column of Table 2.4. Note that any technology set, if the total cost exceeds $B_{tot}^{lim}(P)$, should be removed from the table immediately.

Table 2.4. Sustainability improvement by combined technology sets.

No.	Tech. set	Cost	Achievable categorized sustainability			Overall sust.
			Econ.	Environ.	Soc.	
1	$\{\omega_{1,1},\ \omega_{2,1},\ \cdots, \omega_{M,1}\}$	$B_1^M(T;P)$	$\bar{E}_1^M(T;P)$	$\bar{V}_1^M(T;P)$	$\bar{L}_1^M(T;P)$	$\bar{S}_1^M(T;P)$
2	$\{\omega_{1,1},\ \omega_{2,1},\ \cdots\ \omega_{M,2}\}$	$B_2^M(T;P)$	$\bar{E}_2^M(T;P)$	$\bar{V}_2^M(T;P)$	$\bar{L}_2^M(T;P)$	$\bar{S}_2^M(T;P)$
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
G_{tot}	$\{\omega_{1,G_1},\ \omega_{2,G_2},\ \cdots,\ \omega_{M,G_M}\}$	$B_{G_{tot}}^M(T;P)$	$\bar{E}_{G_{tot}}^M(T;P)$	$\bar{V}_{G_{tot}}^M(T;P)$	$\bar{L}_{G_{tot}}^M(T;P)$	$\bar{S}_{G_{tot}}^M(T;P)$

Step 4. For each grouped technology sets remained in Table 2.4, evaluate $\Delta\bar{E}_i^M(T;P)$'s and $\bar{E}_i^M(T;P)$'s using Eqs. 2.30 and 2.33, respectively, and then enter $\bar{E}_i^M(T;P)$'s in the 4th column of Table 2.4.

Step 5. Calculate $\Delta\bar{V}_i^M(T;P)$'s and $\bar{V}_i^M(T;P)$'s using Eqs. 2.31 and 2.34, respectively, and enter $\bar{V}_i^M(T;P)$'s in the 5th column of Table 2.4.

Step 6. The same type of actions is taken for deriving $\Delta\bar{L}_i^M(T;P)$'s and $\bar{L}_i^M(T;P)$'s using Eqs. 2.32 and 2.35, respectively, and then enter $\bar{L}_i^M(T;P)$'s in the 6th column of Table 2.4.

Step 7. Calculate the overall sustainability, $\bar{S}_i^M(T;P)$, and enter the results in the 7th column of Table 2.4.

All the grouped technology sets remained in Table 2.4 satisfy the strategic goals under the budget limits. In general, the technology sets demonstrate different categorized sustainability improvements. The table can be sorted in descending order according to the individual categorized sustainability performance or the overall performance at the decision makers' choice. The sustainability improvement percentages calculated using Eqs. 2.38 through 2.41 can provide additional valuable information for comparisons of technology sets. With these, the industrial organization should be able to select the most preferred technology set for application. In reality, the technologies available for an industrial organization to choose are normally limited. This makes the computational solution search well manageable, even for a multiple objective problem.

2.5.2 Performance comparison by sustainability cube

The system's sustainability performance using different technology sets that is quantified in Table 2.3 (for a single objective) or Table 2.4 (for multiple objectives) can be shown using a sustainability cube, which is firstly introduced by Piluso *et al*. (2010).

As shown in Fig. 2.1, the three coordinates of the cube are labeled by the composite indices for economic, environmental, and social sustainability, which are all normalized. The corner at (0, 0, 0) represents no sustainability at all that is rare, while the opposite corner at (1, 1, 1) indicates complete sustainability that is ideal. In the figure, the dot labeled as $S(P)$ describes the status quo of an industrial system, while the small solid square labeled as $S^{sp}(P)$ plots the sustainability goal defined by the industrial organization. The small cycle labeled as $S_i(T;P)$ shows the sustainability achieved after adopting the i-th technology set. Each sustainability status is quantified by three composite index values shown in the figure. This plot can help the industrial decision makers compare graphically the solutions in the categorized and/or overall sustainability.

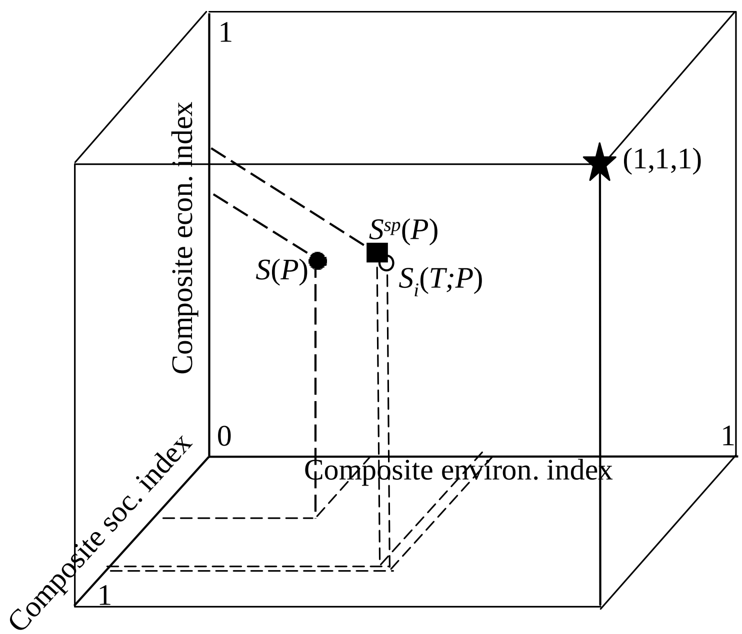


Figure 2.1. Sustainability cube representation.

2.6 Case Study

The introduced methodology has been successfully used to study a number of complex industrial sustainability problems. In this section, a sustainability development problem about biodiesel manufacturing is selected to illustrate the efficacy of the introduced methodology. In this case, a biodiesel plant with the production capacity of 8,000 tons/yr plans to identify suitable technologies for waste reduction, energy recovery, and product quality improvement for its alkali-catalyzed biodiesel manufacturing process (see Figure 2.2). The plant decides to solicit proposals from its engineering departments, which should contain recommended technologies with detailed sustainability assessment under budget limit.

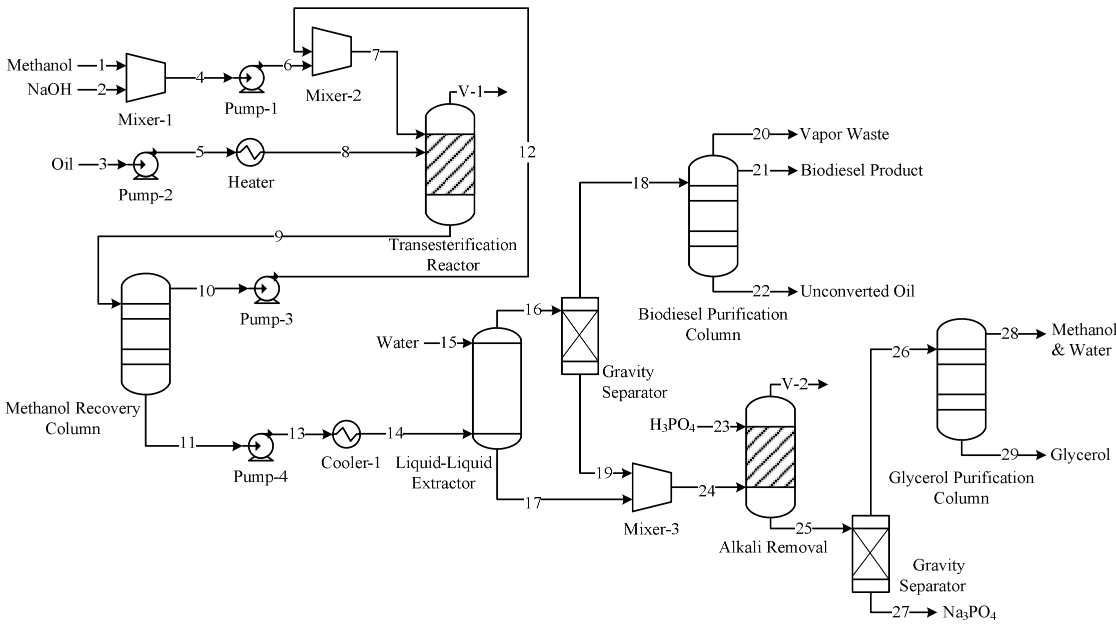


Figure 2.2. Flowsheet of an alkali-catalyzed biodiesel manufacturing process.

2.6.1 Technologies and classification

As a response, the engineering departments have identified ten technologies from different sources (Zhang *et al.*, 2003; Glisic *et al.*, 2009; West *et al.*, 2008), which can be divided into two groups.

Group 1 – Source waste reduction technologies. The four identified technologies are: (1) $T_{1,1}$ - Separation of methanol in the waste stream from the glycerol purification column and its recycle to the transesterificaiton reactor, (2) $T_{1,2}$ - Recycle of the unconverted oil as part of the feedstock after pretreatment, (3) $T_{1,3}$ - Recycle of waste stream of the glycerol purification column to the liquid-liquid extraction column as a washing solvent to replace fresh waster, and (4) $T_{1,4}$ - Recovery of solid waste from the catalyst removal separator as a type of fertilizer.

Group 2 – Energy efficiency and product performance improvement technologies. They are: (1) $T_{2,1}$ - Redesign of product purification sequence, (2) $T_{2,2}$ - Pretreatment of waste cooking oil as a new feedstock, (3) $T_{2,3}$ – Adoption of new catalyst for the transesterificaiton reactor to improve the conversion rate, (4) $T_{2,4}$ - Energy recovery from the glycerol purification process, (5) $T_{2,5}$ - Energy recovery from the transesterificaiton reaction process, and (6) $T_{2,6}$ - Energy recovery from the biodiesel purification system.

2.6.2 Sustainability indicator selection

To facilitate the illustration of methodology application, a small set of sustainability indicators are selected from the IChemE Sustainability Metrics system (IChemE, 2002). The economic indices include: (1) Value added (E_1) and (2) Gross margin per direct employee (E_2). Note that price variation and market fluctuation affecting the calculation of the two indices are expressed by interval numbers. The environmental category has three indices: (1) Total raw materials used per pound of product produced (V_1), (2) Hazardous solid waste per unit value added (V_2), and (3) Fraction of raw materials recycled (V_3). Uncertainties exist due to production fluctuation and feedstock quality variation. In the social sustainability category, the selected indices are: (1) Lost time accident frequency (L_1) and (2) Number of complaints per unit value added (L_2). The available data for evaluation are insufficient and imprecise.

2.6.3 Sustainability assessment

By using the selected sustainability indices, the assessment results of the status quo of system *P* and the two groups of technologies are listed in Table 2.5 and Table 2.6, where most of the results are expressed as intervals due to data uncertainty. Then the categorized sustainability assessment of the process as well as the two groups of technologies are derived using Eqs. 2.9-2.11 and 2.21-2.23; the results are shown in Table 2.7 and Table 2.8.

For instance, the plant sustainability is quantified as [0.500, 0.510] for $\overline{E}(P)$, [0.393, 0.400] for $\overline{V}(P)$, and [0.344, 0.350] for $\overline{L}(P)$ as listed in the 4th column of Table 2.7. Note that the weighting factors for different indices listed in the 3rd column of Table 2.7 and Table 2.8 are provided by the plant. The overall sustainability of the plant, $\overline{S}(P)$, evaluated by Eq. (12) is [0.417, 0.425], where parameters α, β, and γ took the default value of 1, meaning all are equally important.

Table 2.5. Index-specific sustainability assessment of the system and technologies in Group 1.

Category	Index	System	Technologies in Group 1			
		P	$T_{1,1}$	$T_{1,2}$	$T_{1,3}$	$T_{1,4}$
Econ. (E)	E_1	[0.550, 0.570]	0.620	[0.620, 0.640]	0.580	[0.600, 0.610]
	E_2	0.450	[0.500, 0.530]	[0.480, 0.490]	[0.460, 0.480]	[0.490, 0.510]
Environ. (V)	V_1	0.400	0.430	0.450	[0.410, 0.420]	[0.420, 0.430]
	V_2	[0.350, 0.380]	0.400	0.360	[0.390, 0.400]	0.370
	V_3	0.420	[0.410, 0.420]	[0.450, 0.460]	0.400	0.430
Soc. (L)	L_1	[0.335, 0.340]	[0.355, 0.360]	[0.380, 0.390]	0.330	0.350
	L_2	[0.370, 0.380]	0.400	0.380	[0.378, 0.380]	[0.380, 0.385]

Table 2.6. Index-specific sustainability assessment of the technologies in Group 2.

Category	Index	Technologies in Group 2					
		$T_{2,1}$	$T_{2,2}$	$T_{2,3}$	$T_{2,4}$	$T_{2,5}$	$T_{2,6}$
Econ. (E)	E_1	[0.600, 0.610]	[0.580, 0.600]	0.610	[0.620, 0.630]	0.580	[0.590, 0.600]
	E_2	0.510	[0.470, 0.480]	[0.460, 0.470]	0.460	[0.520, 0.530]	[0.460, 0.480]
Environ. (V)	V_1	[0.440, 0.450]	0.420	0.430	[0.460, 0.470]	[0.410, 0.420]	[0.460, 0.470]
	V_2	[0.360, 0.380]	[0.380, 0.400]	[0.360, 0.370]	0.350	0.400	[0.410, 0.420]
	V_3	0.450	[0.400, 0.410]	[0.430, 0.440]	[0.430, 0.440]	[0.420, 0.430]	0.410
Soc. (L)	L_1	[0.310, 0.315]	[0.370, 0.380]	0.330	0.440	[0.390, 0.400]	[0.350, 0.365]
	L_2	0.400	[0.390, 0.410]	[0.380, 0.390]	[0.360, 0.370]	[0.400, 0.410]	0.370

Table 2.7. Assessment of categorized sustainability of the system and technologies in Group 1.

Category	Index	Weighting Factor	Categorized Sustainability Assessment				
			P	$T_{1,1}$	$T_{1,2}$	$T_{1,3}$	$T_{1,4}$
Econ. (E)	E_1	$a_1 = 1$	[0.500, 0.510]	[0.560, 0.575]	[0.550, 0.565]	[0.520, 0.530]	[0.545, 0.560]
	E_2	$a_2 = 1$					
Environ. (V)	V_1	$b_1 = 2$	[0.393, 0.400]	[0.418, 0.420]	[0.428, 0.430]	[0.403, 0.410]	[0.410, 0.415]
	V_2	$b_2 = 1$					
	V_3	$b_3 = 1$					
Soc. (L)	L_1	$c_1 = 3$	[0.344, 0.350]	[0.366, 0.370]	[0.380, 0.388]	[0.342, 0.343]	[0.358, 0.359]
	L_2	$c_2 = 1$					

Table 2.8. Assessment of categorized sustainability of the technologies in Group 2.

Category	Index	Weighting Factor	Categorized Sustainability Assessment				
			$T_{2,2}$	$T_{2,3}$	$T_{2,4}$	$T_{2,5}$	$T_{2,6}$
Econ. (E)	E_1	$a_1 = 1$	[0.525, 0.540]	[0.535, 0.540]	[0.540, 0.545]	[0.550, 0.555]	[0.525, 0.540]
	E_2	$a_2 = 1$					
Environ. (V)	V_1	$b_1 = 2$	[0.405, 0.413]	[0.413, 0.418]	[0.425, 0.433]	[0.410, 0.418]	[0.435, 0.443]
	V_2	$b_2 = 1$					
	V_3	$b_3 = 1$					
Soc. (L)	L_1	$c_1 = 3$	[0.375, 0.385]	[0.343, 0.345]	[0.390, 0.393]	[0.393, 0.403]	[0.355, 0.366]
	L_2	$c_2 = 1$					

2.6.4 Strategic goal setting

After reviewing the assessment results in Tables 2.5 through 2.8, the plant management set the plant's goal for the categorized sustainability to 0.580 for $E^{sp}(P)$, 0.455 for $V^{sp}(P)$, and 0.392 for $L^{sp}(P)$, and the values of η_E, η_V, and η_L are set to 0.05, representing a minimum requirement of 95% goal achievement.

The difference between the sustainability goals and the system performance can be calculated using Eqs. 2.14-2.16, which are [0.070, 0.080], [0.055, 0.062], and [0.042, 0.048], for $\Delta\bar{E}^{imp}(P)$, $\Delta\bar{V}^{imp}(P)$, and $\Delta\bar{L}^{imp}(P)$, respectively. By using the preset values for η_E, η_V, and η_L, the values of $\eta_E E^{sp}(P)$, $\eta_V V^{sp}(P)$, and $\eta_L L^{sp}(P)$ are, respectively, 0.029, 0.023, and 0.020. According to Eqs. 2.18-2.20, a technology based sustainability improvement is needed.

2.6.5 Technology recommendation

The introduced sustainability improvement procedure is executed under two budget constraints set by the plant, i.e., (1) $B^{lim}(P)$ of \$300 K for a single objective task and (2) $B_{tot}^{lim}(P)$ of \$450 K for a two objective task.

Proposal 1 – technology recommendation for source waste reduction. The single objective focused procedure is executed to identify the most appropriate technology set(s) from Group 1 that includes technologies $T_{1,1}$ to $T_{1,4}$.

Step 1. A total of 15 candidate technology sets (2^4-1) are generated, which are listed in the 2nd columns of Table 2.9.

Step 2. The cost for using each technology set is calculated using Eq. 2.37 and listed in the 3rd column of the same table. Note that sets 12 and 15 should be removed since the total cost for using each exceeds the budget limit of \$300 K.

Step 3. For the remaining 13 technology sets, $\Delta\overline{E}_i(T;P)$'s and $\overline{E}_i(T;P)$'s are in turn evaluated using Eqs. 2.30 and 2.33, and $\overline{E}_i(T;P)$'s are listed in the 4th column of Table 2.9. Since the values of $\overline{E}_2^L(T;P)$, $\overline{E}_3^L(T;P)$, $\overline{E}_4^L(T;P)$, $\overline{E}_7^L(T;P)$, and $\overline{E}_{10}^L(T;P)$ are all less than 0.551 (i.e., (1-0.05)$E^{sp}(P)$), the corresponding five technology sets must be deleted from the list. This makes the list containing only eight technology sets.

Table 2.9. Sustainability improvement by source waste reduction technologies.

No.	Tech. set	Cost for tech. set $B_i(T;P)$	System's achievable categorized sustainability $\bar{E}_i(T;P)$	$\bar{V}_i(T;P)$	$\bar{L}_i(T;P)$	Overall sust. $\bar{S}_i(T;P)$
1	$\{T_{1,1}\}$	\$100 K	[0.560, 0.575]	[0.418, 0.420]	Deleted (environ. concern)	
2	$\{T_{1,2}\}$	\$150 K	[0.550, 0.565]	Deleted (econ. concern)		
3	$\{T_{1,3}\}$	\$50 K	[0.520, 0.530]	Deleted (econ. concern)		
4	$\{T_{1,4}\}$	\$80 K	[0.545, 0.560]	Deleted (econ. concern)		
5	$\{T_{1,1}, T_{1,2}\}$	\$250 K	[0.590, 0.650]	[0.438, 0.465]	[0.390, 0.420]	[0.480, 0.521]
6	$\{T_{1,1}, T_{1,3}\}$	\$150 K	[0.560, 0.615]	[0.413, 0.445]	Deleted (environ. concern)	
7	$\{T_{1,2}, T_{1,3}\}$	\$200 K	[0.550, 0.605]	Deleted (econ. concern)		
8	$\{T_{1,1}, T_{1,4}\}$	\$180 K	[0.585, 0.645]	[0.420, 0.450]	Deleted (environ. concern)	
9	$\{T_{1,2}, T_{1,4}\}$	\$230 K	[0.575, 0.635]	[0.430, 0.460]	Deleted (environ. concern)	
10	$\{T_{1,3}, T_{1,4}\}$	\$130 K	[0.545, 0.600]	Deleted (econ. concern)		
11	$\{T_{1,1}, T_{1,2}, T_{1,3}\}$	\$300 K	[0.600, 0.680]	[0.440, 0.483]	[0.382, 0.419]	[0.482, 0.539]
12	$\{T_{1,1}, T_{1,2}, T_{1,4}\}$	\$330 K	Deleted (cost concern)			
13	$\{T_{1,1}, T_{1,3}, T_{1,4}\}$	\$230 K	[0.595, 0.675]	[0.423, 0.468]	Deleted (environ. concern)	
14	$\{T_{1,2}, T_{1,3}, T_{1,4}\}$	\$280 K	[0.585, 0.665]	[0.433, 0.478]	[0.373, 0.408]	[0.472, 0.528]
15	$\{T_{1,1}, T_{1,2}, T_{1,3}, T_{1,4}\}$	\$380 K	Deleted (cost concern)			

Step 4. The calculated values of $\bar{V}_i(T;P)$'s are listed in the 5th column of Table 2.9. It is shown that $\bar{V}_1^L(T;P)$, $\bar{V}_6^L(T;P)$, $\bar{V}_8^L(T;P)$, $\bar{V}_9^L(T;P)$, and $\bar{V}_{13}^L(T;P)$ are all less than 0.432 (i.e., (1-0.05)$V^{sp}(P)$). Therefore, the corresponding five sets are not acceptable. This gives only technology sets No. 5, No. 11, and No. 14 still remained on the candidate list.

Step 5. For the remaining three technology sets, the values of $\bar{L}_i(T;P)$'s are listed in the 6th column of Table 2.9. The values of $\bar{L}_5^L(T;P)$, $\bar{L}_{11}^L(T;P)$, and $\bar{L}_{14}^L(T;P)$ are all greater than or equal to 0.373 (i.e., (1-0.05)$L^{sp}(P)$). Therefore, these three source waste reduction technology sets, i.e., $\{T_{1,1}, T_{1,2}\}$, $\{T_{1,1}, T_{1,2}, T_{1,3}\}$, and $\{T_{1,2}, T_{1,3}, T_{1,4}\}$, are recommended for adoption to improve the process sustainability to the level preset by the plant under the budget limit.

Step 6. The overall sustainability value, $\bar{S}_i(T;P)$, for each of the three identified technology sets is listed in the 7th column of Table 2.9, which could be valuable for the plant management.

Proposal 2 – technology recommendation for energy efficiency and product quality improvement. In this case, six technologies in Group 2, namely $T_{2,1}$ through $T_{2,6}$, need to be evaluated. The single objective focused procedure needs to be executed again. Among 63 technology sets (2^6-1), 30 sets each costs more than \$300K, and thus are removed from the list. After examining the values of $\bar{E}_i(T;P)$'s, 10 more technology sets are deleted. A comparison of the values of $\bar{V}_i(T;P)$'s with the environmental goal leads to elimination of additional nine technology sets. Among the remaining 14 technology sets, five sets are disqualified after checking the values of $\overline{L}_i(T;P)$'s. Finally nine sets are left on the list (see Table 2.10); they all can be recommended to enhance the plant's sustainability goal under the budget limit.

Table 2.10. Sustainability improvement by energy efficiency and product quality enhancement technologies.

No.	Tech. set	Cost for tech. set $B_i(T;P)$	System's achievable categorized sustainability			Overall sustainability $\overline{S}_i(T;P)$
			$\overline{E}_i(T;P)$	$\overline{V}_i(T;P)$	$\overline{L}_i(T;P)$	
1	$\{T_{2,5}, T_{2,6}\}$	\$140 K	[0.555, 0.605]	[0.438, 0.475]	[0.391, 0.431]	[0.466, 0.509]
2	$\{T_{2,1}, T_{2,4}, T_{2,5}\}$	\$270 K	[0.615, 0.670]	[0.450, 0.505]	[0.408, 0.450]	[0.499, 0.550]
3	$\{T_{2,2}, T_{2,4}, T_{2,5}\}$	\$290 K	[0.585, 0.650]	[0.433, 0.485]	[0.451, 0.499]	[0.494, 0.550]
4	$\{T_{2,3}, T_{2,4}, T_{2,5}\}$	\$250 K	[0.595, 0.650]	[0.440, 0.490]	[0.419, 0.459]	[0.491, 0.539]
5	$\{T_{2,3}, T_{2,4}, T_{2,6}\}$	\$270 K	[0.570, 0.635]	[0.465, 0.515]	[0.381, 0.423]	[0.478, 0.531]
6	$\{T_{2,1}, T_{2,5}, T_{2,6}\}$	\$260 K	[0.600, 0.665]	[0.460, 0.515]	[0.374, 0.424]	[0.487, 0.544]
7	$\{T_{2,2}, T_{2,5}, T_{2,9}\}$	\$280 K	[0.570, 0.645]	[0.443, 0.495]	[0.416, 0.473]	[0.481, 0.543]
8	$\{T_{2,3}, T_{2,5}, T_{2,6}\}$	\$240 K	[0.580, 0.645]	[0.450, 0.500]	[0.384, 0.433]	[0.478, 0.533]
9	$\{T_{2,4}, T_{2,5}, T_{2,6}\}$	\$230 K	[0.585, 0.650]	[0.463, 0.515]	[0.431, 0.480]	[0.497, 0.553]

Proposal 3 – technology recommendation for source waste reduction as well as energy efficiency and product quality improvement. In this case, all the improvement areas are targeted. The task is to identify the best possible technology combinations for the plant so that the management can decide if they want to invest more to achieve all or not. In this case, the plant sets the budget limit, $B_{tot}^{lim}(P)$, to \$450 K.

To search for technology combination, the MIT procedure described in the preceding section is executed. For the two-objective task, running Step 1 gives rise to two lists of the recommended technology sets. They are: $\Omega_1 = \{\omega_{1,1}, \omega_{1,2}, \omega_{1,3}\}$, where $\omega_{1,1} = \{T_{1,1}, T_{1,2}\}$, $\omega_{1,2} = \{T_{1,1}, T_{1,2}, T_{1,3}\}$ and $\omega_{1,3} = \{T_{1,2}, T_{1,3}, T_{1,4}\}$ (see Table 2.9), and $\Omega_2 = \{\omega_{2,1}, \omega_{2,2}, \cdots, \omega_{2,9}\}$, where the nine technology sets ($\omega_{2,i}'s$) are listed in the second column of Table 2.10. The list, Q_{tot}, is generated in Step 2, which contains 27 combinations (see the 2nd column of Table 2.11). After calculating the cost for using each combined technology sets, only three out of 27 require the cost less than \$450 K (see the 3rd column of Table 2.11). By using Eqs. 2.33, 2.34, and 2.35, the values of $\overline{E}_i^M(T;P)$, $\overline{V}_i^M(T;P)$, and $\overline{L}_i^M(T;P)$ for the combined technology sets, No. 1, 10, and 19, are derived, which are entered in the 4th, 5th, and 6th columns of Table 2.11. The overall sustainability levels for the three are listed in the 7th column of the same table.

2.6.6 Solution comparison

Different from Proposals 1 and 2, for which the sustainability goals are preset by the plant, Proposal 3 is developed with no specific sustainability goals pre-specified, because the plant wants to review the detailed sustainability improvement levels for a given budget. The three identified combined technology sets shown in Table 2.11 are compared using Eqs. 2.38-2.41; the sustainability improvement analysis, together with the costs for technology adoption are summarized in Table 2.12.

Table 2.11a. Sustainability improvement by combined technology sets for two objectives.

No.	Tech. set	Cost for tech. set $B_i^M(T;P)$	System's achievable categorized sustainability			Overall sust. $\bar{S}_i^M(T;P)$
			$\bar{E}_i^M(T;P)$	$\bar{V}_i^M(T;P)$	$\bar{L}_i^M(T;P)$	
1	$\{T_{1,1}, T_{1,2}\}$, $\{T_{2,5}, T_{2,6}\}$	\$390 K	[0.645, 0.745]	[0.483, 0.540]	[0.434, 0.501]	[0.528, 0.605]
2	$\{T_{1,1}, T_{1,2}\}$, $\{T_{2,1}, T_{2,4}, T_{2,5}\}$	\$520 K	Deleted (cost concern)			
3	$\{T_{1,1}, T_{1,2}\}$, $\{T_{2,2}, T_{2,4}, T_{2,5}\}$	\$540 K	Deleted (cost concern)			
4	$\{T_{1,1}, T_{1,2}\}$, $\{T_{2,3}, T_{2,4}, T_{2,5}\}$	\$500 K	Deleted (cost concern)			
5	$\{T_{1,2}, T_{1,2}\}$, $\{T_{2,3}, T_{2,4}, T_{2,6}\}$	\$520 K	Deleted (cost concern)			
6	$\{T_{1,1}, T_{1,2}\}$, $\{T_{2,1}, T_{2,5}, T_{2,6}\}$	\$510 K	Deleted (cost concern)			
7	$\{T_{1,1}, T_{1,2}\}$, $\{T_{2,2}, T_{2,5}, T_{2,6}\}$	\$530 K	Deleted (cost concern)			
8	$\{T_{1,1}, T_{1,2}\}$, $\{T_{2,3}, T_{2,4}, T_{2,6}\}$	\$490 K	Deleted (cost concern)			
9	$\{T_{1,1}, T_{1,2}\}$, $\{T_{2,4}, T_{2,5}, T_{2,6}\}$	\$480 K	Deleted (cost concern)			
10	$\{T_{1,1}, T_{1,2}, T_{1,3}\}$, $\{T_{2,5}, T_{2,6}\}$	\$440 K	[0.655, 0.775]	[0.485, 0.558]	[0.426, 0.500]	[0.531, 0.622]
11	$\{T_{1,1}, T_{1,2}, T_{1,3}\}$, $\{T_{2,1}, T_{2,4}, T_{2,5}\}$	\$570 K	Deleted (cost concern)			
12	$\{T_{1,1}, T_{1,2}, T_{1,3}\}$, $\{T_{2,2}, T_{2,4}, T_{2,5}\}$	\$590 K	Deleted (cost concern)			
13	$\{T_{1,1}, T_{1,2}, T_{1,3}\}$, $\{T_{2,3}, T_{2,4}, T_{2,5}\}$	\$550 K	Deleted (cost concern)			
14	$\{T_{1,1}, T_{1,2}, T_{1,3}\}$, $\{T_{2,3}, T_{2,4}, T_{2,6}\}$	\$570 K	Deleted (cost concern)			
15	$\{T_{1,1}, T_{1,2}, T_{1,3}\}$, $\{T_{2,1}, T_{2,5}, T_{2,6}\}$	\$560 K	Deleted (cost concern)			

Table 2.11b. Sustainability improvement by combined technology sets for two objectives (cont'd).

No.	Tech. set	Cost for tech. set $B_i^M(T;P)$	System's achievable categorized sustainability $\overline{E}_i^M(T;P)$	$\overline{V}_i^M(T;P)$	$\overline{L}_i^M(T;P)$	Overall sust. $\overline{S}_i^M(T;P)$
16	$\{T_{1,1}, T_{1,2}, T_{1,3}\}$, $\{T_{2,2}, T_{2,5}, T_{2,6}\}$	\$580 K	Deleted (cost concern)			
17	$\{T_{1,1}, T_{1,2}, T_{1,3}\}$, $\{T_{2,3}, T_{2,5}, T_{2,6}\}$	\$540 K	Deleted (cost concern)			
18	$\{T_{1,1}, T_{1,2}, T_{1,3}\}$, $\{T_{2,4}, T_{2,5}, T_{2,6}\}$	\$530 K	Deleted (cost concern)			
19	$\{T_{1,2}, T_{1,3}, T_{1,4}\}$, $\{T_{2,5}, T_{2,6}\}$	\$420 K	[0.640, 0.760]	[0.478, 0.553]	[0.421, 0.489]	[0.521, 0.611]
20	$\{T_{1,2}, T_{1,3}, T_{1,4}\}$, $\{T_{2,1}, T_{2,4}, T_{2,5}\}$	\$550 K	Deleted (cost concern)			
21	$\{T_{1,2}, T_{1,3}, T_{1,4}\}$, $\{T_{2,2}, T_{2,4}, T_{2,5}\}$	\$670 K	Deleted (cost concern)			
22	$\{T_{1,2}, T_{1,3}, T_{1,4}\}$, $\{T_{2,3}, T_{2,4}, T_{2,5}\}$	\$530 K	Deleted (cost concern)			
23	$\{T_{1,2}, T_{1,3}, T_{1,4}\}$, $\{T_{2,3}, T_{2,4}, T_{2,6}\}$	\$550 K	Deleted (cost concern)			
24	$\{T_{1,2}, T_{1,3}, T_{1,4}\}$, $\{T_{2,1}, T_{2,5}, T_{2,6}\}$	\$540 K	Deleted (cost concern)			
25	$\{T_{1,2}, T_{1,3}, T_{1,4}\}$, $\{T_{2,2}, T_{2,5}, T_{2,6}\}$	\$560 K	Deleted (cost concern)			
26	$\{T_{1,2}, T_{1,3}, T_{1,4}\}$, $\{T_{2,3}, T_{2,4}, T_{2,5}\}$	\$520 K	Deleted (cost concern)			
27	$\{T_{1,2}, T_{1,3}, T_{1,4}\}$, $\{T_{2,4}, T_{2,5}, T_{2,6}\}$	\$510 K	Deleted (cost concern)			

To further help the plant management in technology selection, their sustainability performance data are plotted in Fig. 2.3, which depicts the system's status quo ($S(P)$), its goal ($0.95S^{sp}(P)$), and the minimum achievable sustainability levels by the combined technology sets ($S_1^L(T;P), S_{10}^L(T;P)$, and $S_{19}^L(T;P)$).

Table 2.12. Sustainability improvement percentage comparison

No.	Tech. set	Cost $B_i^M(T;P)$	System sustainability improvement (%)			
			$\bar{E}_i^{imp}(T;P)$	$\bar{V}_i^{imp}(T;P)$	$\bar{L}_i^{imp}(T;P)$	$\bar{S}_i^{imp}(T;P)$
1	$\{T_{1,1}, T_{1,2}\}, \{T_{2,5}, T_{2,6}\}$	\$390 K	[26.5, 49.0]	[20.8, 37.4]	[24.0, 45.6]	[24.2, 45.1]
10	$\{T_{1,1}, T_{1,2}, T_{1,3}\}, \{T_{2,5}, T_{2,6}\}$	\$440 K	[28.4, 55.0]	[21.3, 42.0]	[21.7, 45.3]	[24.9, 49.2]
19	$\{T_{1,2}, T_{1,3}, T_{1,4}\}, \{T_{2,5}, T_{2,6}\}$	\$420 K	[25.5, 52.0]	[19.5, 40.7]	[20.3, 42.2]	[22.6, 46.5]

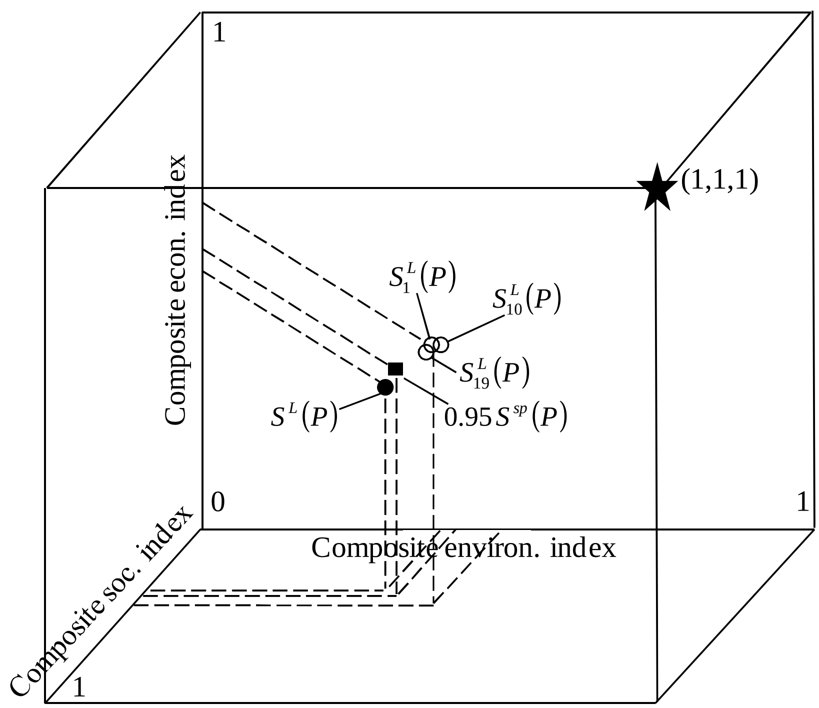


Figure 2.3. Sustainability performance of system, combined technologies, and strategic goals.

2.7 Discussion

The solution approach adopted in the introduced methodology is essentially an exhaustive search approach. Therefore, the solution(s) identified should be guaranteed optimal. We all know that such a solution approach is not preferred when a solution search space is huge. However, this is not an issue for solution identification for sustainability improvement through adopting limited technologies. Note that for most industrial problems, the identified technologies are always for specific purposes; thus they can be divided into a small number of purpose-based groups (practically no more than 10). In each group, the number of technology candidates is usually not large (rarely more than 10). Therefore, the number of solution candidates in each group is in the range of 1,000 or so, and the total number of solution candidates for all groups will be simply an addition of those in all groups. Moreover, when evaluating solution candidates using the procedure for single or multiple objective tasks, those candidates with the costs beyond the given budget will be immediately removed from the candidate list. Only the remaining candidates will be required for economic sustainability satisfaction checking. Again, only those candidates capable of making the process to meet the economic sustainability requirement will be kept. This further shortens the candidate list, which will be used to examine their capability of meeting the requirements of environmental and then social sustainability. Note that the computations involved in each step of checking are only algebraic calculations. Therefore, it is certain that for any industrial applications involving a few technology groups, each of which has 10~15 technology candidates, the computational time using a usual personal computer should be no more than a few seconds.

It is possible that for an industrial problem, an execution of the solution search procedure does not generate any feasible solution. This is mostly because the sustainability goals set by the industrial organization are not achievable by the technology candidates. In this case, the industrial organization should reset its goals more realistically. The other possible reason for no solution is the budget limit that is too low; this will eliminate some effective technology sets before being evaluated for sustainability improvement. In this case, the organization should consider a possibility of raising the budget limit.

Note that for an industrial organization seeking sustainability improvement of their systems, a commitment on capital investment is always required. The proposed methodology can then be used to provide recommendations on technology adoption. Each recommendation will include a detailed analysis on the categorized and overall sustainability improvement levels. In this work, only a few widely used indicators are selected from the IChemE Sustainability Metrics System for the illustration purpose. In real application, an industrial organization should carefully select sustainability indicators. For instance, in the economic sustainability category, it may include indicators related to the return on investment, the net profit after tax, etc. In the social sustainability category, the indicators related to job creation and the amount of tax paid could also be included.

2.8 Chapter Summary

Numerous technologies have been developed for improving energy and material use efficiency, reducing source waste, ensuring process safety and health in production systems. These technologies, before adoption, should be evaluated carefully by sustainability metrics in order to ensure that system sustainability performance be improved cost-effectively. Note that the available data and information about the industrial system and technologies are frequently incomplete, imprecise, and uncertain. This can make technology identification very difficult. In this chapter, we have introduced a simple, yet systematic interval-parameter-based methodology for identifying quickly superior solutions to improve industrial system's sustainability performance. The interval-parameter-based information processing and decision-making method is capable of processing consistently and effectively a variety of uncertain information. The logically designed solution identification procedure can make the combinatorial problem to be solved efficiently through reducing the solution space stage-wisely using different criteria set by the industrial organization. The derived solutions are sufficiently detailed which can greatly facilitate the industrial organization to make decisions on technology selection. This general methodology should be applicable to the study on sustainability enhancement problems of any size and scope.

CHAPTER 3

SUSTAINABLE STRATEGIC PLANNING FOR REGIONAL BIODIESEL MANUFACTURING UNDER UNCERTAINTY

Biodiesel, a clean burning alternative fuel, can be manufactured by transesterification of feedstock (e.g., vegetable oil and animal fats) with alcohol (e.g., methanol or ethanol). A variety of biodiesel manufacturing technologies have been developed, such as those alkali or acid catalyzed, and non-catalyzed under supercritical condition (Zhang *et al*., 2003; Santana *et al*., 2009; West *et al*., 2008; Glisic *et al*., 2009; Apostolakou *et al*., 2009). Adoption of these technologies depends largely on regional feedstock availability, fuel demand, manufacturing cost, transportation cost, regulations, etc. In the past decade, about 190 biodiesel plants were built in more than 40 states in the U.S., with a total manufacturing capacity of about 10 million tons per year (biodieselmagazine, 2012). Nevertheless, a recent survey shows that many biodiesel plants in different regions are either idle or are operated below its design capacity, because the production could not be economically justified (American Soybean Association, 2010). On the other hand, tens of new plants are under construction in many states in the U.S. due to the availability of renewable resources as well as increasing demands on fuels (biodieselmagazine, 2012). It is predicted that the U.S. biodiesel manufacturing capacity will be further increased. Apparently, biodiesel production must be carefully planned in order to meet the goals of manufacturing sustainability.

Strategic planning for biodiesel manufacturing is all about selection of suitable manufacturing technologies and determination of production capacities in different regions, when feedstock and biodiesel demand are known. Naturally, sustainability assessment of manufacturing technologies is the first task. Zhang *et al.* (2003) and You *et al.* (2008) conducted detailed economic evaluations of several biodiesel manufacturing technologies. Othman *et al.* (2010) introduced a modular-based sustainability assessment approach for process design, which was used to compare two biodiesel processes (alkali-catalyzed versus non-catalyzed with supercritical methanol). In their approach, the net annual profit and the discounted cash flow rate of return were used to estimate economic sustainability, the EPA's potential environmental impact (PEI) evaluation method (Young *et al.*, 1999) was adopted to evaluate environmental sustainability, and a number of soft quality indicators, such as safety, operability, and local demand satisfaction, were utilized to assess social sustainability. Li *et al.* (2011) extended the approach of Othman *et al.* by incorporating exergy analysis (Baral *et al.*, 2010 (a and b); Yi *et al.*, 2004) and inherent safety analysis (Heikkilä, 1999) into the assessment of two alkali-catalyzed biodiesel processes. Note that in those known studies, uncertainties associated with feedstock availability, regional product demands, transportation, etc., were not considered in sustainability assessment and decision-making. Note that in the study of strategic planning of regional manufacturing, those and other uncertainties must be accounted property.

Uncertainties can be normally classified into two categories: the aleatory and the epistemic uncertainties (Parry, 1996). The aleatory uncertainty is referred to the variations associated with physical systems and/or the environment; it is objective and irreversible. By contrast, the epistemic uncertainty is carried due to lack of knowledge and/or information; it is subjective and reducible. The uncertainties encountered in strategic planning can be either aleatory or epistemic.

A variety of mathematical and computational intelligence methods are available for uncertainty handling, such as those by resorting to statistical theory, fuzzy mathematics, and artificial intelligence. For instance, Probability Bounds Analysis (PBA) (Tucker *et al*., 2003) is a method extended from the probability theory (Moore, 1966). It expresses uncertainty using a probability-box (or p-box) approach (Ferson *et al*., 2003), where a p-box represents a range of distribution functions. The method can provide a balance between the expressiveness of imprecision and computational efficiency (Walley, 1991). Note that since the availability of distribution functions is a requirement, and modeling of uncertainty propagation is a real challenge, PBA methods become not suitable in the study of many types of strategic planning problems.

Fuzzy logic and fuzzy programming based approaches are attractive in formulating and manipulating epistemic uncertainties, where rigorous logics are used to deal with fuzzy information that are difficult to compute using conventional mathematical methods (Piluso *et al*., 2009). The solution derivation process is usually transparent, which makes solution reasoning easy to understand. Note that, however, decision quality is largely affected by the definitions of fuzzy sets and fuzzy numbers, where subjective judgments are used to a large extent because of lack of sufficient quality data. Apparently, poor judgments could be detrimental to decision quality.

Information Gap Theory (IGT) (Ben-Haim, 2006) is a fairly new method for expressing uncertainty and making decisions when only the best guess for a specific quantity is available (Ben-Haim, 2005). An info-gap is a disparity between what is known and what needs to be known in order to make a responsible decision. It has some engineering applications (Ben-Haim, 2005; Hine D *et al.*, 2010). However, the mathematics of IGT is complicated and appears to be a distraction from some important goals of modeling decision problems directly (Gelman, 2009).

Interval Parameter (IP) based uncertainty handling is an interesting approach, by which parameter uncertainties are expressed by interval numbers, each of which has the lower and upper bounds; it does not need any data distribution information (Xia D *et al.*, 1997). This type of approaches could be of great usage for various sustainability assessment and decision-making tasks, where no probability function is derivable from the accessible data and no subjective judgment is extensively needed. This is particularly true for the strategic planning based decision-making, since the accessible data are usually limited and uncertain, data ranges of parameters are known, but not data distribution (Piluso *et al.*, 2010).

In this chapter, we introduce an interval-parameter-programming (IPP) based strategic planning methodology. By this methodology, the sustainability performance of biodiesel manufacturing technologies can be formulated as an integral part in a decision-making framework, and the IPP-based optimization can generate an optimal strategic plan for regional biodiesel manufacturing under a variety of uncertainties. The remainder of the chapter is organized as follows. We first define the scope and objective of strategic planning for sustainable regional biodiesel manufacturing and describe the basic approach for organizing the decision-making. Then, the general definition of an interval number and the algorithmic operations of such numbers are introduced. With that, a set of interval-parameter-based formulations are given for three-pillar-based sustainability assessment. After these, an IPP-based optimization is developed by integrating the sustainability performance of biodiesel manufacturing technologies into the optimization formulation, and the solution identification procedure is given in detail. The efficacy of the proposed methodology is illustrated through investigating a strategy identification problem for biodiesel manufacturing in the state of Michigan. Finally, we will conclude the significance of the developed methodology.

3.1 Strategic Planning: Task Definition and Basic Approach

The task of strategic planning for regional biodiesel manufacturing can be stated as follows. As shown in Fig. 3.1, a defined geographic region, O, has a market demand of M tons of biodiesel annually for the following Z years. In this region, the types of feedstock and their annual availability in different areas are known. In addition, the biodiesel product distribution centers in different locations of the region are known, which reflects local biodiesel demands. Moreover, it is known that there are N_T technologies feasible for manufacturing biodiesel using the available types of feedstock in the region. A strategic planning task is to develop a plan for biodiesel manufacturing that can meet the market needs, and demonstrates the best possible short-to-long-term manufacturing sustainability. More specifically, it is required to determine which technologies should be used, how many plants should be built and where, and what the production capacity for each plant should be.

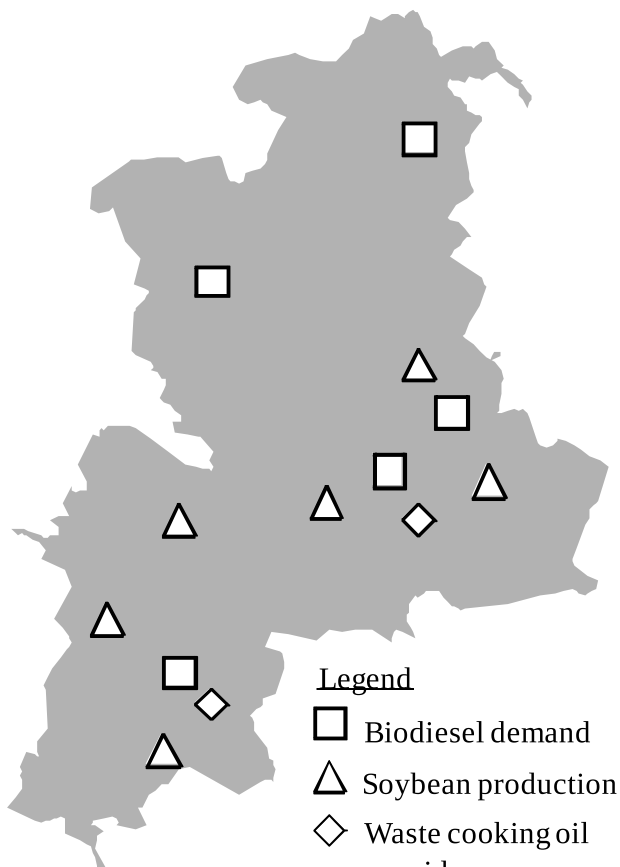
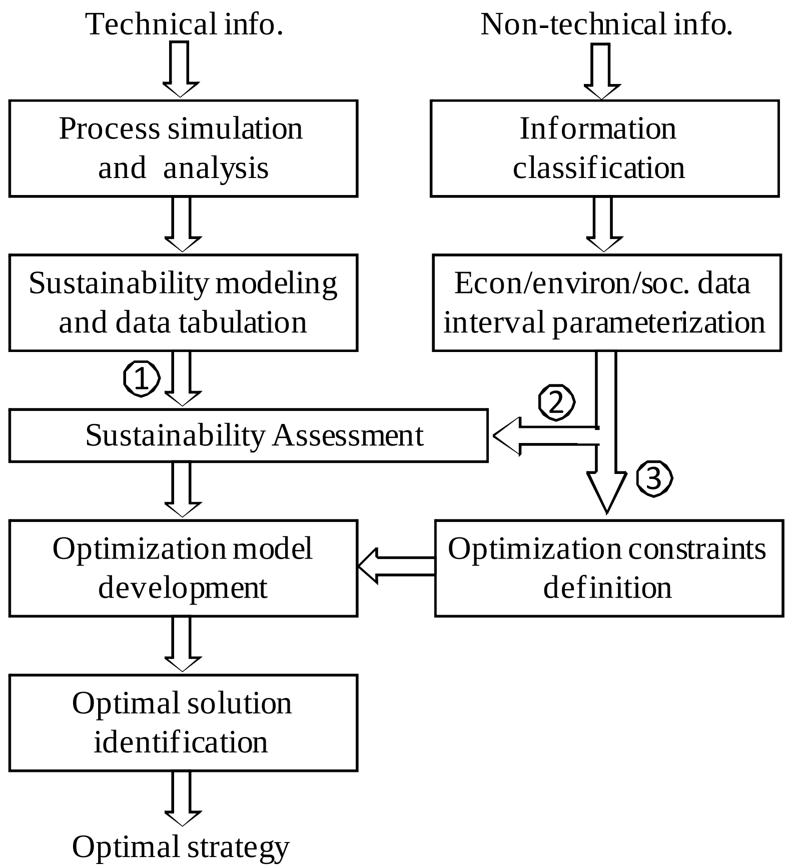


Figure 3.1. Strategic planning of regional biodiesel manufacturing.



1. Models of process variables (see Table 3) and process safety data (see Table 1)
2. Total numbers of pre-selected potential plants; prices of materials, energy, products, transportation cost, etc.; environmental regulations, policies, etc
3. Pre-selected potential plant locations; feedstock availability at each potential plant location; Biodiesel demand in the studied region; land availability, facility size and scale constraints (for identification of the upper limit of single plant capacity); requirement on sustainability performance.

Figure 3.2. Strategic planning structure of regional biodiesel manufacturing under uncertainty.

Such a strategic planning should be conducted in a systematic way. Figure 3.2 shows how the multiple tasks for planning solution identification are organized. As stated, strategic planning is an uncertainty-bearing optimization problem. This optimization task depends on the sustainability assessment of manufacturing technologies. In order to assess quantitatively the sustainability of biodiesel manufacturing technologies, three-pillar-based indices should be selected first, and all the information and data called by each indicator should be collected. Note that uncertainties are always associated with the collected information and data. Therefore, uncertain data must be processed by the interval-parameter-based approach. After obtaining the general sustainability status of a strategic plan, its overall sustainability is then set as the objective function of the optimization model, and the constraints can be specified correspondingly. Due to the appearance of interval-based parameters, such the optimization is an interval-parameter-based programming. Finally, this optimization is solved and the best strategy for sustainable regional biodiesel manufacturing can be recommended from the optimal solutions identified.

3.2 Data Needed

As the initial task of the strategic planning, three categories of data should be provided, namely: (1) the technical data about the processes using different manufacturing technologies, (2) the non-technical data about the "environment" outside the processes, and (3) the potential plant locations.

3.2.1 Technical data

Data in the first category are those directly determined by the biodiesel manufacturing processes, for instance, the unit capital cost, source waste generation, process operating condition, raw material and utilities usage, product and by-product quantities, etc., which can be obtained through process modeling and simulation. Note that some technical data are varied with the change of product capacities. Thus, relations between those data variables and the product capacities should also be identified carefully. Normally, uncertainties are not associated with the data in this category.

3.2.2 Non-technical data

The second category of data is mainly for evaluating market-based economic criteria, regulation-based environmental standards, and social sustainability concerns. For instance, the feedstock availability, price of feedstock and products, etc., that directly affect the economic performance of the strategic plan; the waste discharge permit, regulations on chemical hazard and toxicity, etc., that highly restrict the environmental performance; and those related to employment situation, health and safety at work, community benefits, stakeholder concerns, legal actions, etc., that are mainly concerned when evaluating the social performance. Note that for strategic planning, the trend of those non-technical data must be predicted over the year of interest. It is obvious that for those non-technical factors listed above, the relevant parameters should be mostly quantified by intervals rather than deterministic numbers. Details about the interval-parameter-based uncertainty processing will be given later.

3.2.3 Potential plant locations

The determination of plant location (or manufacturing sites) is a significant part of the strategic planning. In order to practice the optimization-based decision making, a number of potential locations should be selected initially. A number of factors, such as geographical needs of biodiesel and feedstock availability, and geographical constraints, if any, should be considered. Then, the potential plant locations for biodiesel manufacturing within the given region can be pre-selected based on such principles like proximity to low cost feed stocks and to major biodiesel markets, geographical area limits, transportation infrastructure (rail and road access), availability of skilled process plant labor, priced utilities, and existing industrial facilities (Rural Enterprise Management company, 2006). Note that different potential plant locations may be suitable for using different biodiesel manufacturing technologies due to feedstock availability specifics.

3.3 Interval Parameter Based Uncertainty Processing

In strategic planning, the uncertainties are encountered when evaluating the sustainability performance of manufacturing technologies. This is because the performance is determined by many types of time-variant variables of the non-technical data. For instance, the prices of raw materials, waste treatment cost, forthcoming regulations on emissions, policy, safety standard, stakeholders' expectation, etc. Clearly, such predictions have no data distribution information feasibly available. It is thus very reasonable to express the uncertain information by intervals.

By the interval-parameter-based approach, a piece of uncertain information can be expressed as an interval number, specified by the lower and upper bounds. Let $\overline{X}$ be an interval number, and expressed as:

$$\overline{X} = \left[x^L,\ x^U\right], \tag{3.1}$$

where x^L and x^U are real numbers and $x^L \leq x^U$. Note that if x^L equals x^U, then $\overline{X}$ becomes a deterministic number, which means no uncertainty involved, and thus can be written as *X*. Thus, the definition in Eq. 3.1 applies to the deterministic number as a special case.

Let symbol $* \in [+, -, \times, \div]$ present a binary operation on interval numbers. According to Xia *et al.*, (1997) the algorithmic operations of two interval numbers, $\overline{X}$ and $\overline{Y}$, are defined as:

$$\overline{X} * \overline{Y} = \left[min\{x * y\},\ \max\{x * y\}\right]; \qquad x^L \leq x \leq x^U,\ y^L \leq y \leq y^U \tag{3.2}$$

Note that the above definitions are applicable to the operations between an interval number and a deterministic number, as well as between two deterministic numbers, since a deterministic number is a special case of an interval number. In the following text, every interval number is symbolized by a variable with a bar above, and the operations of interval numbers will follow the definition in Eq. 3.2.

3.4 Sustainability Assessment Using Interval Based Information

Successful development of a strategic plan for distributed biodiesel manufacturing in regions requires systematic and comprehensive sustainability assessment on manufacturing technologies as well as their combinations. In this work, the triple-bottom-line-based sustainability assessment is applied, which requires the identification of three sets of sustainability metrics, i.e., sets *E*, *V*, and *H*, which can be used to characterize economic, environmental, and social performance of a system of interest. Each metric set may contain one or more indicators, where the general methodological frame on metric selection and assessment can be found in Liu *et al*. (2012). Since this work is focused on biodiesel manufacturing, a specific sustainability assessment scheme extracted from related studies (Zhang *et al.*, 2003; You *et al.*, 2008; Othman *et al.*, 2010; Li *et al.*, 2011) is given in the following section. Certainly this specific assessment scheme can be extended by following the general framework by Liu *et al*. (2012) in case necessary.

3.4.1 Economic sustainability set

The Net Profit Analysis (Peters and Timmerhaus, 1991) has been widely used as a well acceptable approach of economic assessment of industrial systems, which is adopted in this work to reveal the economic performance for strategic planning over a short-to-long-term. To conduct the Net Profit Analysis of a strategic plan, a complete procedure should be implemented by following the three steps below.

Step 1. Estimate the total capital investment (T_{CI}) for each plant. The total capital investment of a plant can be obtained by conducting an item-based evaluation, where the detailed items to be quantified are listed in Table 3.1.

Table 3.1. Estimation of total capital investment of plant P_i.

Item	**Equation**
Total bare module cost (T_{BMCC})	$T_{BMCC} = \sum_{i=1}^{N_c} C_{\vartheta}^{e}$
Contingency fee (C_F)	$C_F = 0.18\, T_{BMCC}$
Total basic module cost (T_{BMC})	$T_{BMC} = T_{BMCC} + C_F$
Auxiliary facility investment (A_{FI})	$A_{FI} = 0.3 \times T_{BMC}$
Fixed capital investment (F_{CI})	$F_{CI} = T_{BMC} + A_{FI}$
Working capital investment (W_{CI})	$W_{CI} = 0.15\, F_{CI}$
Total capital investment (T_{CI})	$T_{CI} = F_{CI} + W_{CI}$

In the above table, C_{θ}^{e} (\$) is the capital cost of the i-th process equipment and N_c is the total number of process equipments. Note that each C_{θ}^{e} is determined by the plant capacity, x_i.

Step 2. Estimate the interval-based net annual profit after taxes ($\overline{NAPAT}$) for each plant. Table 3.2 shows the detailed items to be quantified. Note that F_{CI} used by Table 3.2 is provided by Table 3.1.

Table 3.2a. Estimation of net annual profit after taxes of plant P_i.

Item	**Equation**
Total raw material cost ($\overline{C}_1$)	$\overline{C}_1 = \sum_{l=1}^{N_r} \overline{P}_l^r \cdot A_l^r$
Operating labor charges (C_2)	$C_2 = 20\,x_i + 4.2\times10^5$
Supervisory and clerical labor charges (C_3)	$C_3 = 0.15C_2$
Utilities Cost ($\overline{C}_4$)	$\overline{C}_4 = \sum_{m=1}^{N_m} \overline{P}_m^u \cdot A_m^u$
Waste disposal cost ($\overline{C}_5$)	$\overline{C}_5 = \sum_{g=1}^{N_g} W_g \cdot A_g$
Maintenance and repairs cost (C_6)	$C_6 = 0.06\, F_{CI}$
Operating supplies cost (C_7)	$C_7 = 0.15C_6$
Laboratory charges (C_8)	$C_8 = 0.15C_2$
Total manufacturing cost ($\overline{C}_9$)	$\overline{C}_9 = \sum_{i=1}^{8} C_i$
Patents and royalties ($\overline{C}_{10}$)	$\overline{C}_{10} = 0.03\,\overline{C}_9$
Total direct manufacturing cost ($\overline{C}_{11}$)	$\overline{C}_{11} = \overline{C}_9 + \overline{C}_{10}$
Overhead, packaging and storage charges (C_{12})	$C_{12} = 0.6(C_2 + C_3 + C_6)$
Local taxes (C_{13})	$C_{13} = 0.015\,F_{CI}$
Insurance cost (C_{14})	$C_{14} = 0.005\,F_{CI}$
Total indirect manufacturing cost (C_{15})	$C_{15} = C_{12} + C_{13} + C_{14}$
Annual depreciation change (C_{16})	$C_{16} = 0.1\,F_{CI}$
Administrative costs (C_{17})	$C_{17} = 0.25\,C_{12}$
Transportation cost ($\overline{C}_{18}$)	$\overline{C}_{18} = a_t \cdot x_i \cdot \left(f_{i,j} \cdot D_{i,j} + d_{i,k} \cdot D_{i,k}\right)$
Research and development charges ($\overline{C}_{19}$)	$\overline{C}_{19} = 0.05\,\overline{C}_9$
Total general expenses ($\overline{C}_{20}$)	$\overline{C}_{20} = C_{17} + \overline{C}_{18} + \overline{C}_{19}$
Total production cost ($\overline{C}_{21}$)	$\overline{C}_{21} = \overline{C}_{11} + C_{15} + C_{16} + \overline{C}_{20}$
Revenue from biodiesel and byproducts ($\overline{C}_{22}$)	$\overline{C}_{22} = \sum_{k=1}^{N_p} \overline{PP}_k \cdot AP_k$

Table 3.2b. Estimation of net annual profit after taxes of plant P_i (cont'd).

Item	**Equation**
Net annual profit ($\overline{C}_{23}$)	$\overline{C}_{23} = \overline{C}_{22} - \overline{C}_{21}$
Income taxes ($\overline{C}_{24}$)	$\overline{C}_{24} = 0.5\,\overline{C}_{23}$
Net annual profit after taxes ($\overline{NAPAT}$)	$\overline{NAPAT} = \overline{C}_{24}$

In table 3.2a and 3.2b, A_l^r, A_m^u, and A_g are the amount of the l-th type of raw material, the u-th type of utility, and the g-th type of waste, respectively.

Step 3. Calculate the net profit over the total life of strategic plan, $\overline{E}(SP)$. The value of $\overline{E}(SP)$ can be calculated using Eqs. 3.3 through 3.8:

$$\overline{E}(SP) = R_1(SP) + \overline{R}_2(SP) - R_3(SP) - R_4(SP) - R_5(SP) \tag{3.3}$$

where

$$R_1(SP) = \sum_{i=1}^{N} 0.2\, I_i \cdot F_{CI}(P_i) \tag{3.4}$$

$$\overline{R}_2(SP) = \sum_{i=1}^{N} I_i \left(Z \cdot \overline{NAPAT}(P_i) + F_{CI}(P_i)\right) \tag{3.5}$$

$$R_3(SP) = \sum_{i=1}^{N} 0.15\, I_i \cdot F_{CI}(P_i) \tag{3.6}$$

$$R_4(SP) = \sum_{i=1}^{N} I_i \cdot F_{CI}(P_i) \tag{3.7}$$

$$R_5(SP) = \sum_{i=1}^{N} 0.1\, I_i \cdot F_{CI}(P_i) \tag{3.8}$$

$R_1(SP)$ ($) is the land, salvage, and working capital recovery at the end of the plant project, $\overline{R}_2(SP)$ ($) is the interval-based total net profit of all plants over Z years of interest, $R_3(SP)$ (\$) is the working capital investment of all plants, $R_4(SP)$ (\$) is the fixed capital investment of all plants, $R_5(SP)$ (\$) is the investment of land by all plants, N is the total number of plants, I_i is a binary variable representing the existence of the i-th plant, $F_{CI}(P_i)$ is the fixed capital investment of the i-th biodiesel plant, and $\overline{NAPAT}(P_i)$ (\$/yr) is the interval-based net annual profit after taxes of the i-th plant.

Note that $F_{CI}(P_i)$ is determined by the corresponding plant capacity, x_i, and the plant existence, I_i (see Table 3.1), and $\overline{NAPAT}(P_i)$ is determined by the corresponding plant capacity, x_i, and the plant existence, I_i, transportation schemes, $f_{i,j}$ and $d_{i,k}$, and the interval-based price and cost information, $\overline{P}_l^{\,r}, \overline{P}_m^{\,u}, \overline{P}_n^{\,p}, \overline{W}_g$ (see Table 3.2), where x_i (ton) is the capacity of the i-th plant, $f_{i,j}$ is the percentage of x_i manufactured by the feedstock from the j-th feedstock provider, $d_{i,k}$ is the percentage of x_i distributed to the k-th demand market, $\overline{P}_l^{\,r}$, $\overline{P}_m^{\,u}$, and $\overline{P}_n^{\,p}$ (\$/ton) are the interval-based unit price of the l-th type of raw material, the m-th type of utility, and the p-th type of product or by-product, respectively, and $\overline{W}_g$ (\$/ton) is the interval-based unit cost for the treatment of the q-th type of waste.

3.4.2 Environmental sustainability set

To represent the environmental impact by the biodiesel manufacturing, three indicators regarding the waste generation, raw material consumption, and energy consumption, are selected as the environmental sustainability set. Thus, we have $V=\{V_1, V_2, V_3\}$.

Indicator 1. Potential environmental impact (V_1), which is quantified by using EPA's WAR algorithm (Young *et al.*, 1999). The algorithm is designed to evaluate the environmental impact at the manufacturing stage, thus it is suitable for environmental impact assessment at the design stage for future or current chemical processes (Othman *et al.*, 2010). By the WAR algorithm, the potential environmental impact (PEI) of a strategic plan, *SP*, can be quantified by using Eqs. 3.9 to 3.11. Appendix A provides more detailed information about this PEI calculation.

$$\bar{V}_1(SP)=\sum_{i=1}^{N}\left(\bar{I}_{we,i}^{(cp)}(P_i)+I_{we,i}^{(ep)}(P_i)\right) \tag{3.9}$$

where

$$\bar{I}_{we}^{(cp)}(P_i)=\sum_{\alpha=1}^{8}\sum_{\beta=1}^{N_\beta}\sum_{\lambda=1}^{N_\lambda}A_\alpha\, c_\lambda \bar{a}_{\alpha,\lambda} \tag{3.10}$$

$$I_{we}^{(ep)}(P)=\sum_{\alpha=1}^{8}\sum_{\psi=1}^{N_\psi}G_\psi\, a_{\alpha,\psi} \tag{3.11}$$

$\bar{I}_{we,i}^{(cp)}(P_i)$ and $I_{we,i}^{(ep)}(P_i)$ are the mass and energy based PEI of the i-th plant, respectively; A_α (kg) is the amount of the α-th waste material stream, which is determined by the plant capacity, x_i; c_λ (kg/kg) is the mass-based chemical composition of the λ-th chemical component in the waste stream; $\bar{a}_{\alpha,\lambda}$ (PEI/kg) is the normalized value of the specific potential environment impact of the λ-th chemical component associated with impact category α; G_ψ (J) is the amount of the ψ-th energy stream consumed, which is determined by the plant capacity, x_i; $a_{\alpha,\psi}$ (PEI/J) is the normalized value of the specific potential environment impact of the ψ-th energy stream associated with impact category α; and N_β, N_λ, and N_ψ are the total number of the waste material streams, the chemical components, and the consumed energy streams, respectively. Note that for most of traditional chemicals, their specific potential environment impact values are defined by EPA as certain values. However, the specific potential environment impact value of some special chemicals (for instance, biodiesel) has not been well identified due to the incomplete data and information. For those chemicals, we define their PEI values in interval-based numbers.

Indicator 2. Material efficiency by biodiesel manufacturing (V_2), which is defined as the ratio between the amount of total raw material used and the total amount of product produced. The formula for calculating V_2 on a strategic plan, *SP*, is given in Eq. 3.12.

$$V_2(SP) = \frac{\sum_{l=1}^{N_r} r_l}{M} \tag{3.12}$$

where N_r is the total number of raw material types, r_l (ton/yr) is the amount of the l-th raw material consumed, and *M* (ton/yr) is the total annual biodiesel demand in the region. Note that there is no uncertainty considered in the evaluation of $V_2(SP)$, and $V_2(SP)$ is determined by the corresponding plant capacity, x_i.

Indicator 3. Energy efficiency by biodiesel manufacturing (V_3), which is defined as the ratio between the total amount of energy used (GJ/yr) and the total amount of product produced (tons/yr). This indicator is quantified for a strategic plan, *SP*, using Eq. 3.13.

$$V_3(P) = \frac{\sum_{e=1}^{N_e} q_e}{M}, \tag{3.13}$$

where q_e is the amount of the e-th type of energy used (GJ/yr), and N_e is the total number of energy types. Note that there is no uncertainty considered in the evaluation of $V_3(SP)$, and $V_3(SP)$ is determined by the corresponding plant capacity, x_i.

3.4.3 Social sustainability set

In the social sustainability assessment, inherent safety (*H*) is a suitable indicator for representing the most critical issue concerned by the biodiesel manufacturing. Inherent safety of a chemical process can be quantified by an index-based approach developed by Heikkila (1999). By this approach, 11 sub-indicators are evaluated and combined into the overall inherent safety index for revealing the safety status of a chemical plant. These sub-indicators can be divided into two groups, one takes into account the chemical inherent safety, and the other group focus on the process inherent safety. For each sub-index, a scale of scores were given by Heikkila (1999). The sum of all the sub-indices scores is the inherent safety index value. Note that the higher is the inherent safety index value, the more unsafely is the process (Carvalhoa *et* *al.*, 2008).

Table 3.3. List of safety indicators and their scores.

Index	**Score**
Chemical inherent safety index	
Sub-indices for reactions hazards	
1. Heat of the main reaction (h_1)	0-4
2. Heat of the side reactions (h_2)	0-4
3. Chemical interactions (h_3)	0-4
Sub-indices for hazards substances	
4. Flammability (h_4)	0-4
5. Explosiveness (h_5)	0-4
6. Toxicity (h_6)	0-6
7. Corrosivity (h_7)	0-2
Process inherent safety index	
Sub-indices for process conditions	
8. Temperature (h_8)	0-4
9. Pressure (h_9)	0-4
10. Safety of Equipment (h_{10})	0-5
11. Inventory intensity ($\bar{h}_{11}$)	$\bar{v}x / M$
Total inherent safety index for plant j	$\bar{H} = \sum_{i=1}^{10} h_i + \bar{h}_{11}$

In the above table, $\bar{v}$ is the interval-based inventory intensity coefficient, x is the plant capacity, and M is the total demand of biodiesel product in the given region, which has a value of 50,000 tons/yr in the case study.

The entire set of sub-indicators and the corresponding scales are specified in Table 3.3. Note that the 11-th indicator, Inventory ($\bar{h}_{11}$), is determined by the corresponding plant capacity, x_i, and affected by the interval-based fluctuation coefficient, $\bar{v} \in [1, 1.5]$. After obtaining $\bar{H}(P_i)$ for each individual plant P_i, Eq. 3.14 is used to calculate $\bar{H}(SP)$ for the complete strategic plan, SP, by taking the summation of $\bar{H}(P_i)$ of all plants.

$$\bar{H}(SP) = \sum_{i=1}^{N} I_i \cdot \bar{H}(P_i) \tag{3.14}$$

where $\bar{H}(P_i)$ is the interval-based inherent safety value of the i-th plant.

3.4.4 Indicator normalization

The triple-bottom-line-based sustainability indicators defined above are in different units and scales. For the sake of further combining them into a single value of the overall sustainability, these indicators should be normalized. Different from commonly practicing approaches for sustainability assessment where each indicator is evaluated using deterministic data, we use interval-based information to conduct the assessment. Therefore, a new normalization scheme for handling interval-based information is proposed as follows.

Let $\bar{\Theta}$ be an interval-based sustainability metric, the normalized value of it, $\bar{\Theta}_N$, can be calculated by Eq. 3.15 when a higher value is preferred by $\bar{\Theta}$.

$$\bar{\Theta}_N(SP) = \frac{\bar{\Theta}(SP) - min\left\{\bar{\Theta}(T_i)^L \middle| i = 1,2,\cdots,N_T\right\}}{max\left\{\bar{\Theta}(T_i)^U \middle| i = 1,2,\cdots,N_T\right\} - min\left\{\bar{\Theta}(T_i)^L \middle| i = 1,2,\cdots,N_T\right\}} \tag{3.15}$$

where $\bar{\Theta}(T_i)$ is the evaluated interval number of a categorized sustainability performance when a single technology T_i is used for biodiesel manufacturing in the entire region. $\overline{\Theta}(T_i)^L$ and $\overline{\Theta}(T_i)^U$ are the lower and upper boundary of the interval-based value of $\overline{\Theta}(T_i)$, respectively. Note that when Θ is E (economic sustainability), the normalization in Eq. 3.8 can only be directly used because a higher value is preferred; however, for V_i (Environmental sustainability, i = 1, 2, 3) and L (social sustainability), since a lower value is preferred, the normalization result should be changed to 1-$\overline{\Theta}_N$.

After conducting the normalization on those three environmental indicators, the composite environmental sustainability can be calculated by taking the multi-criteria combination in Eq. 3.16.

$$\overline{V}_N(SP) = a_v\overline{V}_{1,N}(SP) + b_vV_{2,N}(SP) + c_vV_{3,N}(SP) \tag{3.16}$$

where

$$a_v + b_v + c_v = 1 \tag{3.17}$$

$\overline{V}_1(SP)$, $V_2(SP)$, and $V_3(SP)$ are the normalized environmental indicators, respectively, and a_v , b_v , and c_v $\in$ [0, 1] are the weighting factors associated with the corresponding indicators, reflecting the relative importance of an individual index over others in overall assessment.

3.4.5 Overall sustainability assessment

The concept of Sustainability Cube introduced by Piluso *et al.* (2010) is used to integrate the triple-bottom-line composite sustainability indexes into an overall sustainability. By this approach, the following formula is used to derive a normalized overall sustainability, namely, $\bar{S}$, for a strategic plan, *SP*.

$$\bar{S}(SP) = \frac{1}{\sqrt{3}} \left\| \left(\bar{E}_N(SP),\ \bar{V}_N(SP),\ \bar{H}_N(SP) \right) \right\| \tag{3.18}$$

3.5 Interval Parameter Based System Optimization

The sustainability performance of biodiesel manufacturing technologies and their combinations is formulated as an integral part in a decision-making framework, where the IPP-based optimization can generate an optimal strategic plan for regional biodiesel manufacturing under a variety of uncertainties.

3.5.1 Objective function and decision variables

Since the strategic planning goal is to pursue sustainable biodiesel manufacturing, the overall sustainability is set as the objective function, where the triple-bottom-line aspects are to be maximized integrally, i.e.,

$$\underset{x_i, I_i, f_{i,k}, d_{i,l}}{Max} \quad \bar{S}(SP) = \frac{1}{\sqrt{3}} \left\| \left(\bar{E}_N(SP),\ \bar{V}_N(SP),\ \bar{H}_N(SP) \right) \right\| \tag{3.19}$$

Note that the normalized economic, environmental, and social sustainability in this objective function are derived by using Eqs. 3.3 through 3.17, where three types of decision variables are involved:

(1) The production capacities of all potential plants, namely, x_i (i = 1, …, N), which are continuous variables.

(2) The transportation scheme variables, namely, $f_{i,j}$ (i = 1, …, N, and j = 1, …, N_j) and $d_{i,k}$ (i = 1, …, N, and k = 1, …, N_k), which are continuous variables.

(3) Binary variables representing the existence of each plant, namely, I_i (i = 1, …, N).

Also note that we have three types of interval-based parameters representing uncertainties in the objective functions, they are:

(1) Interval-based unit price and cost parameter, namely, $\overline{P}_l^{\,r}$, $\overline{P}_m^{\,u}$, $\overline{P}_n^{\,p}$, and $\overline{W}_g$ (\$/ton).

(2) Interval-based potential environment impact of undefined chemical components, namely, $\overline{a}_{\alpha,\lambda}$ (PEI/kg).

(3) Interval-based fluctuation coefficient, $\overline{v}$.

3.5.2 Constraints

The optimization constraints can be classified into several categories regarding the feedstock availability, demand market satisfaction, sustainability requirement, etc. Note that interval-based parameters are involved in some constraints due to the existence of uncertainties.

<u>Sustainability assessment equations.</u> As demonstrated in the sustainability assessment section, the overall sustainability of the objective function is derived by using Eqs. 3.3 through 3.17. Therefore, these assessment equations must be involved

in the optimization constraints.

Limit on the feedstock availability. Feedstock availability is one major constraint for biodiesel manufacturing. In this work, the limited availability of one feedstock source is expressed by the limit on the plant capacity manufactured by using this feedstock, i.e.,

$$\sum_{i=1}^{N} f_{i,j}\, x_i \leq F_j, \quad j = 1, 2, \cdots, N_j \tag{3.20}$$

where F_j (tons/yr) is the upper limit of the biodiesel production capacity supplied by the j-th feedstock provider, and N_j is the total number of feedstock providers. Since $f_{i,j}$ represents the percentage of plant capacity, the restriction by Eq. 3.21 holds naturally.

$$\sum_{j=1}^{N_j} f_{i,j} = 1, \quad i = 1, 2, \cdots, N \tag{3.21}$$

Satisfaction on the local demand market. The biodiesel products manufactured by each plant must be distributed to meet the demand at each local market, which is expressed by Eq. 3.22.

$$\sum_{i=1}^{N} d_{i,k}\, x_i = B_k, \quad k = 1, 2, \cdots, N_k \tag{3.22}$$

where B_k (tons/yr) is the biodiesel demand at the k-th local market and N_k is the total number of demand markets within the studied region. Note that the percentage of plant capacity, $d_{i,k}$, is under the following restriction by Eq. 3.23.

$$\sum_{k=1}^{N_k} d_{i,k} = 1, \quad i = 1, 2, \cdots, N \tag{3.23}$$

Upper limit on single plant capacity. An upper limit has been set to each plant capacity in order to avoid the unreality result, i.e.,

$$x_i \le T \tag{3.24}$$

where T (tons/yr) is the upper limit on a single plant capacity.

Requirement on sustainability performance. In a strategic planning, the decision-maker may assign various requirements on the desired sustainability performance. For instance, one typical requirement on economic sustainability is that the resulting strategy must make profits. Similarly, requirement can be set to environmental and social sustainability indicators. This type of constraints can be described by Eqs. 3.25 to 3.27.

$$\overline{E}_N(SP) \ge E^r \tag{3.25}$$

$$\overline{V}_{i,N}(SP) \ge V_i^r,\ i = 1, 2, \text{ and } 3 \tag{3.26}$$

$$\overline{H}_N(SP) \ge H^r \tag{3.27}$$

where E^r, V_i^r, and H^r is the minimum acceptable value for each sustainability indicator, respectively.

3.5.3 Solution identification

The optimization model by Eqs. 3.3 through 3.27 is an interval-parameter-based mixed-integer-non-liner-programming. The best strategy for biodiesel manufacturing, in terms of the number of plants and their locations in the given region, and the technology and production capacity of each plant, can be proposed based on the optimal solutions derived. The key for solving this optimization problem is how to handle uncertainties as interval-based parameters in both the objective function and constraints. The approach by Li *et al*. (2006) was adopted and modified in this work for solving the optimization, where the detailed methodology is given below.

Due to the involvement of interval-based parameters, the optimal solution of the objective function should be an interval as well, where the lower bound and upper bound of this interval are the lowest and highest value when solving the optimization along the whole interval ranges. Based on this judgment, the interval-parameter-based optimization problem is transformed into two sets of deterministic sub-problems, where the two bounds of the optimal solution can be identified by solving each of them separately. The detailed solution identification procedure, which contains three steps, is given as follows.

Step 1. Formulate the sub-model corresponding to the upper bound of the objective function. This sub-model corresponding to $S^U(SP)$, can be formulated by taking the lower bound value on each of $\overline{P}_l^{\,r}$, $\overline{P}_m^{\,u}$, $\overline{W}_g$, $\overline{a}_{\alpha,\lambda}$, and $\overline{v}$ in Eqs. 3.5, 3.10, 3.14, 3.25, 3.26, and 3.27 respectively, and the upper bound value on $\overline{P}_n^{\,p}$ in Eqs. 3.5 and 3.15. The sub-model obtained is a deterministic MINLP, which can be solved by GAMS. The optimal solutions obtained determine the upper-bound values of the optimized objective function, $S^U(SP)_{opt}$, and the associated decision variables, namely, $(x_i^U)_{opt}$, $(I_i^U)_{opt}$, $(f_{i,j}^U)_{opt}$, and $(d_{i,k}^U)_{opt}$.

Step 2. Formulate the sub-model corresponding to the lower bound of the objective function. In contrast to the first sub-model, the sub-model of $S^L(SP)$ takes the upper bound value on each of $\overline{P}_l^{\,r}$, $\overline{P}_m^{\,u}$, $\overline{W}_g$, $\overline{a}_{\alpha,\lambda}$, and $\overline{v}$ in Eqs. 3.5, 3.10, 3.14, 3.25, 3.26, and 3.27, respectively, and the lower bound value on $\overline{P}_n^{\,p}$ in Eqs. 3.5 and 3.15. Note that among those three types of decision variables, the plant capacities, x_i, should be guaranteed that their lower bound solutions are not higher than the upper bound solutions. Therefore, another technical constraint should be further added into this sub-model as follows.

$$x_i^L \le \left(x_i^U\right)_{opt} \tag{3.28}$$

where $\left(x_i^U\right)_{opt}$ is the optimal upper bound value of plant capacities identified by solving the sub-model corresponding to $S^U(SP)$. The sub-model corresponding to $S^L(SP)$ is also a deterministic MINLP, where the optimal solutions obtained determine the optimal lower-bound of the interval for the objective function value, $S^U\left(SP\right)_{opt}$, and the associated decision variables, namely, $\left(x_i^L\right)_{opt}$, $\left(I_i^L\right)_{opt}$, $\left(f_{i,j}^L\right)_{opt}$, and $\left(d_{i,k}^L\right)_{opt}$..

Step 3. Combine the optimal solutions of the two sub-models into the complete interval-based solutions. As stated before, the optimized solution is essentially an interval, where the lower and upper bound values are provided as the solutions by the first and the second sub-model, respectively. Thus, the interval-based optimal solution can be summarized in Eq. 3.29.

$$\overline{S}\left(SP\right)_{opt} = \left[S^L\left(SP\right)_{opt}, S^U\left(SP\right)_{opt}\right] \tag{3.29}$$

The optimal strategies can then be recommended, where the most optimistic scenario and the most conservative scenario of the overall sustainability performance after planning are given by $S^U(SP)_{opt}$ and $S^L(SP)_{opt}$, respectively. Moreover, for the most optimistic scenario, the plant existence and capacity to be developed at each pre-selected location by using each technology (with index *i*) is identified as $\left(x_i^U\right)_{opt}$ and $\left(I_i^U\right)_{opt}$, the feedstock acquisition scheme from each provider (with index *j*) to each plant (with index *i*) is given by $\left(f_{i,j}^U\right)_{opt}$, and the biodiesel product distribution scheme from each plant (with index *i*) to each demand market (with index *k*) is indicated by $\left(d_{i,k}^U\right)_{opt}$. For the most conservative scenario, the plant capacity to be developed at each pre-selected location by using each technology, the feedstock acquisition scheme from each provider to each plant, and the biodiesel product distribution scheme from each plant to each demand market are identified respectively as $\left(x_i^L\right)_{opt}$, $\left(I_i^L\right)_{opt}$ $\left(f_{i,j}^L\right)_{opt}$, and $\left(d_{i,k}^L\right)_{opt}$.

3.6 Case Study

The introduced methodology has been used to study a number of complex strategic planning problems for sustainable biodiesel manufacturing in various regions. In this section, a sophisticated case study from a strategic planning for biodiesel manufacturing at state of Michigan is selected to illustrate the efficacy of the methodology. The objective is to generate a strategic proposal for developing the biodiesel manufacturing capacity of 50,000 tons/yr in a given region as shown in Fig. 3.3, where the strategy should provide the best sustainability performance over the next 10 years.

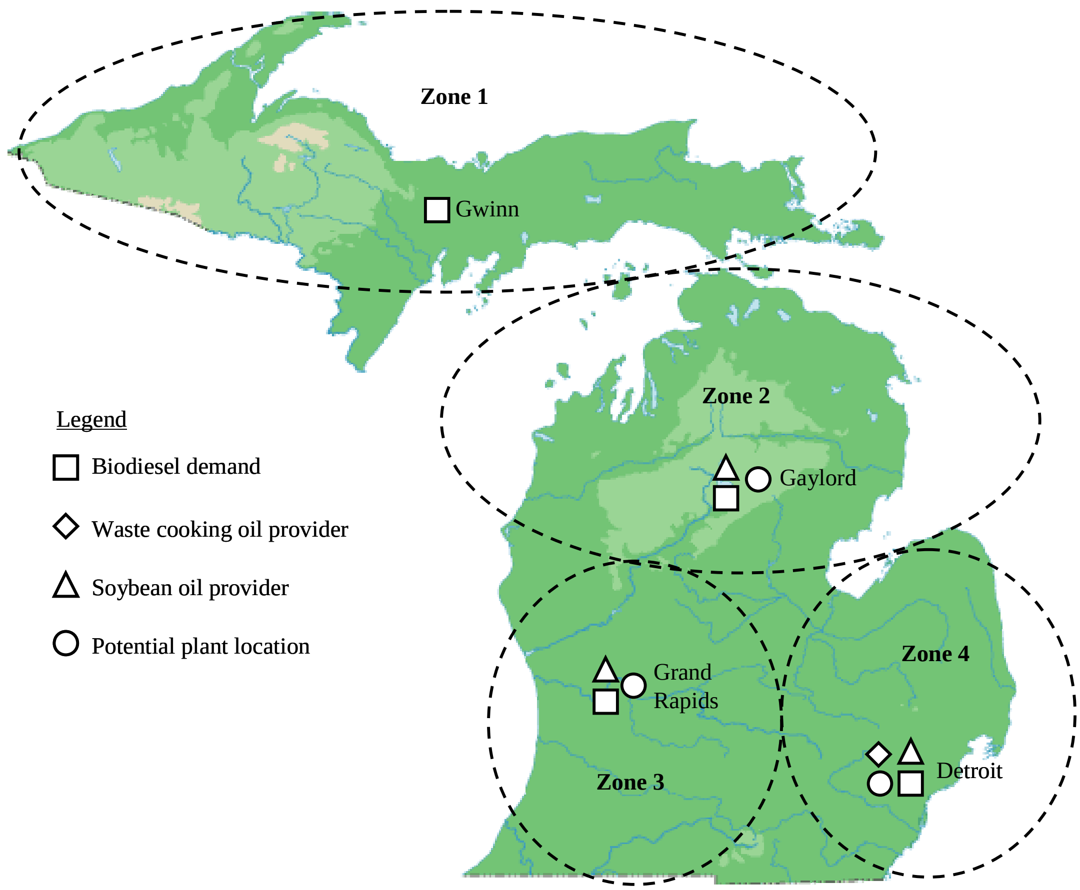


Figure 3.3. Sketch map of the locations of feedstock providers, biodiesel demand markets, and pre-selected plants.

3.6.1 Problem description

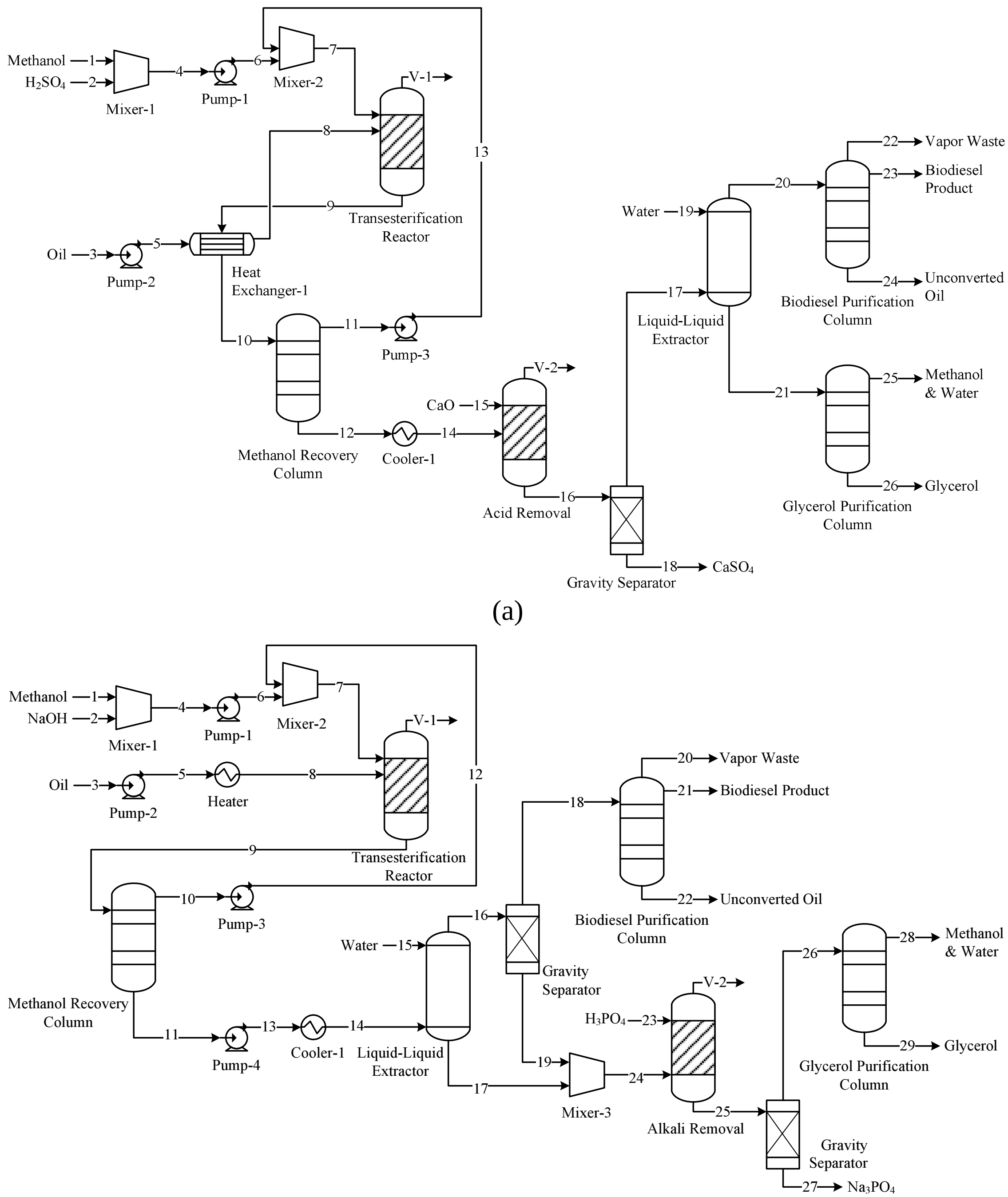
It is known that the entire region of state of Michigan given in Fig. 3.3 currently has a shortage of biodiesel production at the amount of 50,000 tons/yr. Now it is to seek the best possible decisions about how to add this new manufacturing capacity in this region. More specifically, strategies are needed to determine the number of plants and their locations in the given region as well as the technology and production capacity of each plant. Note that the proposed strategy is desired to be fully justified through sustainability assessment.

The proposed methodology was implemented for studying this strategic planning problem, where details are given in the following sections. The best strategy was obtained which meets the objective and requirements given by the problem description. Those results can help decision makers to identify desired biodiesel manufacturing strategies with maximized profits, minimized environmental impacts, and maximized social benefits in terms of process safety.

3.6.2 Biodiesel manufacturing technologies

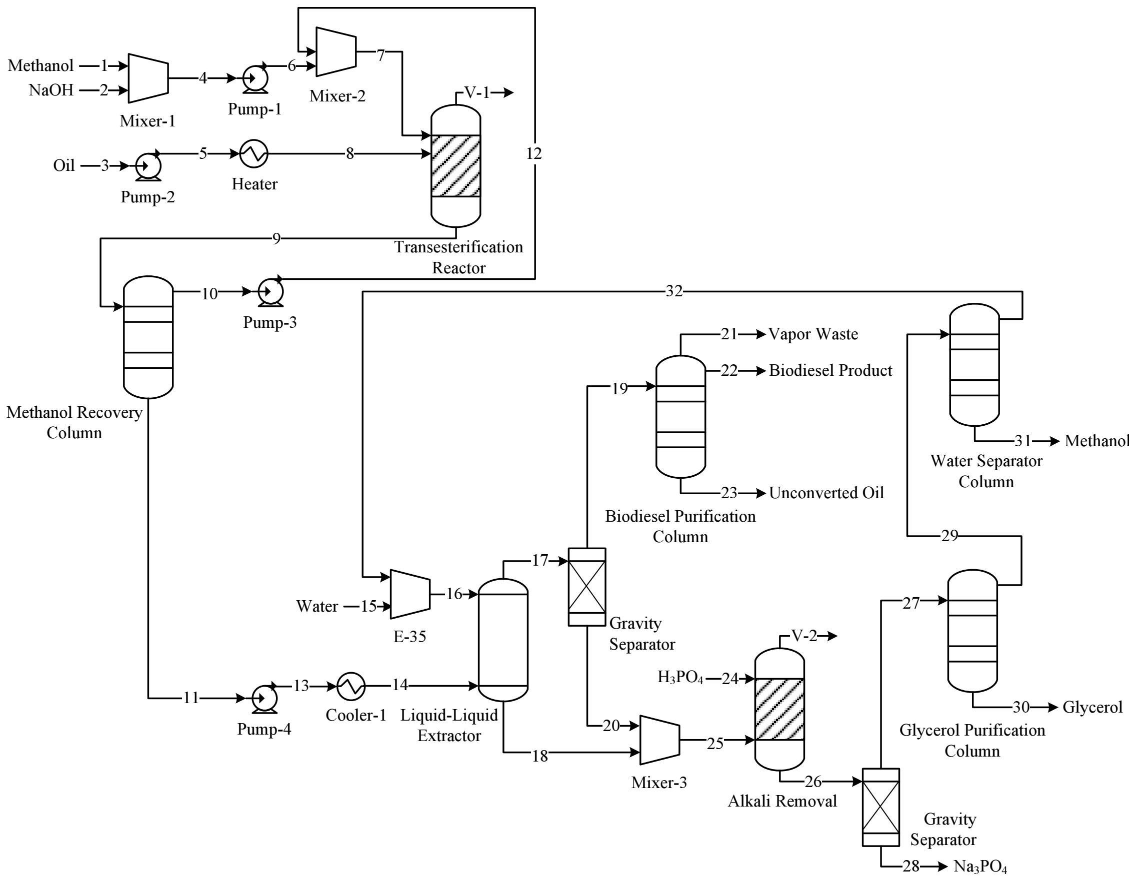
Four biodiesel manufacturing technologies are taken into consideration in this case study, where the flow sheets are shown respectively in Fig. 3.4.

Technology 1: Acid-Catalyzed process. This process can generate biodiesel by using waste cooking oil as the feedstock, which has a much cheaper price than the traditional feedstock, vegetable oil, required by other types of technologies. Acid catalyst is needed by this technology, which will cause solid waste generation. Moreover, the system of this process is not sensitive to both water and free fatty acids in the feedstock (Zhang *et al.*, 2003).

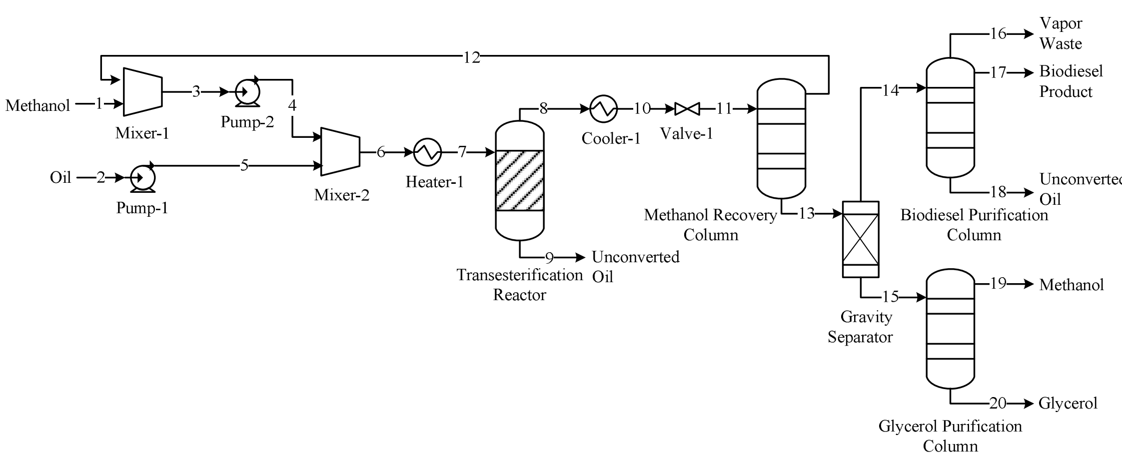


(b)

Figure 3.4a. Simulation flowsheets of biodiesel manufacturing processes: (a) acid-catalyzed, and (b) alkali-catalyzed.



(c)



(d)

Figure 3.4b. Simulation flowsheets of biodiesel manufacturing processes (cont'd): (c) retrofit of alkali-catalyzed, and (d) non-catalyzed.

Technology 2: Alkali-Catalyzed process. This process requires virgin vegetable oil as feedstock for the production of biodiesel. Alkali catalyst is needed by this technology, which will cause solid waste generation. The limit of this process is the sensitivity of the system to both water and free fatty acids in the feedstock, which must be will operated in order to ensure smooth production (West *et al.*, 2008).

Technology 3: Retrofit alkali-catalyzed process. This process is a retrofit of the Technology 2 by separating water from the liquid waste stream and recycling back to replace part of the fresh water. In order to make this modification, another distillation column should be added and more energy will be consumed for stream separation. However, after separation, all the resulting streams are useful, where no liquid waste can be found.

Technology 4: Non-Catalyzed process. This process requires vegetable oil as feedstock for the production of biodiesel. However, no catalyst is needed by this technology, which will not cause solid waste generation. Instead, this process requires a super-critical condition of methanol for the transesterificaiton reaction to happen, which corresponds to a high temperature and pressure, and indicates great energy consumption and potential safety issues (Santana *et al.*, 2009).

3.6.3 Data collection

The technical data, non-technical data, and the potential plant locations are collected through different ways as follows.

Technical data. The four biodiesel manufacturing processes are simulated to collect technical data directly determined by those processes. Note that for those technical data that are varied with the change of product capacities, the process simulation was performed at different production capacities and data regression was used to identify their general capacity-variant functions.

Non-technical data. Data about the "environment" outside the processes that is needed by the sustainability assessment are searched and their trends are predicted over the next 10 years of interest. Among those non-technical data, the following are identified as uncertain parameters, they are:

(1) In the evaluation of economic sustainability: the purchase price of soybean oil ($\overline{P}_1^{\,r}$), the sale price of biodiesel product ($\overline{P}_1^{\,p}$), the cost of waste water treatment by acid-catalyzed and alkali-catalyzed process ($\overline{W}_1$ and $\overline{W}_2$, respectively) due to the EPA's regulation change, where the interval-based values are given below.

$$\overline{P}_1^{\,r} = [0.88, 0.90] \text{ \$/kg} \tag{3.30}$$

$$\overline{P}_1^{\,p} = [1.2, 1.3] \text{ \$/kg} \tag{3.31}$$

$$\overline{W}_1 = [0.53, 0.58] \text{ \$/kg} \tag{3.32}$$

$$\overline{W}_2 = [2.65, 2.70] \text{ \$/kg} \tag{3.33}$$

(2) For environmental sustainability assessment: the unclear potential environment impact value of biodiesel on the sixth impact categories - human toxicity potential by inhalation/dermal exposure:

$$\overline{a}_{1,6} = [0.05, 0.15] \tag{3.34}$$

(3) For social sustainability assessment, the interval-based inventory coefficient, $\bar{v}$, is defined in Eq. 3.35.

$$\bar{v} = [1.0, 1.5] \tag{3.35}$$

3.6.4 Potential plant location pre-selection

To simplify the identification of the most suitable locations for potential biodiesel manufacturing, the whole region given in Fig. 3.3 was divided into four zones. In Zone 1, there is no feedstock for biodiesel manufacturing and the biodiesel demand is low at 2,000 tons/yr. For Zone 2, it has a soybean oil refinery, which can supply 10,000 tons/yr biodiesel manufacturing, and this zone has a biodiesel demand market of 7,000 tons/yr. Zone 3 has a soybean oil refinery, which can supply 25,000 tons/yr biodiesel manufacturing, and the biodiesel demand market in this area is 12,500 tons/yr. In Zone 4, there is a waste cooking oil provider, which can supply 4,000 tons/yr biodiesel manufacturing using acid-catalyzed technology, and a soybean oil refinery, which can supply 25,000 tons/yr biodiesel manufacturing. Zone 4 also has the highest biodiesel demand market at 28,500 tons/yr. Finally, there is no geographical area limits in all zones, and all zones have good rail and road access.

The principles suggested by Rural Enterprise Management Company[25] are used to pre-select the potential plant locations in those zones. In the consideration of building biodiesel plants near to the feedstock providers and the demand markets, no plants are desired to be built in Zone 1. In Zone 2 and 3, only Technology 2 through 4 using soybean oil as the feedstock are desirable. For Zone 4, all the four technologies are applicable. With those conclusions, three most representative cities, i.e., Gaylord, Grand Rapids, and Detroit are pre-selected from each of Zone 2, 3, and 4 (see Fig. 3.3), and the total number of potential biodiesel plants, i.e., N, can be calculated as follows:

$$N = N_2 + N_3 + N_4 = 3 + 3 + 4 = 10 \tag{3.36}$$

where N_2, N_3, and N_4 are the total number of potential plants in Zone 2, 3, and 4, which each counts all desired technologies in that zone. Note that in this case, the waste cooking oil can only be provided by and consumed in Zone 4, which requests no transportation; and the soybean oil providers in Zone 3 and 4 are assumed very near to the pre-selected plant location of each zone, respectively, which requests no transportation between them as well.

3.6.5 Optimization model derivation

The overall sustainability in Eq. 3.19 is set as the objective function, where the decision variables are: (1) the 10 plant capacities, namely, x_i (i = 1, 2, ..., 10); (2) 10 binary variables indicating plant existence, I_i (i = 1, 2, ..., 10); (3) 30 percentage variables indicating the feedstock transportation layout, $f_{i,j}$ (i = 1, 2, ..., 10, and j = 1, 2, 3); and (4) 40 percentage variables indicating the biodiesel product transportation layout, $d_{i,k}$ (i = 1, 2, ..., 10, and k = 1, 2, ..., 4).

According to the problem description, the following coefficients are identified for constraint formulation in Eqs. 3.20 through 3.27.

(1) Let F_1 through F_3 be the upper bound of the production capacity (ton/yr) supplied by the soybean oil provider in Zone 2 through 4, and F_4 be the upper bound of the production capacity (ton/yr) supplied by the waste cooking oil in Zone 4. Their values are then given in Eq. 3.37:

$$(F_1 \quad F_2 \quad F_3 \quad F_4)^T = (10{,}000 \quad 25{,}000 \quad 25{,}000 \quad 4{,}000)^T \tag{3.37}$$

(2) Let B_1 through B_4 be the local biodiesel demand (ton/yr) in Zone 1 through 4. Equation 3.38 gives their specific values:

$$(B_1 \quad B_2 \quad B_3 \quad B_4)^T = (2{,}000 \quad 7{,}000 \quad 12{,}500 \quad 28{,}500)^T \tag{3.38}$$

(3) The upper limit of each plant capacity, namely, T is specified at 25,000 tons/yr in Eq. 3.24.

(4) Only one sustainability performance requirement is given, which is on the economic sustainability asking that the net profit of biodiesel manufacturing over the total life of project cannot be negative, i.e., E^r is equal to 0 in Eq. 3.25.

3.6.6 Best strategy proposal

The optimization problem derived for this case study is an interval parameter based mixed integer non-linear programming (IP-MINLP). According to the three-step solution identification procedure proposed, the following results are obtained.

Step 1. Formulate the sub-model corresponding to the upper bound of the objective function, $S^U(SP)$, by taking 0.9, 1.2, 0.58, 2.7, 0.15, and 1.5 for $\overline{P}_1^{\,r}$, $\overline{P}_1^{\,p}$,

$\overline{W}_1$, $\overline{W}_2$, $\overline{a}_{1,6}$, and $\overline{v}$ in Eqs. 3.5, 3.10, 3.14, 3.25, 3.26, and 3.27 respectively. Solving the deterministic MINLP sub-model obtained, the optimized upper bound solutions of the decision variables are obtained as follows.

$$\left(x_5^U\right)_{opt} = \left(x_6^U\right)_{opt} = 25{,}000 \text{ and all other } \left(x_i^U\right)_{opt} = 0, (i = 1, 2, ..., 10) \quad (3.39)$$

$$\left(I_5^U\right)_{opt} = \left(I_6^U\right)_{opt} = 1 \text{ and all other } \left(I_i^U\right)_{opt} = 0, (i = 1, 2, ..., 10) \quad (3.40)$$

$$\left(f_{5,2}^U\right)_{opt} = \left(f_{6,3}^U\right)_{opt} = 1, \text{ and all other } \left(f_{i,j}^U\right)_{opt} = 0,$$

$$(i = 1, 2, ..., 10, \text{ and } j = 1, 2, 3) \quad (3.41)$$

$$\left(d_{5,1}^U\right)_{opt} = 0.08, \left(d_{5,2}^U\right)_{opt} = 0.28, \left(d_{5,3}^U\right)_{opt} = 0.5, \left(d_{5,4}^U\right)_{opt} = 0.14, \left(d_{6,4}^U\right)_{opt} = 1,$$

$$\text{and all other } \left(d_{i,k}^U\right)_{opt} = 0, (i = 1, 2, ..., 10, \text{ and } l = 1, 2, ..., 4) \quad (3.42)$$

This solution suggests to building the following two plants: (1) One plant at Grand Rapids using retrofit alkali-catalyzed technology with the capacity of 25,000 tons/yr, which uses soybean oil from the provider in Zone 3 as the feedstock, and sends 8%, 28%, 50%, and 14% biodiesel products to Gwinn, Gaylord, Grand Rapids, and Detroit, respectively; (2) Another plant at Detroit with the same capacity and technology as the first one, which uses soybean oil from the provider in Zone 4 as the feedstock, and consumes all biodiesel products in Detroit. With this strategy, the total capital investment will be \$10 million, and the transportation cost will be \$0.05 million/yr due to the distribution of biodiesel products. Detailed transportation routes are illustrated in Fig. 3.5, and the Optimized upper bound sustainability performance is listed in Table 3.4, which has optimal values of 0.962, 0.999, and 1.000 for the triple-bottom-line sustainability performance, and 0.987 for the overall sustainability.

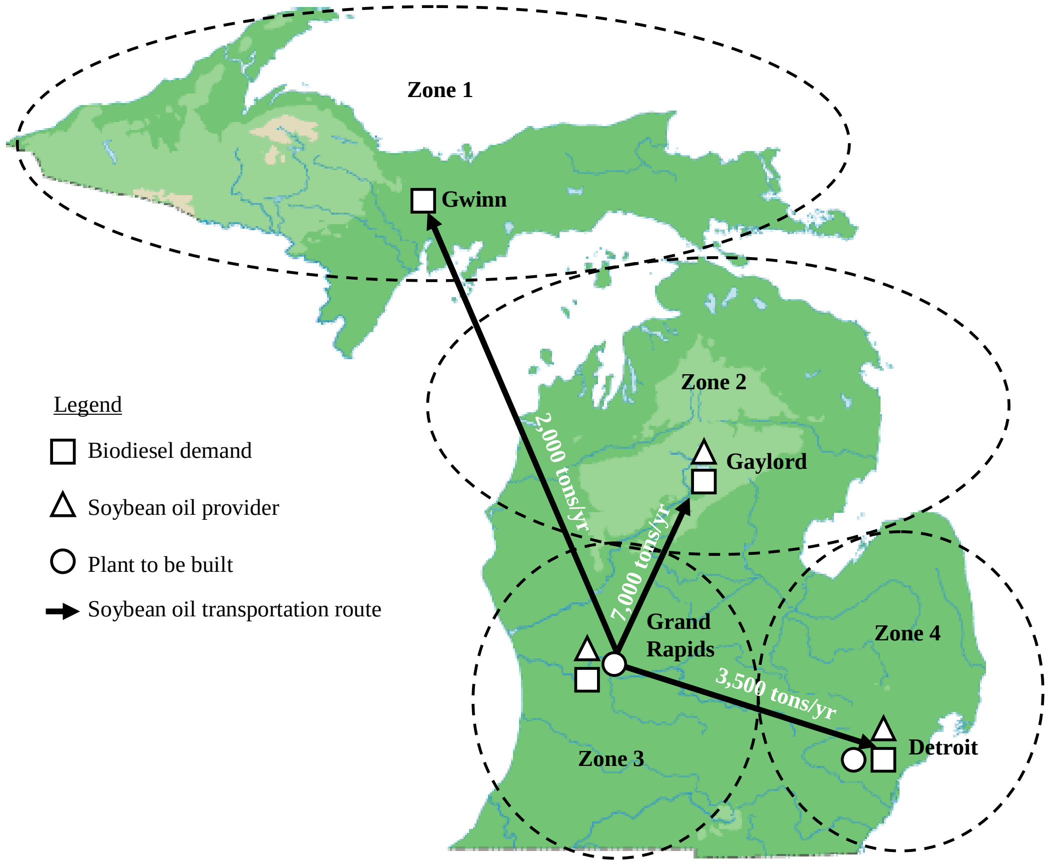


Figure 3.5. Illustration of the optimized transportation scheme of the case study.

Step 2. Formulate the sub-model corresponding to the lower bound of the objective function, $S^L(SP)$, by taking 0.88, 1.3, 0.53, 2.65, 0.05, and 1.0 for $\overline{P}_1^r$, $\overline{P}_1^p$, $\overline{W}_1$, $\overline{W}_2$, $\overline{a}_{1,6}$, and $\overline{v}$ in Eqs. 3.5, 3.10, 3.14, 3.25, 3.26, and 3.27, respectively. Solving this deterministic MINLP sub-model, the optimized upper bound solutions of the decision variables are obtained as follows.

$$\left(x_5^L\right)_{opt} = \left(x_6^L\right)_{opt} = 25{,}000 \text{ and all other } \left(x_i^L\right)_{opt} = 0, (i = 1, 2, ..., 10) \tag{3.43}$$

$$\left(I_5^L\right)_{opt} = \left(I_6^L\right)_{opt} = 1 \text{ and all other } \left(I_i^L\right)_{opt} = 0, (i = 1, 2, ..., 10) \tag{3.44}$$

$\left(f_{5,2}^{L}\right)_{opt} = \left(f_{6,3}^{L}\right)_{opt} = 1$, and all other $\left(f_{i,j}^{L}\right)_{opt} = 0$,

(i = 1, 2, ..., 10, and j = 1, 2, 3) (3.45)

$\left(d_{5,1}^{L}\right)_{opt} = 0.08$, $\left(d_{5,2}^{L}\right)_{opt} = 0.28$, $\left(d_{5,3}^{L}\right)_{opt} = 0.5$, $\left(d_{5,4}^{L}\right)_{opt} = 0.14$, $\left(d_{6,4}^{L}\right)_{opt} = 1$,

and all other $\left(d_{i,k}^{L}\right)_{opt} = 0$, ($i$ = 1, 2, ..., 10, and l = 1, 2, ..., 4) (3.46)

This solution suggests the same two plants and the same feedstock transportation and product distribution layout as the upper bound results. However, the optimized lower bound sustainability performance is different from the upper bound values (see Table 3.4), which has optimal values of 0.754, 0.997, and 0.917 for the triple-bottom-line sustainability performance, and 0.895 for the overall sustainability.

Table 3.4. Sustainability performance corresponding to the upper and lower boundary of the optimized objective function.

Category	Indicator	Weight	Categorized Evaluation	Overall sustainability
ECON	$E^U(SP)_{opt} = 0.962$ $E^L(SP)_{opt} = 0.754$	1.00	$E^U(SP)_{opt} = 0.962$ $E^L(SP)_{opt} = 0.754$	$S^U(SP)_{opt} = 0.987$ $S^L(SP)_{opt} = 0.895$
ENV	$V_1^U(SP)_{opt} = 1.000$ $V_1^L(SP)_{opt} = 0.995$	0.40	$V^U(SP)_{opt} = 0.999$ $V^L(SP)_{opt} = 0.997$	
	$V_2^U(SP)_{opt} = 1.000$ $V_2^L(SP)_{opt} = 1.000$	0.30		
	$V_3^U(SP)_{opt} = 0.997$ $V_3^L(SP)_{opt} = 0.997$	0.30		
SOC	$H^U(SP)_{opt} = 1.000$ $H^L(SP)_{opt} = 0.917$	1.00	$H^U(SP)_{opt} = 1.000$ $H^L(SP)_{opt} = 0.917$	

Step 3. The solutions of the two sub-models are integrated to obtain the overall solution for the objective function, which gives the interval in Eq. 3.42.

$$\bar{S}(SP)_{opt} = \left[S^{L}(SP)_{opt}, S^{U}(SP)_{opt}\right] = [0.895, 0.987] \tag{3.47}$$

As a conclusion, although the same optimal planning is suggested for the most optimistic scenario and the most conservative scenario, the overall sustainability by this optimal planning under uncertainties will be within the interval from 0.895 to 0.987, demonstrating the most conservative and optimistic predictions under the uncertain information.

3.7 Chapter Summary

Strategic planning for biodiesel manufacturing in regions is always a challenge due to different advantages and disadvantages of technologies, inherent uncertainties and system constraints. A systematic sustainability assessment based decision making methodology is proposed in this chapter for conducting strategic planning of biodiesel manufacturing in regions. By this methodology, the best strategy for biodiesel manufacturing in regions can be identified systematically. The key feature of the methodology is its system analysis and decision making under uncertainty. The methodology is general and systematic to apply for the strategic plans of biodiesel and other types of industrial manufacturing in any region as states and countries. The case study on strategies identification for biodiesel manufacturing in the state of Michigan over next ten years has clearly shown the efficacy of the methodology. The solutions obtained can help decision makers to identify desired manufacturing strategies with maximized sustainability performance under uncertain data and information.

CHAPTER 4

FUZZY LOGIC BASED TRIPLE-A TEMPLATE FOR SUSTAINABILITY ENHANCEMENT

Inappropriate use of energy and materials for industrial development in the past decades have led to serious problems in nonrenewable resource depletion, and green house gas emissions and many other types of problems. Today, industries are seeking ways to ensure development to be sustainable. Owing to inherent complexity and uncertainty, however, industrial sustainability problems are always very difficult to deal with, which has made industrial practice for sustainability enhancement mostly experience based.

To assist industries in sustainability assessment and decision making in a holistic way, a variety of methodologies have been developed. A methodology on identifying the opportunities of chemical manufacturing processes in order to purse sustainable development has proposed by Lange (2002). Efficiency of both the material and energy bases are used for evaluating nearly 50 chemical processes and those processes with low performance are identified by comparisons. However, the author only directed possible opportunities by the ideas of recycling and reuse, where no design alternatives are generated. Another mass and energy indicator-based methodology was proposed by Uerdingen *et al.* (2005). By this methodology, several pre-defined cost-efficiency indicators are first checked for a chemical process, then the critical points in the process are determined by local sensitivity analysis and feasible design alternatives are further generated. However, these feasible alternatives are only compared with each other in terms of economic aspects for determining the best alternative, and no design uncertainty was considered by this methodology. Carvalho *et al.* (2008) further extended this approach and introduced a process retrofit design methodology for deriving sustainable design configurations, but no design parameter related uncertainty was considered. In addition, the methodology is limited to scenario-based decision making, and thus no design optimality was addressed. Piluso *et al.* (2008) introduced a sustainability assessment methodology through extending an existing Ecological Input-Output Analysis (EIOA) approach (Baily *et al*., 2004). The methodology is capable of quantitatively evaluating the sustainability level of industrial systems when different system enhancement strategies are implemented. It is particularly applicable to large industrial systems, such as industrial zone problems. However, as decision-making is concerned, it relies on the availability of scenarios.

In this work, we introduce a sustainability enhancement methodology where certain types of uncertainties can be handled systematically. This methodology, by resorting to fuzzy logic, is featured by the use of so-called Triple-A Template, which reflects the major execution steps to be followed in solution derivation, i.e., the steps of (i) assessment, (ii) analysis, and (iii) action. The main advantage of the introduced methodology is its capability of effectively and systematically identifying the most sustainable enhancement strategies for a complex industrial system problem under uncertainty. The applicability of the methodology will be illustrated through analyzing the sustainability issues and developing action plans for a surface coating centered industrial zone.

4.1 Sustainability Enhancement Framework

As stated, the methodology is developed by applying fuzzy logic techniques in the three major steps of problem solving. They are: (i) Assessment, which determines the sustainability status of the system under various types of uncertainties, (ii) Analysis, which is designed to identify potential design alternatives for improving sustainability, and (iii) Action, where the most desirable enhancement strategies is derived. The detailed functionality and the implementation procedure in each step are described below.

4.1.1 Fuzzy logic based double-layer sustainability assessment

In studying a sustainability problem, the first step towards solution identification is assessment, i.e., to assess the sustainability status of the system under uncertainty. The uncertainties are always associated with the required data and information and possessed domain or heuristic knowledge (Piluso *et al.*, 2010). Uncertainties can be either aleatory or epistemic (Parry, 1996), both occurring in sustainability assessment and decision making activities. There exists a variety of techniques for uncertainty handling by resorting to probability theory and computational intelligence (Ayyub and Gupta, 1997; Graham and Jones, 1988; Kanovicha and Vauzeillesb, 2007; Yang, 2001;

Cawleya *et al.*, 2001; Meinrath, 2000; Li *et al.*, 2006; and Zimmermann, 1991). In this work, a fuzzy logic based approach by Piluso *et al.* (2010) is adopted to develop a sustainability assessment approach, as it is capable of formulating and manipulating both types of uncertainties.

The fuzzy logic based assessment is constructed by expressing uncertainties as fuzzy numbers and intervals, and conducted by utilizing a knowledge base with a number of fuzzy rules.

Rule structure. The knowledge base contains three rule sets, namely sets R_e, R_v, and R_l, for assessing economic, environmental, and social sustainability, respectively. Each set contains a number of fuzzy rules, $R_j = \left\{ R_j^i \;\middle|\; i = 1, 2, \cdots, N_j^M \right\}$, where j is the index of sustainability category ($j = e$ (economic), v (environmental), or l (social)); N_j^M represents the total number of rules in rule set R_j. The rules in the knowledge base have the following uniform IF-THEN structure.

$$R_j^i: \quad \text{IF} \quad \left\{ x_{j,k} \ is\ A_{j,k}^i \;\middle|\; k = 1, 2, \cdots, N_j \right\} \tag{4.1}$$

$$\text{THEN} \quad S_j^i = \sum_{k=1}^{N_j} a_{j,k}^i \, \tilde{x}_{j,k}$$

where

$x_{j,k}$ = the *k*-th indictor in the *j*-th sustainability category

$\tilde{x}_{j,k}$ = the *k*-th indictor (normalized) in the *j*-th sustainability category

$A_{j,k}^i$ = the fuzzy set defined for indicator $x_{j,k}$ in rule R_j^i

$a_{j,k}^i$ = the coefficient associated with normalized indicator $\tilde{x}_{j,k}$ in rule R_j^i

N_j = the total number of indicators included in rule R_j^i to evaluate sustainability

S_j^i = the j-th sustainability category derived by rule R_j^i

j = the sustainability index category (e: economic; v: environmental; l: social)

Note that an indicator $x_{j,k}$ is to be evaluated by using system parameters based on the industrial system under study, and it is possible that a number of system parameters are required for obtaining one indicator. Since indicators are always quantified with different units and scales, they should be normalized and then combined into the composite sustainability result in the THEN part with a value between 0 and 1. Those fuzzy sets associated with sustainability indicators can be defined based on the approaches introduced by Ayyub and Gupta (1997) and Bilgic *et al.* (2003) using available data and/or heuristic knowledge.

Fuzzy reasoning. It is recognized that the fuzzy rules in the knowledge base can be used in a logical and systematic way. The MIN-MAX algorithm developed by Zimmermann (1991) is still the most effective technique for fuzzy reasoning and decision-making, and in this case, fuzzy rule based sustainability assessment. The algorithm can be expressed as:

$$\mu_j(x) = max\left\{min\left\{\mu_i(x_{j,k}) \middle| k = 1, 2, \cdots, N_j\right\}; i = 1, 2, \cdots, N_i^M\right\} \tag{4.2}$$

where

$\mu_i(x_{j,k})$ = the fuzzy membership for indicator $x_{j,k}$ in the i-th rule of the j-th sustainability category

$\mu_j(x)$ = the derived membership after the MIN-MAX operation on the rules in the j-th sustainability category

x = general representation of variables $x_{j,k}$'s

Note that the application of the MIN-MAX operation to the knowledge base will activate only one most suitable in each of the three rule sets, which give the assessment of economic, environmental, and social sustainability separately.

Overall Sustainability Assessment. Since each of the composite sustainability indices, S_e, S_v, and S_l, are normalized to have a value between 0 and 1. It is highly desirable that the overall sustainability level, S, is also normalized. According to Piluso (2010), the following formula can be used to derive a normalized S value, which demonstrates a Cube-based sustainability status representation:

$$S = \frac{1}{\sqrt{3}} \left\| \left(S_e,\ S_v,\ S_l \right) \right\| \tag{4.3}$$

4.1.2 Sustainability analysis using fish bone diagram and design of experiment methods

After the sustainability status is assessed, the industrial system must be analyzed to identify sustainability improvement opportunities. In this analysis step, a fishbone-based approach is introduced to identify the root causes of existing problems. The fishbone diagram is also known as the Ishikawa diagram or cause-and-effect diagram. Analysis is conducted through tracing backwards from the identified sustainability status (i.e., the effect) to the root causes of the sustainability problem, if there are. For those identified potential causes, Design of Experiments (DOE) techniques will be used to rank the causes, which will be critical for identifying the most important causes.

Root cause identification. The fishbone diagram, introduced by Ishikawa (1990), has been widely used in product design and quality control, as it can help effectively identify potential factors. The fishbone diagram for sustainability analysis is shown in Fig. 4.1. In the diagram, each bone represents a potential source (causes or reasons) of sustainability variation, and the causes are grouped into individual sustainability categories based on the triple-bottom-line principle. Such a fishbone diagram can be developed using domain and/or heuristic knowledge (Breyfogle, 1999).

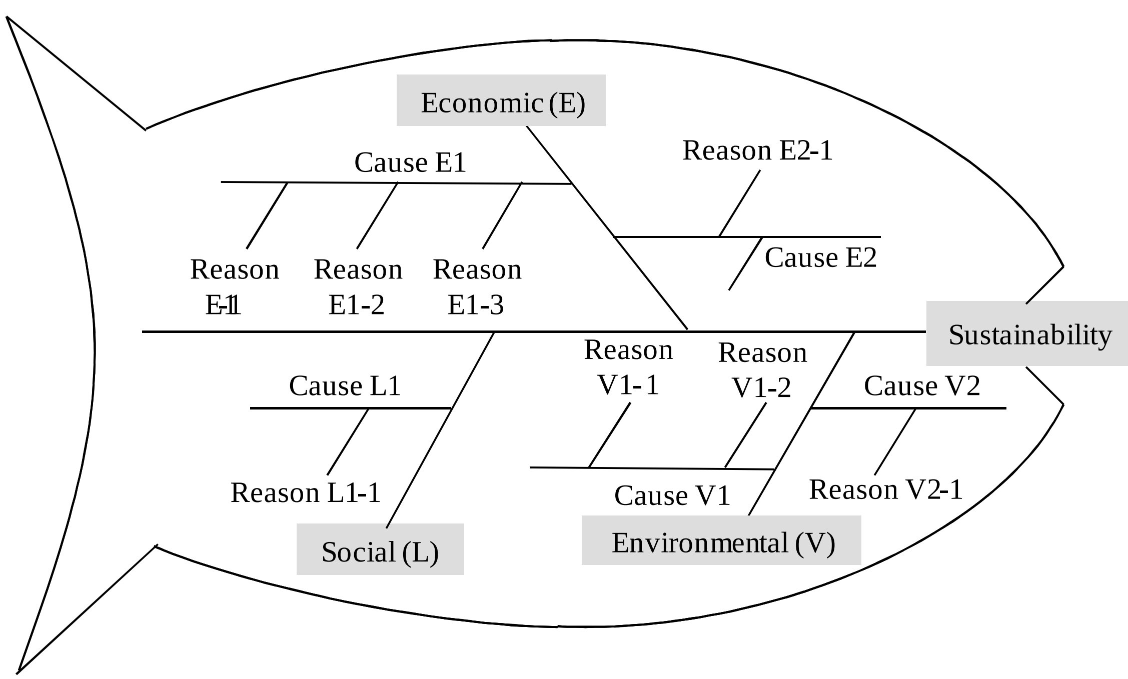


Figure 4.1. Artificial fishbone diagram for sustainability analysis.

For a sustainable analysis problem, many potential causes could be identified with the help of a fishbone diagram. It is understandable that the causes identified may have different levels of influence on sustainability. Moreover, different types of correlations may exist among the potential causes due to the complex nature of industrial sustainability; such correlations need to be carefully handled as well. For this purpose, a sensitivity analysis on the causes and correlations needs to be conducted.

Cause and correlation screening. The 2^K DOE technique (Breyfogle, 1999) is applied to conduct sensitivity analysis of potential causes and correlations to sustainability, which can provide the information of actual degrees of the changes on potential actions. Note that the DOE technique is used to conduct a certain number of statistically designed trials. In each trial, a combination of different potential causes is set as an input to an industrial system, and the sustainability status of the system is obtained as its output response. A general example of implementation of the 2^K DOE technique is shown in Table 4.1.

Table 4.1. Example of implementing 2^K DOE technique (K: the number of potential causes).

	Factor Designation								
Trial No.	A	…	K	AB	…	AK	…	A⋯K	Response
1	+	…	+	+	…	+	…	+	S_1
2	+	…	-	+	…	-	…	-	S_2
3	+	…	+	-	…	+	…	-	S_3
⋮	⋮								⋮
2^K	-	…	-	+	…	+	…	-	S_{2^K}

In the table, the symbols, "+" and "-", represent an activation and inactivation, respectively, of a change of a potential cause (or correlation). The details about activation assignment for each potential cause in a trial can be found in Breyfogle (1999).

The data of all the trials should be used to quantify the level of sensitivity of each potential cause and correlation to a sustainability variation. This quantification can be obtained through calculating mean effects on the related cause and correlation. For a DOE dealing with K potential causes, a total of K mean effects can be calculated for each individual cause as follows:

$$\bar{S}_{o[k^+]} - \bar{S}_{o[k^-]} = \frac{1}{2^{K-1}}\left(\sum S_{o[k^+]} - \sum S_{o[k^-]}\right) \tag{4.4}$$

where

k = the index of potential cause between A and K

$S_{o[k^+]}$ = a sustainability response obtained when “+” is given for cause k

$S_{o[k^-]}$ = a sustainability response obtained when “-” is given for cause k

Note that the difference between $\bar{S}_{o[k^+]}$ and $\bar{S}_{o[k^-]}$ is the mean effect of potential cause k to the sustainability variation of the industrial system. Furthermore, the information on cause-correlation can be derived below, which accounts for all the mean effects.

$$\bar{S}_{o[k_i \cdots k_j^+]} - \bar{S}_{o[k_i \cdots k_j^-]} = \frac{1}{2^{K-1}}\left(\sum S_{o[k_i \cdots k_j^+]} - \sum S_{o[k_i \cdots k_j^-]}\right) \tag{4.5}$$

where

$k_i \cdots k_j$ = a general representation of the correlation of cause k_i through cause k_j

$S_{o[k_i \cdots k_j^+]}$ = the sustainability response obtained when "+" is given for the correlation of cause k_i through cause k_j

$S_{o[k_i \cdots k_j^-]}$ = the sustainability response obtained when "-" is given for the correlation of cause k_i through cause k_j

Note that the difference between $\bar{S}_{o[k_i \cdots k_j^+]}$ and $\bar{S}_{o[k_i \cdots k_j^-]}$ is the mean effect of the correlation of cause k_i through cause k_j to the sustainability variation of the industrial system.

Comparison of obtained mean effects can effectively indicate sensitivity difference, which can be used to distinguish significant causes and correlations from those insignificant ones. This can provide a better understanding of the system in the following aspects: (i) the causes (or correlations) giving higher mean effects are more significant to the sustainability enhancement than those having lower mean effects, and (ii) only those significant causes and correlations are suggested to be kept for further study on sustainability enhancement. This is important as the available funds are always limited, which requires a best possible funds distribution for a number of actions.

4.1.3 Action taking based on fuzzy optimization

Action, as the third step in this Triple-A Template based approach, is to derive the most suitable sustainability enhancement strategies under uncertainty. Instead of generating heuristic strategies based on limited scenarios, the actions to be taken are based on the strategies derived systematically using a fuzzy logic based approach proposed below, which can reflect cause-effect efficiency. In a fuzzy optimization model, the objective function is defined to maximize the sustainability level through distributing the budget that is needed for action taking, which is subjected to various constraints, such as budget availability, system specification, etc.

Fuzzy optimization model. To derive optimal action strategies for sustainability enhancement under uncertainty, a fuzzy optimization technique (Lai and Hwang, 1992) is utilized. A general optimization model is shown below, where S is the indicator of sustainability level. It is to maximize the sustainability level through optimally distributing the funds for different action strategies under the various constraints related to total budget availability (fuzzily defined), system models, etc.

$$\max_{U_k, k \in N} \; J = S\left(S_i, i = e, v, l\right) \quad (4.6)$$

s.t. $$S_i = f\left(U_{i,j};\, j = 1, 2, \cdots, N\right) \quad (4.7)$$

$$\sum_{k=1}^{N} U_k \leq \tilde{U}^{up} \quad (4.8)$$

$$U_k \geq 0 \quad (4.9)$$

where

S = the sustainability level of an industrial system

S_i = the i-th sustainability category

i = the sustainability category index: e (economic), v (environmental), and l (social)

$U_{i,j}$ = the budget for the j-th action in the i-th sustainability category

U_k = the budget for the k-th action

N = the total number of action strategies

$\tilde{U}^{up}$ = the upper limit of the budget available (fuzzily defined)

Budget acceptance and sustainability satisfaction. Note that the total budget constraint may not be very strict. This means if an industrial system's sustainability improvement can be more satisfactory, then it might be acceptable if the total budget for actions exceeds its upper limit to some extent. This shows a type of flexibility in decision making using fuzzy logic. To pursue it, two types of fuzzy sets should be defined: one for sustainability satisfaction, and the other for budget request acceptance. Figure 4.2 illustrates an example of fuzzy set definitions for the sustainability satisfaction and the budget request acceptance. As shown in Fig. 4.2(a), if the sustainability (S) after action taking has a value less than S_L, then it will be completely unsatisfactory, and the satisfaction indicator, $\mu(S)$ is 0. If the value of S is between S_L and S_U, the system performance is partially satisfactory as indicated by a specific value of $\mu(S)$ between 0 and 1. If the value of S is greater than S_U, the system performance is completely satisfactory, and $\mu(S)$ will always have a value of 1. Figure 4.2(b) shows that if the budget (U) is less than U_L, then it is entirely acceptable ($\mu(U)$ = 1). If the value of U is between U_L and U_U, the budget request becomes less acceptable (see a decreasing value of $\mu(U)$ from 1 towards 0). If a value of U is greater than U_U, the budget request will be completely unacceptable ($\mu(U)$ = 0), and the optimization fails completely.

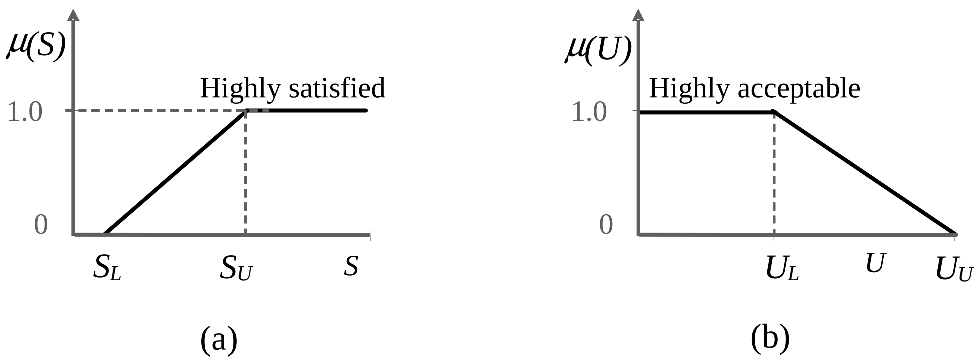


Figure 4.2. Fuzzy set definition for: (a) sustainability satisfaction, and (b) budget request acceptance.

4.2 Case Study

A number of industrial sustainability problems have been studied using the introduced methodology. In this section, a sustainable enhancement problem of an industrial zone is selected to illustrate the applicability of the methodology. This industrial zone is featured by its surface coating centered manufacturing for the automotive industry.

4.2.1 Problem description

The industrial zone under study is sketched in Fig. 4.3. This industrial zone consists of two chemical suppliers to the electroplating plants (H1 and H2), two electroplating shops (H3 and H4), two end users, in this case, two original equipment manufacturers (OEM) for the automotive industry (H5 and H6) and a regional wastewater treatment facility (WWTF). The WWTF is charged with cleaning the waste streams, from each of the component plants, to a level that is environmentally satisfactory for discharge into the local river and environment. The system flow information under the current situation is shown as the original values in Table 4.2. This study is to investigate the sustainability level of the industrial zone, and then to develop effective strategies for sustainability improvement, for which a very limited fund is available for action taking.

Sustainability metrics selection. For the case study described above, two indicators were selected for each sustainability category based on the IChemE's sustainable development progress metrics (IChemE, 2002). In real application, users can select any number of sustainability metrics if adequate, and an interesting example is given by Piluso *et al.* (2010). The selected metrics for this illustration are as follows.

(a) For economic sustainability assessment, the selected indicators are: (1) Value added ($x_{e,1}$), which is defined as the difference of the sales and the total cost of goods, raw materials (including energy), and services purchased, and (2) Taxes paid as a percentage of income before tax ($x_{e,2}$).

(b) In the environmental sustainability category, the selected indicators are: (1) Total raw materials used per lb. product produced ($x_{v,1}$), which is the ratio between the pounds of raw material used and the pounds of product produced, and (2) Total waste generated per lb. product produced ($x_{v,2}$).

(c) For social sustainability assessment, the suitable indicators are: (1) Potential collaboration through zone-wide material recycle and reuse ($x_{l,1}$), and (2) Total number of complains per unit value added ($x_{l,2}$).

Table 4.2. System flow information before and after enhancement.

State	Original Value ($\times 10^3$ lbs/yr)	Value after Enhancement ($\times 10^3$ lbs/yr)
Inflow		
z_{10}^{Zn}	50.00	50.00
z_{20}^{Zn}	70.00	70.00
Interflow		
$f_{3,1}^{Zn}$	46.50	46.50
$f_{4,2}^{Zn}$	33.88	33.88
$f_{4,4}^{Zn}$	4.04	4.18
$f_{3,5}^{Zn}$	2.61	4.62
$f_{5,4}^{Zn}$	18.37	19.06
$f_{4,6}^{Zn}$	0.60	0.62
$f_{3,2}^{Zn}$	27.72	27.72
$f_{3,3}^{Zn}$	4.04	10.60
$f_{5,3}^{Zn}$	68.75	76.03
$f_{4,5}^{Zn}$	1.74	3.09
$f_{6,4}^{Zn}$	15.03	15.60
Waste		
$y_{w,01}^{Zn}$	3.50	3.50
$y_{w,02}^{Zn}$	8.40	8.40
$y_{w,03}^{Zn}$	8.09	2.81
$y_{w,04}^{Zn}$	2.82	2.91
$y_{w,05}^{Zn}$	4.36	1.80
$y_{w,06}^{Zn}$	0.60	0.62
Product		
$y_{p,05}^{Zn}$	78.41	85.59
$y_{p,06}^{Zn}$	13.83	14.36

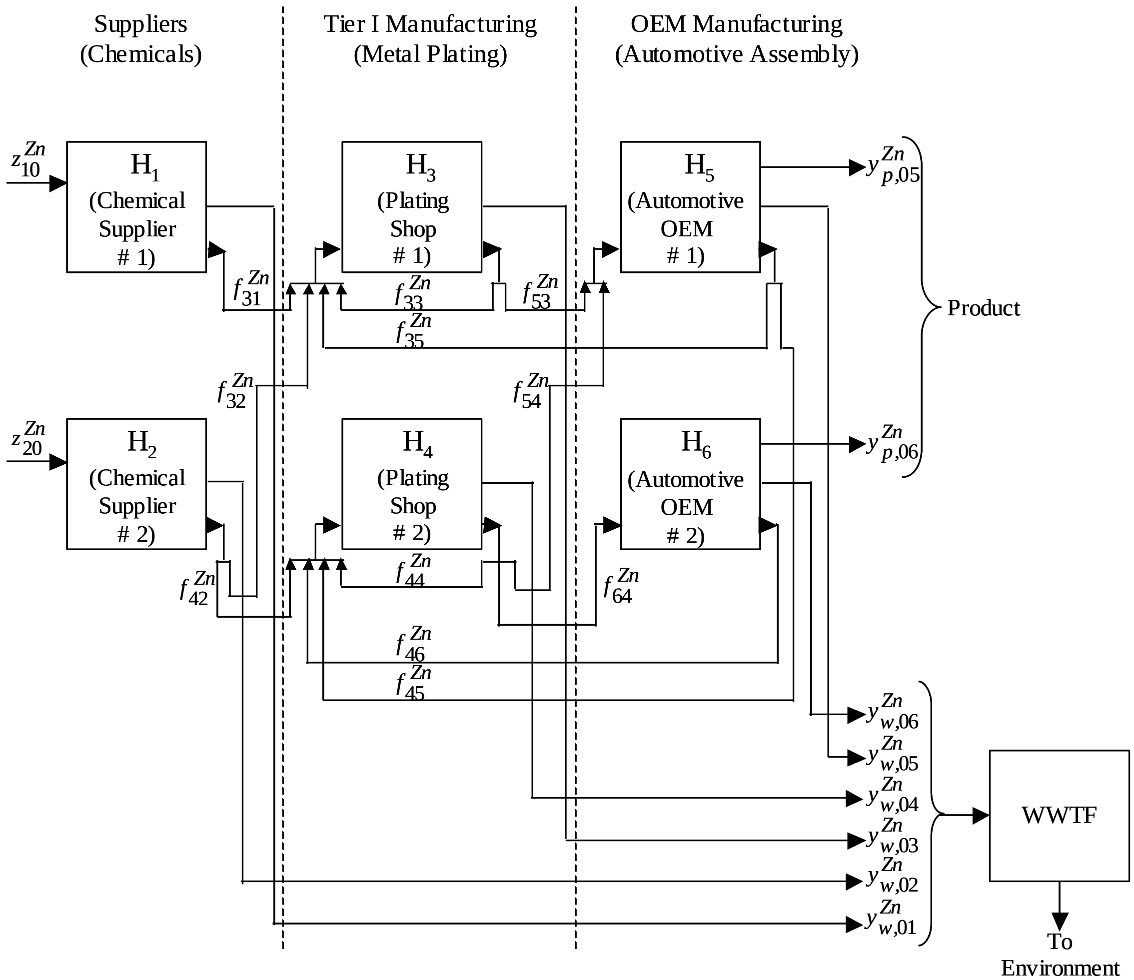


Figure 4.3. Sketch of a surface coating centered industrial zone.

Sustainability assessment. As stated, the knowledge base for assessing sustainability has two layers, where the lower one contains three fuzzy rule sets, namely R_e, R_v, and R_l, for respectively assessing economic, environmental, and social sustainability, and the upper layer uses the cube based calculation for combining results from the lower layer into the overall sustainability. In this case, the lower layer has 27 rules, including nine rules in set R_e, nine rules in set R_v, and nine rules in set R_l. While the uniform rule structure has already been given in Eq. 4.1, the first rules in each of the three rules sets are listed below as examples.

$$R_e^1: \quad \text{IF} \quad x_{e,1} \text{ is } A_{e,1}^L \text{ and } x_{e,2} \text{ is } A_{e,2}^L, \qquad \text{THEN } S_e = 0.5\tilde{x}_{e,1} + 0.5\tilde{x}_{e,2} \tag{4.10}$$

where

$A_{e,1}^L$ and $A_{e,2}^L$ = the fuzzy sets that are defined as "LOW" $x_{e,1}$, and "LOW" $x_{e,2}$, respectively.

$x_{e,1}$ and $x_{e,2}$ = the metrics defined for economic sustainability.

$\tilde{x}_{e,1}$ and $\tilde{x}_{e,2}$ = the normalized indictors in the economic sustainability category.

S_e = the derived economic sustainability category.

Note that the definitions of the two fuzzy sets ($A_{e,1}^L$, and $A_{e,2}^L$) are shown in Fig. 4.4(a) and (b). In fact, those two figures contain four other fuzzy sets ($A_{e,1}^M$, $A_{e,1}^H$, $A_{e,2}^M$, and $A_{e,2}^H$) that are used by other eight rules in rule set R_e.

$$R_v^1: \quad \text{IF} \quad x_{v,1} \text{ is } B_{v,1}^H \text{ and } x_{v,2} \text{ is } B_{v,2}^L, \qquad \text{THEN } S_v = 0.65\tilde{x}_{v,1} + 0.35\tilde{x}_{v,2} \tag{4.11}$$

where

$B_{v,1}^H$ and $B_{v,2}^L$ = the fuzzy sets that are defined as "HIGH" $x_{v,1}$, and "LOW" $x_{v,2}$, respectively.

$x_{v,1}$ and $x_{v,2}$ = the metrics defined for environmental sustainability.

$\tilde{x}_{v,1}$ and $\tilde{x}_{v,2}$ = the normalized indictors in the environmental sustainability category.

S_v = the derived environmental sustainability category.

The definitions of the fuzzy sets ($B^H_{v,1}$, and $B^L_{v,2}$) are shown in Fig. 4.4(c) and (d). Four other fuzzy sets ($B^L_{v,1}$, $B^M_{v,1}$, $B^M_{v,2}$, and $B^H_{v,2}$) that are used by other eight rules in rule set R_v are also given in such figures.

$$R^1_l: \quad \text{IF} \quad x_{l,1} \text{ is } C^L_{l,1} \text{ and } x_{l,2} \text{ is } C^H_{l,2}, \tag{4.12}$$

$$\text{THEN } S_l = 0.8\tilde{x}_{l,1} + 0.2\tilde{x}_{l,2}$$

where

$C^L_{l,1}$ and $C^H_{l,2}$ = the fuzzy sets that are defined as "LOW" $x_{l,1}$, and "HIGH" $x_{l,2}$, respectively.

$x_{l,1}$ and $x_{l,2}$ = the metrics defined for social sustainability.

$\tilde{x}_{l,1}$ and $\tilde{x}_{l,2}$ = the normalized indictors in the social sustainability category.

S_l = the derived social sustainability category.

The definitions of the fuzzy sets ($C^L_{l,1}$, and $C^H_{l,2}$) are shown in Fig. 4.4(e) and (f), where also contain four other fuzzy sets ($C^M_{l,1}$, $C^H_{l,1}$, $C^L_{l,2}$, and $C^M_{l,2}$) that are used by other eight rules in rule set R_l.

The upper layer of the knowledge base employs Eq. 4.3 for the assessment of overall sustainability, which demonstrates a cube-based sustainability status representation.

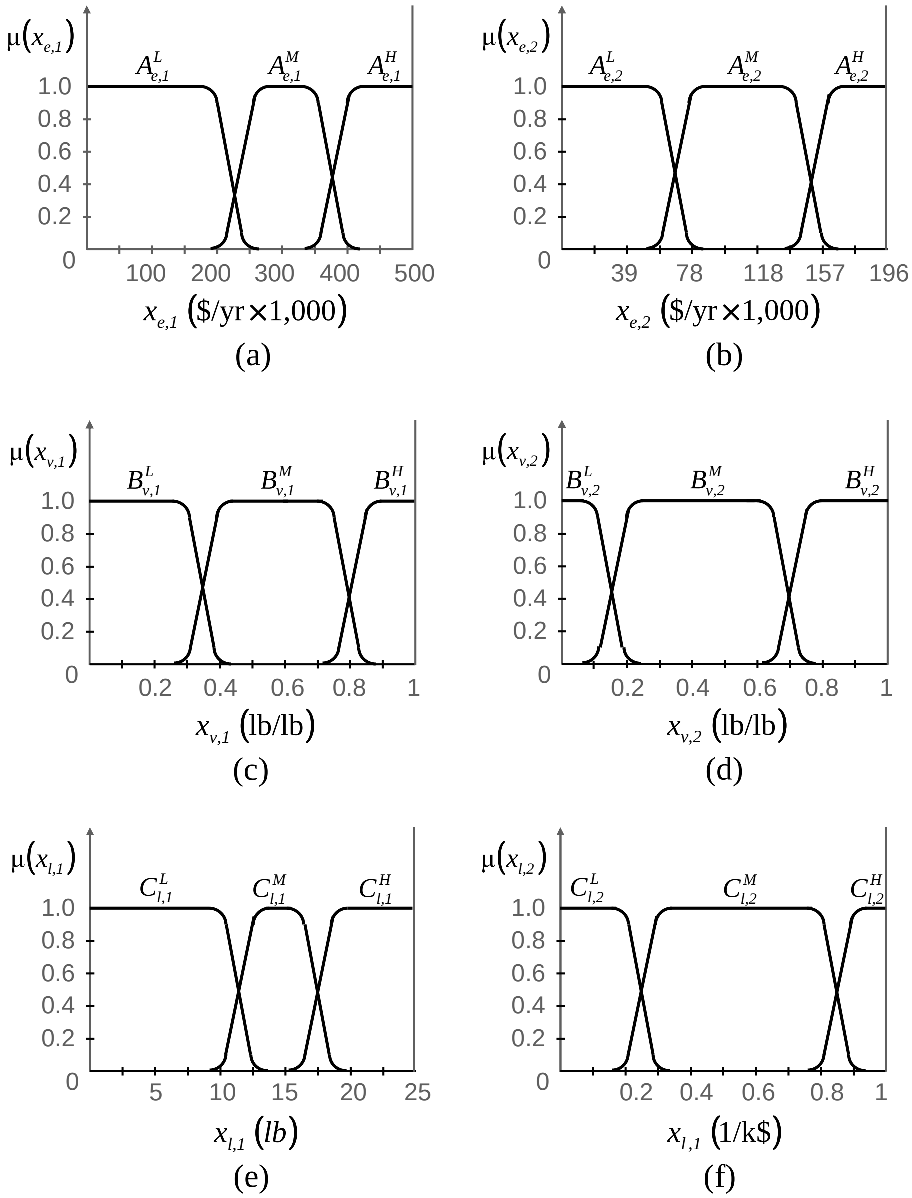


Figure 4.4. Definition of fuzzy sets for sustainability indicators:
Economic indicators: (a) Value added ($x_{e,1}$), and (b) Tax paid ($x_{e,2}$),
Environmental indicators: (c) Total raw materials used per lb. product produced ($x_{v,1}$), and (d) Total waste generated per lb. product produced ($x_{v,2}$),
Social indicators: (e) Collaboration through zone-wide material recycle and reuse ($x_{l,1}$), and (f) Total number of complains per unit value added($x_{l,2}$).

Rule sets for fuzzy optimization. The two fuzzy sets are shown in Fig. 4.5 for evaluating the levels of sustainability satisfaction and budget request acceptance, after obtaining decisions on budget distribution for specific sustainability enhancement action taking.

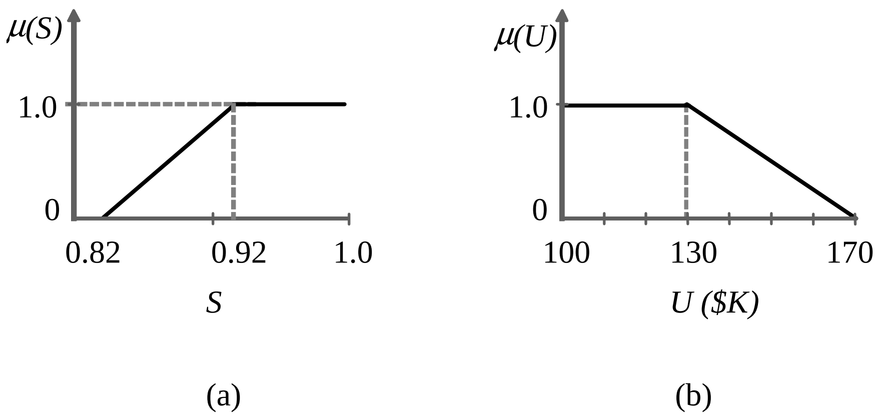


Figure 4.5. Definition of two fuzzy sets for quantifying: (a) the satisfactory level of the sustainability achieved, and (b) the acceptance level of the budget to be requested.

4.2.2 Methodology implementation

For the problem described above, sustainability enhancement strategies are obtained in three steps that are briefly described below.

Assessment. The sustainability status is evaluated first. By implementing the methodology, the assessment is initiated from the lower layer based on the rules to be activated in each rule sets. Taking the economic sustainability rule set as an example, one rule should be activated from nine rules through performing the MIN-MAX operation. Table 4.3 gives the details of the results after the operation. As the inputs by the user, the data for variables $x_{e,1}$ and $x_{e,2}$ are first provided. Then, the membership function values for the condition part of each rule, $\mu_i(x_{e,k})$ (i = 1, 2, $\cdots$, 9; k = 1 and 2) are all listed, based on the fuzzy sets given in Fig. 4.4(a) and (b). The MIN operation gives rise to $\tau_{e,1}$, $\tau_{e,2}$, $\cdots$, $\tau_{e,9}$ in Table 4.3. The MAX operation identifies that $\tau_{e,9}$ has the largest value (1.00). Therefore, rule R_e^9 is activated.

$$R_e^9: \quad \text{IF} \quad x_{e,1} \text{ is } A_{e,1}^H \text{ and } x_{e,2} \text{ is } A_{e,2}^H, \qquad (4.13)$$

$$\text{THEN} \quad S_e = 0.6\tilde{x}_{e,1} + 0.4\tilde{x}_{e,2}$$

The rule application for the economic sustainability quantification generates the results in the top section of Table 4.4. As shown, the dimensional input data for $x_{e,1}$ and $x_{e,2}$ are first normalized (i.e. $\tilde{x}_{e,1}$, and $\tilde{x}_{e,2}$ in Table 4.4.). With that, the quantified value for economic sustainability, S_e from Eq. 4.13, is calculated to be 0.892.

Following the same evaluation procedure as that for the economic sustainability assessment, the activated rules in the environmental rule set and the social rule set are found to be:

$$R_v^5: \quad \text{IF} \quad x_{v,1} \text{ is } B_{v,1}^M \text{ and } x_{v,2} \text{ is } B_{v,2}^M \qquad (4.14)$$

$$\text{THEN} \quad S_v = 0.7\tilde{x}_{v,1} + 0.3\tilde{x}_{v,2}.$$

$$R_l^6: \quad \text{IF} \quad x_{l,1} \text{ is } C_{l,1}^M \text{ and } x_{l,2} \text{ is } C_{l,2}^H \qquad (4.15)$$

$$\text{THEN} \quad S_l = 0.88\tilde{x}_{l,1} + 0.12\tilde{x}_{l,2}$$

Table 4.3. Economic sustainability – Evaluation of rule set and rule selection.

Variable	$x_{e,1}$	$x_{e,2}$	MIN operation	MAX operation
Input data	429.8	177.2		
Rule No.	$\mu_i(x_{e,1})$	$\mu_i(x_{e,2})$	$\tau_{e,i}$	τ_e
R_e^1	0.00	0.00	0.00	1.00
R_e^2	0.00	0.00	0.00	
R_e^3	0.00	0.00	0.00	
R_e^4	0.00	0.00	0.00	
R_e^5	0.00	0.00	0.00	
R_e^6	0.00	1.00	0.00	
R_e^7	1.00	0.00	0.00	
R_e^8	1.00	0.00	0.00	
R_e^9	1.00	1.00	1.00	

Table 4.4. Sustainability assessment before enhancement.

ECON indicators	Input data (dimensional)	Normalized value ($\tilde{x}_{e,i}$)	$\alpha_{e,i}$	Categorized sustainability $(S_e)_{cur}$	b_e	Overall sustainability $(S_o)_{cur}$
$x_{e,1}$	429.8	0.883	0.60	0.892	1.00	0.745
$x_{e,2}$	177.2	0.904	0.40			
ENV indicators	Input data (dimensional)	Normalized value ($\tilde{x}_{v,i}$)	$\beta_{v,i}$	Categorized sustainability $(S_v)_{cur}$	b_v	
$x_{v,1}$	0.769	0.769	0.70	0.748	1.00	
$x_{v,2}$	0.301	0.699	0.30			
SOC indicators	Input data (dimensional)	Normalized value ($\tilde{x}_{l,i}$)	$\gamma_{l,i}$	Categorized sustainability $(S_l)_{cur}$	b_l	
$x_{l,1}$	13.00	0.522	0.88	0.559	1.00	
$x_{l,2}$	0.171	0.829	0.12			

Using these rules, the quantified values for environmental and social sustainability are 0.748 and 0.559, respectively. Next, those results obtained in the lower layer are sent to the upper layer as inputs for overall sustainability assessment. Through performing Eq. 4.3, a value of 0.745 is obtained to the current sustainability status.

Analysis. The above evaluation provides specific information. As shown, the current industrial system is more economic and environmental sustainability focused as compared with its social sustainability performance, as the value of $\tilde{x}_l$ is much smaller than the values of $\tilde{x}_e$ and $\tilde{x}_v$. A fishbone diagram in Fig. 4.6 shows the identified four causes only for social sustainability analysis, which are: Cause A – insufficient recycle of $f_{3,3}$ in electroplating plant H_3, Cause B – insufficient recycle of $f_{4,4}$ in electroplating plant H_4, Cause C – insufficient recycles of $f_{3,5}$ and $f_{4.5}$ from OEM H_5 to electroplating plants H_3 and H_4, respectively, and Cause D – too much waste (W_2) generated by chemical supplier H_2.

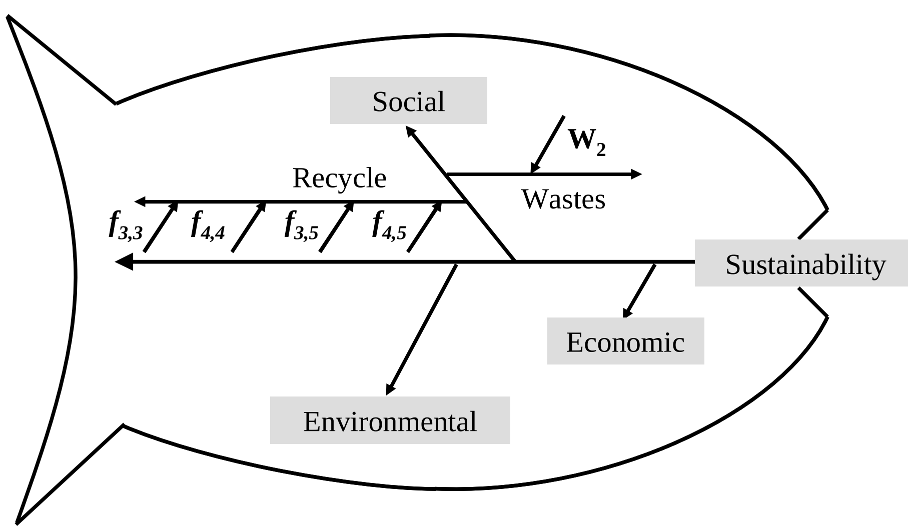


Figure 4.6. Modified fishbone diagram
for sustainability enhancement of the studied case.

Limited funds can be used to improve the social sustainability through addressing some key issues that are related to those identified causes. Thus, a sensitivity analysis must be conducted using the 2^k DOE technique. In this effort, 15 trails are made and the results are demonstrated in Table 4.5. The data of all the trials are further used to quantify the level of sensitivity of each potential cause and correlation to a sustainability variation. In this case, four mean effects of each potential cause are calculated using Eqs. 4.4 and other mean effects of correlations are calculated using Eq. 4.5. The calculation results are plotted in Fig. 4.7, and as examples, the calculation of mean effects on cause A and the correlated cause BD is given in Eqs. 4.16 and 4.17.

Table 4.5. 2^k DOE technique implementation on the studied case.

	Factor Designation															
Trial No.	A	B	C	D	AB	AC	AD	BC	BD	CD	ABC	ABD	ACD	BCD	ABCD	Response
1	+	-	-	-	-	-	-	+	+	+	+	+	+	-	-	0.7539
2	+	+	-	-	+	-	-	-	-	+	-	-	+	+	+	0.8627
3	+	+	+	-	+	+	-	+	-	-	+	-	-	-	-	0.8646
4	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	0.9382
5	-	+	+	+	-	-	-	+	+	+	-	-	-	+	+	0.9354
6	+	-	+	+	-	+	+	-	-	+	-	-	+	-	-	0.8052
7	-	+	-	+	-	+	-	-	+	-	+	-	+	-	-	0.9331
8	+	-	+	-	-	+	-	-	+	-	-	+	-	+	+	0.7548
9	+	+	-	+	+	-	+	-	+	-	-	+	-	-	-	0.9360
10	-	+	+	-	-	-	+	+	-	-	-	+	+	-	-	0.8617
11	-	-	+	+	+	-	-	-	-	+	+	+	-	-	-	0.8031
12	+	-	-	+	-	-	+	+	-	-	+	-	-	+	+	0.8057
13	-	+	-	-	-	+	+	-	-	+	+	+	-	+	+	0.8598
14	-	-	+	-	+	-	+	-	+	-	+	-	+	+	+	0.7465
15	-	-	-	+	+	+	-	+	-	-	-	+	+	+	+	0.8028
16	-	-	-	-	+	+	+	+	+	+	-	-	-	-	-	0.7454

$$\bar{S}_{o[A^+]} - \bar{S}_{o[A^-]} =$$
$$\frac{1}{8}\big((0.754 + 0.863 + 0.865 + 0.938 + 0.805 + 0.755 + 0.936 + 0.806\big) \qquad (4.16)$$
$$-\big(0.935 + 0.933 + 0.862 + 0.803 + 0.860 + 0.747 + 0.803 + 0.745)\big) = 0.002$$

$$\bar{S}_{o[BD^+]} - \bar{S}_{o[BD^-]} =$$
$$\frac{1}{8}\big((0.754 + 0.938 + 0.935 + 0.933 + 0.755 + 0.936 + 0.747 + 0.745\big) \qquad (4.17)$$
$$-\big(0.863 + 0.865 + 0.805 + 0.862 + 0.803 + 0.806 + 0.860 + 0.803)\big) = 0.005$$

As shown clearly by Fig. 4.7, the two causes, namely B and D, as well as the correlated cause, BD, are much more significant than the rest causes and their combinations.

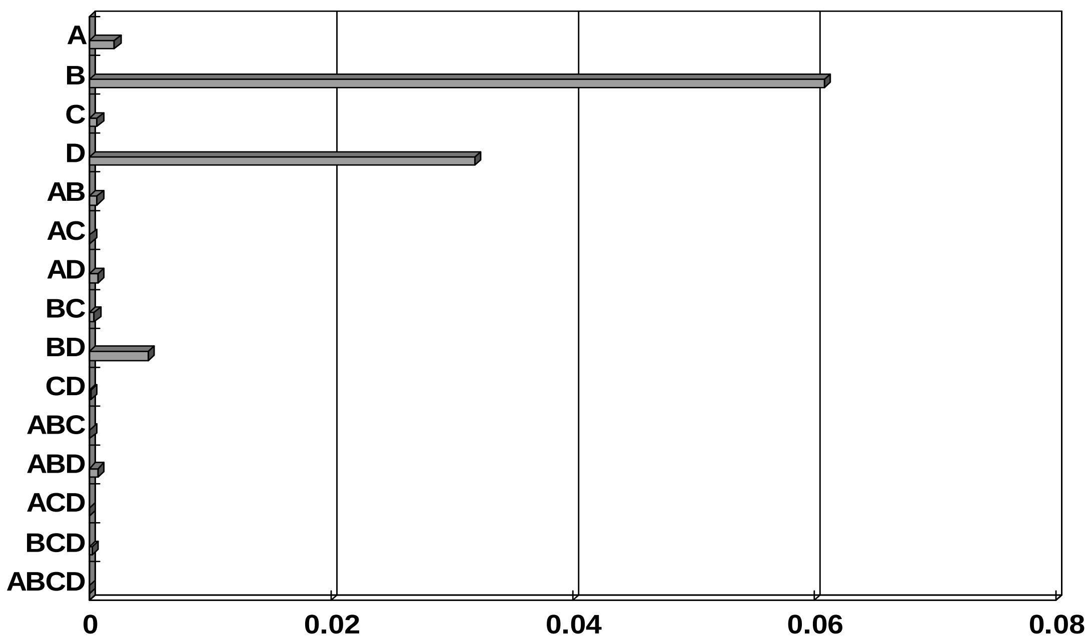


Figure 4.7. Mean effects of potential causes and correlations to the sustainability of the surface finishing industrial region.

Action. The above results are used to derive a relationship between the budget distribution for action taking based on the main causes and correlations and the sustainability level. Equation 4.18 is the relationship obtained, which can be used to determine a new sustainability level, S_{new}, when funds are used to solve the problems caused by Causes B and D and Correlation BD.

$$\begin{aligned} S_{new} &= 0.745 + 2.43\times10^{-3}\, u_B + 1.54\times10^{-3}\, u_D \\ &\quad - 1.23\times10^{-5}(u_B)^2 - 8.56\times10^{-6}(u_D)^2 - 6.46\times10^{-7}\, u_B u_D \end{aligned} \tag{4.18}$$

where

U_B = the budget for implementing an action on B

U_D = the budget for implementing an action on D

Note that Eq. 4.18 is essentially the objective function of the fuzzy optimization in this case. It is to determine the best way for budget distribution so that the sustainability can be mostly enhanced. The optimization problem in this case is defined below.

$$\begin{aligned} \max S_{new} &= 0.745 + 2.43\times10^{-3}\, u_B + 1.54\times10^{-3}\, u_D \\ &\quad - 1.23\times10^{-5}(u_B)^2 - 8.56\times10^{-6}(u_D)^2 - 6.46\times10^{-7}\, u_B u_D \end{aligned} \tag{4.19}$$

s.t. $$U_B + U_D \le \widetilde{130} \tag{4.20}$$

$$0 \le U_B, U_D \tag{4.21}$$

The above optimization is solved readily by Genetic Algorithm (Sanchez, 1997) with the following results:

(i) Budget distribution:

$$U_B = 82 \tag{4.22}$$

$$U_D = 54 \tag{4.23}$$

(ii) New sustainability data:

$$S_{new} = 0.906 \tag{4.24}$$

Note that the total budget request for actions on B and D is \$136K, exceeding the soft upper limit of \$130K. The acceptance level of this requested budget can be obtained using the fuzzy set defined in Fig. 4.6(b), which is 85% as $\mu(U_B + U_D)$ has a value of 0.85. Furthermore, the satisfaction level of the sustainability can be observed according to Fig. 4.6(a), which is 86% as $\mu(S_{new})$ is 0.86.

In summary, according to the obtained solution, the best sustainability enhancement strategies are: (i) to invest \$82K for increasing the internal recycle ($f_{4,4}$) in electroplating plant H_4, (ii) to invest \$54 k\$ for reducing the waste (W_2) generated by chemical supplier H_2. In this way, the sustainability, S_{new}, after implementing strategies reaches 0.906; in more detail (see Table 4.6), the new economic, environmental, and social sustainability levels are 0.96, 0.82, and 0.92, respectively. This is about 21.6% of improvement overall, as compared with the sustainability status before improvement (0.740). The system flow information after implementing the strategies is given as the "Value after Enhancement" in Table 4.2. Clearly, the system has some other improvement opportunities as the new status of overall sustainability has a satisfaction of 0.86. If more budgets are available, the overall sustainability should be further improved.

Table 4.6. Sustainability assessment after enhancement.

ECON indicators	Input data (dimensional)	Normalized value ($\tilde{x}_{e,i}$)	$\alpha_{e,i}$	Categorized sustainability $(S_e)_{new}$	b_e	Overall sustainability $(S_o)_{new}$
$x_{e,1}$	462.9	0.951	0.60	0.960	1.00	0.906
$x_{e,2}$	190.9	0.974	0.40			
ENV indicators	Input data (dimensional)	Normalized value ($\tilde{x}_{v,i}$)	$\beta_{v,i}$	Categorized sustainability $(S_v)_{new}$	b_v	
$x_{v,1}$	0.833	0.833	0.65	0.821	0.90	
$x_{v,2}$	0.201	0.799	0.35			
SOC indicators	Input data (dimensional)	Normalized value ($\tilde{x}_{l,i}$)	$\gamma_{l,i}$	Categorized sustainability $(S_l)_{new}$	b_l	
$x_{l,1}$	23.18	0.927	0.91	0.922	1.10	
$x_{l,2}$	0.124	0.876	0.09			

4.3 Chapter Summary

A fuzzy-logic-based Triple-A Template embedded methodology has been introduced for sustainability enhancement in this section. The methodology can be used to conduct sustainability studies on industrial problems of any size in a systematic way, where uncertainties associated with the problem can be effectively processed. The problem solving procedure, through system assessment, analysis, and action, can characterize the system thoroughly, identify root causes deeply, and derive solutions conveniently and reasonably. The methodological efficacy has been successfully demonstrated through studying a complicated industrial zone problem. This methodology can be further enhanced by integrating more domain and heuristic knowledge.

CHAPTER 5

SUSTAINABILITY GOAL ORIENTED DECISION MAKING VIA MONTE CARLO BASED SIMULATION AND SYSTEM OPTIMIZATION

Sustainability, in the most general sense, is the capacity to maintain a certain process or state indefinitely. As applied to the human community, "sustainable development is development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (WCED, 1987). The economic, environmental and social aspects are normally accepted as the triple bottom lines for industrial sustainability evaluation.

Industrial sustainability is pursued by people to achieve the long-term sustainable development (SD) of a given industrial zone defined as a geographic area comprised of a network of industrial sectors, each composed of a number of entities. In practice, decisions and strategies for sustainable development must be made, reviewed, and assessed by industrial planners, business leaders, and involving communities from time to time.

However, industrial sustainability problems are always difficult to be fully investigated and further optimized, because of the large size and scope that carries highly complexness, and inevitable uncertainties that are associated with data, information, and knowledge. Therefore, most known studies on sustainability decision-making are scenario based, where the degrees of sustainability of the scenarios as well as the decisions are compared, and then the best scenario associated with decisions are selected (Piluso and Huang, 2008). This type of decision-making approach heavily relies on the identified scenarios, and decision-making is always a heuristic based. Moreover, no uncertainties are being considered in making decisions, which is inconsistent with the real situation.

A well-structured industrial zone is highly integrated by different functional sectors， and more thoroughly, the entities within each sector. In the supply chain point of view, each sector or entity extreme dependents on its suppliers and customers throughout the product. Thus, a good development decision must be made by considering and coordinating the zone, sectors and entities and improving their performance in terms of economic, environmental and social aspects. This requires the industrial decision makers to possess system-wide analysis abilities. Moreover, the optimal decisions are forever expected in terms of the decision's cause-effect efficiency, which asks for systematic optimization in making decisions.

Another key issue in making the sustainability development decisions is the inevitable uncertainties. Due to the imperfect understanding of the data, information and knowledge about the history of the zone, and more critical, its future trends, many types of uncertainties are challenging the decision making for an industrial zone. Many methods regarding how to handle these various types of uncertainties currently exist, which include techniques that are fuzzy logic, artificial intelligence, or statistical based (Ayyub and Gupta 1997, Graham 1988, Zimmermann 1991). Despite the numerous types of inherent uncertainties that exist and methods to handle these uncertainties, this work strictly focuses on the uncertainties in future zone planning and a Monte Carlo based approach will be used to evaluate the sustainable development of an industrial zone among these uncertainties. Examples of uncertainties that arise in future zone planning include uncertain market demand, uncertain price of the product, uncertain cost of the raw materials, uncertain efficient on technologies improvements, etc.

In this work, an approach consisting of both the system optimization and Monte Carlo based simulation is introduced to guide the decision-making process for more effectively identifying solutions of sustainability improvement. The main advantage of this approach is its capability of identifying optimal choice effectively with the consideration of system uncertainties. The efficacy of the proposed approach is illustrated through analyzing the sustainability issues and developing strategies for enhancing the sustainability of an automotive manufacturing centered industrial zone.

5. 1 Decision Making Framework

A typical scenario based sustainability decision-making methodology was proposed by Piluso *et al.* (2008). Extended from the existing Ecological Input-Output (EIO) Analysis (Leontief, 1936), this systematic methodology is capable to quantitatively evaluate various sustainable development decisions for a given industrial zone. The general scheme of the extended EIO-based SD decision-analysis can be demonstrated in Fig. 5.1. Defining each entity of the given industrial zone in the way of basic elements of input-output flow analysis (see, Fig. 5.1(a), where the raw material input to entity i is denoted as z_{i0}, the intermodal flows from entity j to entity i are symbolized as $f_{i,j}$, and the streams that run from entity i to the environment are denoted as $y_{w,0i}$ for a waste and $y_{p,0i}$ for a product stream, respectively.), such the system information are imported to the EIOA module for detailed analysis.

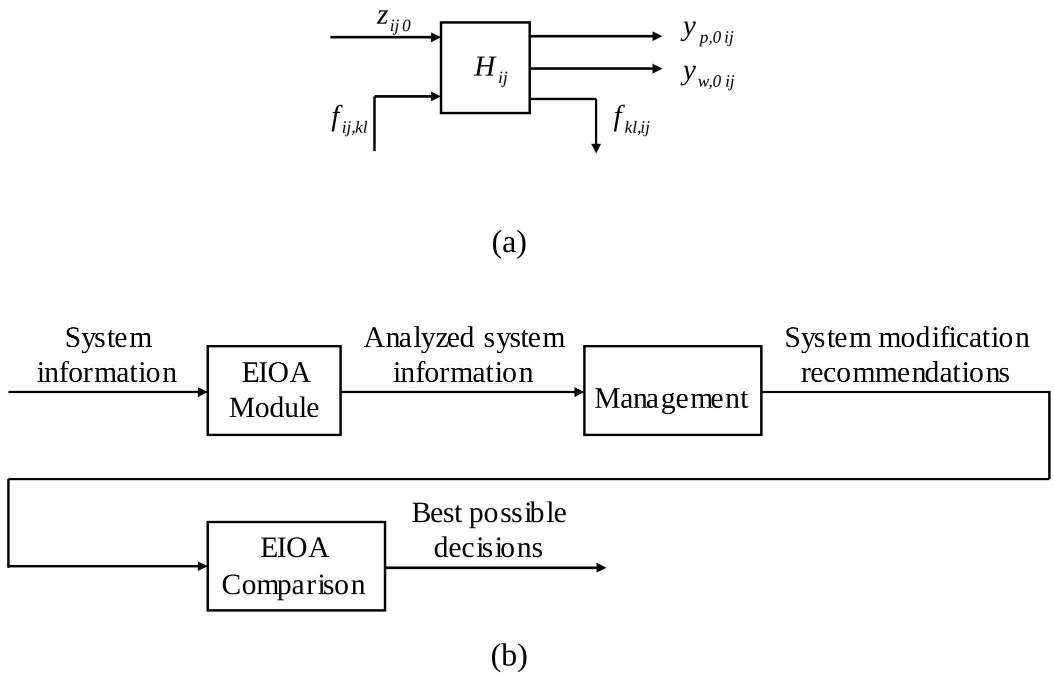


Figure 5.1. General scheme of the extended EIO-based SD decision-analysis: (a) basic elements of input-output flow analysis of i-th entity of a given industrial zone, and (b) general scheme of the extended EIO-based SD decision-analysis.

Within the EIOA module, the system production matrix is first generated, then the throughout flow of each node is calculated. After that, a creaon inflow analysis (Bailey *et al*. 2004) is applied to obtain the instantaneous fractional inflow matrix and the transitive closure inflow matrix, which accounts for all direct and indirect nodal inter-relationships. Finally, the input environ of the system, which represents the amount of inflow, internodal and intranodal flow, and throughflow needed to support a unit of outflow from each node, is derived and further exported as the analyzed system information out of the EIOA module.

By checking those analyzed system information, potential modifications are able to be suggested through the management function for achieving possible sustainability improvement of the given industrial zone. In the last step of the Extended EIO-based SD decision-analysis, which is also the most characteristic part as a typical scenario based approach, various system modification scenarios (with either one potential modification or a combination of several potential modifications) are proposed, then the degrees of sustainability of the scenarios as well as the decisions are compared, and the best scenario associated with decisions are selected as the best possible decisions.

Such the Extended EIO-based SD decision-analysis is capable to provide sustainable development decisions. However, this methodology has some functional limitations heavily restricting its application on the industrial practice: (i) the methodology heavily relies on the identified scenarios. Due to the limited ability in generating scenarios, the final best possible decisions are always heuristic based, and more important, far from optimal. (ii) the methodology does not reflect the decision's cause-effect efficiency, which is critical in industrial practice. In reality, no matter how good the decision's effect is, if its implementation must with too much money investment, then the decision cannot be acceptable. (iii) there is no uncertainty being considered in making decisions, which is inconsistent with the real situation.

In summary, there is a need to extend the EIO-based SD decision-analysis by considering decision's cause-effect efficiency, uncertainties with the sustainability, and obtaining the best possible optimal decisions. Thus, a new methodology consisting of both the system optimization and Monte Carlo based simulation is introduced to guide the decision-making process for more effectively identifying solutions of sustainability improvement. The details of the new methodology will be given in the following sections.

The basic algorithm of the proposed approach is structured in the following way (see, Fig. 5.2). First, the Extended EIO-based SD decision-analysis is borrowed to obtain the potential modification options for achieving possible sustainability improvement of the given industrial zone. Second, an industrial sustainability is described as a system optimization problem, whose objective function is the overall sustainability criteria of the whole system, and constraints are those subjected by the system's characteristic and budget limits. Third, a Genetic Algorithm approach is implemented to solve the optimization problem (Tillman *et al.*, 1977). The local optimal solutions obtained from Genetic Algorithm approach will be recorded as candidates for further uncertainty analysis. Fourth, uncertainties are introduced into the system by changing the properties of some system parameters from constants to their corresponding domains of possible values. In the next step, Monte Carlo simulation is applied to recheck the sustainability performance of each candidate under the introduced uncertainties. Finally, the best possible decisions will be readily identified from the candidate solutions through aggregating the results of each individual Monte Carlo sample for a result.

Since the details of Extended EIO-based SD decision-analysis can be found in Piluso and Huang (2008), this step for obtaining the potential modifications will not be discussed in this chapter, and the potential modifications are assumed to be obtained already. In order to illustrate the methodology clearly, several basic concepts will be first described, and the rest steps of the proposed methodology will be given in detail later.

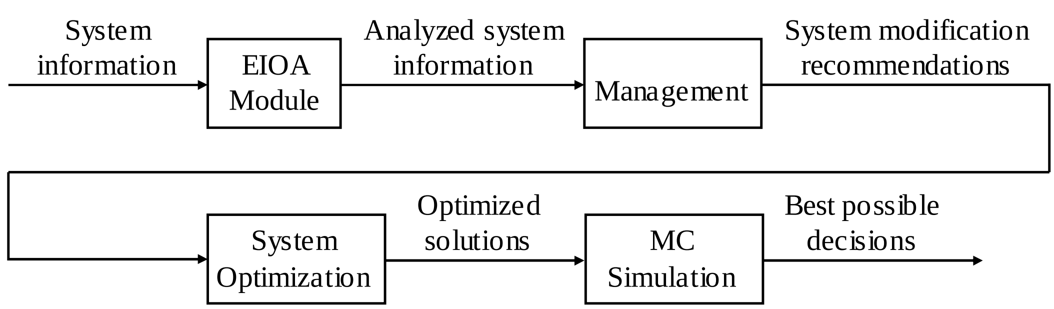


Figure 5.2. General scheme of the SD decision-making via Monte Carlo based simulation and system optimization.

5.1.1 Industrial zone modeling

An SD decision-making problem is to design SD decision-making approaches that help people determine the strategies for effectively improving the sustainability performance of an industrial zone defined as a geographic area comprised of a network of industrial sectors, each composed of a number of entities. An industrial zone can be defined as follows:

$$Z = \left\{ H_i \mid i = 1,2,\cdots,I \right\} \tag{5.1}$$

Where I is the total number of the plants in zone Z. For each plant H_{ij}, it is defined as basic elements of input-output flow analysis described in Fig. 5.1(a), where the raw material input to entity i is denoted as z_{i0}, the intermodal flows from entity j to entity i are symbolized as $f_{i,j}$, and the streams that run from entity i to the environment are denoted as $y_{w,0i}$ for a waste and $y_{p,0i}$ for a product stream, respectively. Furthermore, all the raw material input, intermodal flows, and the out streams are called zone states, and the total zone state vector, $\boldsymbol{X}$, can be defined as:

$$\boldsymbol{X} = \left(z_{110}, \cdots, z_{IN_I}, f_{11,11}, \cdots, f_{IN_I,IN_I}, y_{w,011}, \cdots, y_{w,0IN_I}, y_{p,011}, \cdots, y_{p,0IN_I} \right)^T \tag{5.2}$$

Sustainability Assessment Based on Zone States. In discussing sustainability problems, one of the key and most arguable issues is how to quantify the sustainability of the interested system. Although there are different assessment indicator systems, a common agreement is that a system's sustainably can be well assessed by checking its economic, environmental, and social aspects. Based on this triple-bottom-line concept, a simple and direct sustainability quantification approach is introduced as follows. First, the overall sustainability of an interested system (G_{sys}), is defined as a combination of its economic indicator (G_{sys}^{eco}), environmental indicator (G_{sys}^{env}), and social indicator (G_{sys}^{socl}). i.e.,

$$G_{sys} = f_{sys}\left(G_{sys}^{eco}, G_{sys}^{env}, G_{sys}^{socl} \right) \tag{5.3}$$

Note that the interested system can be the entire industrial zone or any sector/entity of the zone. Furthermore, a perspicuous sustainability quantifier, sustainability cube, is introduced with the general function of Eq. 5.3 takes the specific expression defined in Eq. 5.4.

$$G_{sys} = \frac{1}{\sqrt{3}} \left\| \left(\overline{G}_{sys}^{eco}, \overline{G}_{sys}^{env}, \overline{G}_{sys}^{socl} \right) \right\| \tag{5.4}$$

where $\overline{G}_{sys}^{eco}$, $\overline{G}_{sys}^{env}$, and $\overline{G}_{sys}^{socl}$ are the normalized economic, environmental and social indicators respectively, whose values are restricted within the range from 0 to 1. Such a sustainability cube can be visually displayed in Fig. 5.3, whose left-bottom corner is defined as the origin of the interested system, where indicates the situation of no sustainability. On the contrary, the right-upper corner of the cube has the maximum indicator values of the triple-bottom-lines, where represents the best optimal sustainability of the system. At any given time stage, t, the sustainability of the interested system, $G_{sys}(t)$, can be identified in the cube (see the black dot) according to its indicator values of the triple-bottom-lines.

Second, each of these triple main indicators in Eq. 5.3 can be obtained by grouping several sub-indicators in their categories, i.e.,

$$G_{sys}^{eco} = f_{sys}^{eco}\left(G_{sys}^{eco,1}, \cdots, G_{sys}^{eco,N_{eco}}\right) \tag{5.5}$$

$$G_{sys}^{env} = f_{sys}^{env}\left(G_{sys}^{env,1}, \cdots, G_{sys}^{env,N_{env}}\right) \tag{5.6}$$

$$G_{sys}^{socl} = f_{sys}^{socl}\left(G_{sys}^{socl,1}, \cdots, G_{sys}^{socl,N_{socl}}\right) \tag{5.7}$$

where N_{eco}, N_{env}, and N_{socl} are the total numbers of the sub-economic indicators, the sub-environmental indicators, and the sub-social indicators, respectively.

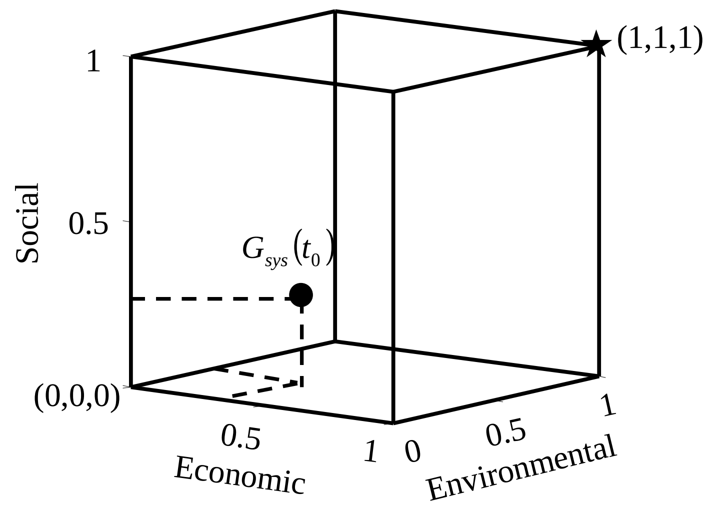


Figure 5.3. Conceptual illustration of a sustainability cube.

Finally, each of the sub-indicator can be calculate by using the zone states, i.e.,

$$G_{sys}^{eco,i} = f_{sys}^{eco,i}(\boldsymbol{X}), \quad i = 1, 2, \cdots, N_{eco} \tag{5.8}$$

$$G_{sys}^{env,j} = f_{sys}^{env,j}(\boldsymbol{X}), \quad j = 1, 2, \cdots, N_{env} \tag{5.9}$$

$$G_{sys}^{socl,k} = f_{sys}^{socl,k}(\boldsymbol{X}), \quad k = 1, 2, \cdots, N_{socl} \tag{5.10}$$

From Eqs. 5.3 through 5.10, the overall sustainability is essentially related to the zone states:

$$G_{sys} = g_{sys}(\boldsymbol{X}) \tag{5.11}$$

Such the sustainability assessment is general. Thus, it can be applied at any specific time stage for quantifying the sustainability of any interested system.

Zone State Transition Equations and Decision Based Cause-Effect

Relationship. The essential of the sustainable development of an industrial zone is the effective and efficient zone state transition from one time stage to the other due to the efforts put into the zone. The efforts can be substantial (for instance, investment) or non-substantial (for instance, new policy force). In this point of view, the decisions need to be made are the determination of what kind of efforts should be given, and how much for each given effort. Therefore, two issues must be addressed here for understanding the relationship between decision efforts and the improvements of sustainability, (i) zone state transitions, and (ii) decision based cause-effect.

The equations of zone state transition gives the state transition rule from current time stage to the final time stage. Normally, a general state transition equation has the following discretized expression:

$$\boldsymbol{X}(t_0) = \boldsymbol{X}(t_0) + \varDelta\boldsymbol{X}(t_0) \tag{5.12}$$

where $\boldsymbol{X}(t_0)$ is the zone state vector at time t_0, $\Delta\boldsymbol{X}(t_0)$ the transfer term of the zone state vector from time t_0 to time t_e. Therefore, knowing the zone states at one time stage, finding the next time stage zone states is equal to finding the transfer term of the zone state vector at this time stage, which can be obtained through the decision based cause-effect analysis.

Decision based cause-effect relationship illustrates the quantitative relations between the efforts and their effects to the zone states, which has the following expression:

$$\Delta\boldsymbol{X}^i(t_0) = f_{u^i}\left(\boldsymbol{X}(t_0), u^i(t_0)\right), \quad i = 1, 2, \cdots, N_{eff} \tag{5.13}$$

$$\Delta \boldsymbol{X}(t_0) = f_X\left(\Delta \boldsymbol{X}^1(t_0), \cdots, \Delta \boldsymbol{X}^{N_{eff}}(t_0)\right) \tag{5.14}$$

where $u^i(t_0)$ is the i-th type of effort, N_{eff} the total number of different types of efforts, and $\Delta \boldsymbol{X}^i(t_0)$ is the improving amount of the directly affected zone state vector due to the i-th type of effort.

From Eqs. 5.12 through 5.14, the general state transition equation can be expressed as:

$$\boldsymbol{X}(t_e) = g_X\left(\boldsymbol{X}(t_0), u^1(t_0), \cdots, u^{N_{eff}}(t_0)\right) \tag{5.15}$$

Furthermore, the following relationship can be obtained based on Eqs. 5.10 and 5.14:

$$G_{sys}(t_e) = f_{sys}^X\left(\boldsymbol{X}(t_0), u^1(t_0), \cdots, u^{N_{eff}}(t_0)\right) \tag{5.16}$$

5.1.2 System optimization for obtaining sustainable development options

The goal of a general SD decision-making is to pursue the maximum sustainability performance in the future under limited amount of efforts and other kinds of constraints. Having the industrial zone model, sustainability assessment, zone state transition equations and decision based cause-effect relationship, an industrial zone based SD decision-making after pre-EIO-based analysis can be further specified as follows: given different types of effort options and certain limited amount of the total effort, what's the best possible future sustainability of the whole industrial zone can be obtained without hurting the sustainability benefits of any entity within the zone, and what kind of effort distribution on each option should be? In the systematic analysis point of view, such an industrial zone based SD decision-making can be studied by the following system optimization.

$$J = \underset{u^i(t_0),\, i=1,\cdots,\, N_{eff}}{Max} \quad G_{zone}(t_e) \tag{5.17}$$

$$s.t. \quad E(t_0) = f\left(u^1, \cdots, u^{N_{eff}}\right) \le \left(E(t_0)\right)_{\mathbf{max}} \tag{5.18}$$

$$0 \le u^i(t_0) \le \left(u^i(t_0)\right)_{\mathbf{max}}, \quad i = 1, 2, \cdots, N_{eff} \tag{5.19}$$

$$G_{zone}^{eco}(t_e) \ge G_{zone}^{eco}(t_0), \quad G_{zone}^{env}(t_e) \ge G_{zone}^{env}(t_0), \quad G_{zone}^{socl}(t_e) \ge G_{zone}^{socl}(t_0) \tag{5.20}$$

$$G_i^{eco}(t_e) \ge G_i^{eco}(t_0), \quad G_i^{env}(t_e) \ge G_i^{env}(t_0), \quad G_i^{socl}(t_e) \ge G_i^{socl}(t_0), \quad i = 1, 2, \cdots, I \tag{5.21}$$

where $G_{zone}(t_e)$ is the sustainability of the whole industrial zone in the future which takes the expression in Eq. 5.4, $E(t_0)$ is defined as the total effort at the current time stage combined by each effort option, $\left(E(t_0)\right)_{max}$ is the upper-limit of the total effort, and $\left(u^i(t_0)\right)_{max}$ is the upper-limit of the i-th effort option.

In the above optimization, the objective function (see, Eq. 5.17) is to find the maximum sustainability of the entire industrial zone in the future, and the adjustable variables are the efforts spent on different options. Moreover, the optimization should subject to the constraints on both the effort limits and the SD development requirements. These are, on one hand, the total available efforts and the effort available on each individual option are all limited (see, Eqs. 5.18 and 5.19), and on the other hand, the future sustainability in terms of the triple-bottom-lines should be better or at least equal to the current situation for not only the whole industrial zone (see, Eq. 5.20), but also each individual entity (see, Eq. 5.21).

Due to the multi-factors within the optimization, it frequently results in non-linear optimization problems. Therefore, the Genetic Algorithm, which is effective for solving non-linear optimization, will be applied in this study **(**Ruszczyński 2006, Bartholomew and Michael 2005). The detailed steps for applying the Genetic Algorithm can be easily found in many of the literatures. The results obtained will be numbers of local optimal value sets for both the objective function and the corresponding adjustable variables (see, Eq. 5.22).

$$Set\ n = \begin{Bmatrix} G^{*}_{zone,\,n}(t_e) \\ u^{i*}_{n}(t_0) \end{Bmatrix}, \quad n = 1, 2, \cdots, N_{GA}, \quad i = 1, 2, \cdots, N_{eff} \tag{5.22}$$

where N_{GA} is the total number of local optimal results from the Genetic Algorithm, $G^{*}_{zone}(t_e)$ represents the n-th set local maximum sustainability of the whole industrial zone at next time stage, and $u^{i*}_{n}(t_0)$ is the n-th set local optimal effort distributed on the i-th option. Finally, as the output information from the system optimization step, these local optimal solutions will be recorded as decision candidates for further uncertainty analysis in the next Monte Carlo based simulation.

5.1.3 Monte Carlo based simulation for handling stochastic uncertainties

After system optimization, numbers of local optimal SD decisions are obtained.

However, there is no uncertainty considered in obtaining these solutions, which is inconsistent with the real situation. In order to make the SD decision-making study more consistent with the real, uncertainties will be further introduced into the system and Monte Carlo based simulation will be applied to recheck the sustainability performance of each candidate under the introduced uncertainties. Note that, this work strictly focuses on the uncertainties in future zone planning, which relates to the uncertain market demand, uncertain price of the product, uncertain cost of the raw materials, uncertain efficiency on technologies improvements, etc.

To introduce uncertainties into the system, the properties of related system parameters are changed from constants to the domains of possible values. For instance, a system parameter, the price of product A should be changed from \$100/lb to an uncertain value within the domain from \$80/lb to \$120/lb.

With the uncertainties introduced, the SD decision-making becomes infeasible for handling with deterministic system engineering techniques. Thus, Monte Carlo methods that rely on repeated random sampling to obtain computational results is applied to recheck the sustainability performance of each candidate under the introduced uncertainties **(**Malvin and Paula 2008, Gentle 1998**).** In detail, a four-step procedure is implemented as follows:

Step 1. Define domains of possible parameter values.

Step 2. Generate parameter values randomly from the domains, and perform a deterministic computation to obtain the total sustainability for each decision candidates recorded in system optimization.

Step 3. Sort the decision candidates based on their total sustainability status obtained in *Step 2*. Note that *Step 2* and *3* should be repeated for enough numbers of times to obtain various random sample results.

Step 4. Aggregate the results of the individual computations for a final result according to the sorting.

Finally, the decision candidate solution with the best aggregating results will be selected as the best possible SD decisions of the given industrial zone, and the average future sustainability will be calculated through all the random samples as the prediction for the future. This kind of Monte Carlo based simulation embodies uncertainties in making decisions by checking a large number of random samples with different uncertainty combinations and taking aggregated results from them, therefore, makes the SD decision making much more consistent with the real situation

5.1.4 Decision making with non-equal weights on triple bottom lines

The general industrial sustainability decision-making methodology via Monte Carlo based simulation and system optimization is fully demonstrated in 3.1 through 3.4. In the system optimization step, the objective function (see, Eq. 5.17) is to find the maximum sustainability of the whole industrial zone in the future, and the zone based sustainability takes the expression in Eq. 5.4 with *sys* = *zone*.

$$G_{zone} = \frac{1}{\sqrt{3}} \left\| \left(\overline{G}_{zone}^{eco}, \overline{G}_{zone}^{env}, \overline{G}_{zone}^{socl} \right) \right\| \tag{5.23}$$

This sustainability quantifier gives equal emphasis on each aspect of the triple-bottom-lines, therefore, can be directly illustrated by using the conceptual tool of sustainability cube. On one hand, putting equal emphasis on the triple-bottom-lines is the simplest way and most frequently being applied in making decisions. However, non-equal emphasis on each aspect of the triple-bottom-lines also should be considered when the SD decision makers prefer more benefits on one (or two) aspect of the triple-bottom-lines.

Equation 5.4 can be further expended as:

$$G_{sys} = \frac{1}{\sqrt{3}}\left(\left(\overline{G}_{sys}^{eco}\right)^2 + \left(\overline{G}_{sys}^{env}\right)^2 + \left(\overline{G}_{sys}^{socl}\right)^2\right)^{\frac{1}{2}} \tag{5.24}$$

which is substantively a simplified case from Eq. 5.25 when α, β and γ are 1.

$$G_{sys} = \frac{1}{\sqrt{3}}\left(\alpha\left(\overline{G}_{sys}^{eco}\right)^2 + \beta\left(\overline{G}_{sys}^{env}\right)^2 + \gamma\left(\overline{G}_{sys}^{socl}\right)^2\right)^{\frac{1}{2}} \tag{5.25}$$

Thus, if these 3 parameters take different values, a non-equal preference on each aspect of the triple-bottom-lines can be realized. For instance, an SD decision maker may select $\alpha = 5$, $\beta = 2$ and $\gamma = 1$ to purse more economic and environmental benefits than the social benefits in the future.

5.1.5 Target driven decision making

The decision-making methodology introduced in 3.1 through 3.5 are all effort oriented, i.e., given different types of effort options and certain limited amount of the total effort, find the best possible future sustainability of the whole industrial zone under uncertainties and the corresponding effort distribution on each option. On the other hand, there is also a need to consider the SD decision-making in a target-driven way, i.e., known different types of effort options and a pre-set future sustainability goal of the whole industrial zone, determine the total effort which should be implemented for achieving such the pre-set future sustainability goal under uncertainties, and the corresponding effort distribution on each option.

To analyze such the target-driven decision-making problem, the general methodology via Monte Carlo based simulation and system optimization is implemented under a kind of trial and error guidance as follows:

Step 1. Set the future sustainability goal of the entire industrial zone.

Step 2. Make a guess on the total effort, and use it to fulfill the system optimization and Monte Carlo based simulation to obtain the best possible future sustainability of the entire industrial zone under uncertainties, and the corresponding effort distribution on each option.

Step 3. If the best possible future sustainability obtained in *Step 2* is lower than the future sustainability goal set in *Step 1*, *Step 2* will be repeated with a higher total effort. On the contrary, if the best possible future sustainability obtained in *Step 2* is higher than the future sustainability goal set in *Step 1*, *Step 2* will be repeated with a lower total effort.

Note that *Step 2* and *Step 3* should be repeated until obtaining a best possible future sustainability within the acceptable region around the goal set in *Step 1*. Then the final best possible future sustainability results and the corresponding effort distribution on each option will be selected as the target-driven decision solutions.

5.2 Case Study

To demonstrate the efficacy of proposed SD decision-making methodology via Monte Carlo based simulation and system optimization, a case study on sustainability improvement of a surface finishing centered industrial system is given below. The industrial problem has three manufacturing sectors: the chemical supply sector of two chemical solvent plants, the surface finishing sector of two electroplating plants, and the automotive sector of two OEM plants (see, Fig. 5.4), which gives $I = 6$ in Eq. 5.1. Moreover, the values of zone states at the current time stage and the system parameters (in terms of the economic flow value of zone states) are listed in Table 5.1.

According to Piluso and Huang (2008), four types of potential technology modifications (N_{eff} = 4 in Eqs. 5.13 through 5.19) are suggested after the extended EIO-based decision-making analysis for improving the sustainability of the surface finishing centered industrial system.

Modification 1: Plating shop 1 (H_3) enhances its in-plant zinc recycling technologies, thereby improving internal recycle capabilities (see, $f_{3,3}^{Zn}$ in Fig. 5.4).

Modification 2: Plating shop 2 (H_4) enhances its in-plant zinc recycling technologies, thereby improving internal recycle capabilities (see, $f_{4,4}^{Zn}$ in Fig. 5.4).

Modification 3: OEM 1 (H_5) improves plant efficiency, thereby improving its recycle back to both plating companies (see, $f_{3,5}^{Zn}$ and $f_{4,5}^{Zn}$ in Fig. 5.4).

Modification 4: Chemical supplier 2 (H_3) improves process efficiency and thus reduces its waste generation (see, $y_{w,3}^{Zn}$ in Fig. 5.4).

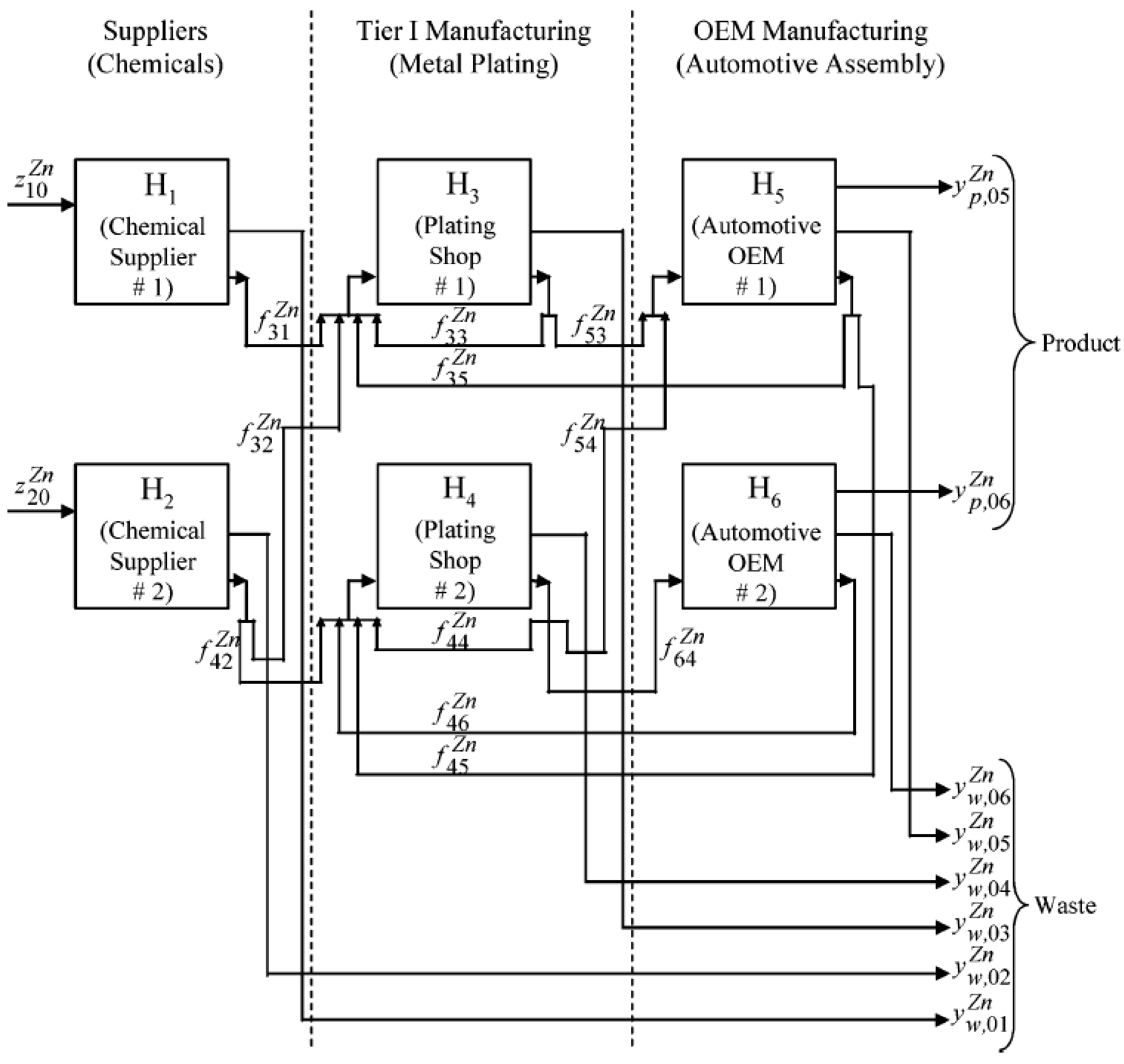


Figure 5.4. Schematic diagram of the zone states used in the component-based surface finishing centered industrial system.

Table 5.1. Values of zone states at the current time stage.

Variable	Zone State Value ($\times 10^3$ lbs/yr)	Economic flow value of zone state ($/lb)
z_{10}^{Zn}	50.00	0.58
z_{20}^{Zn}	70.00	0.55
$f_{3,1}^{Zn}$	46.50	0.89
$f_{3,2}^{Zn}$	27.72	0.88
$f_{4,2}^{Zn}$	33.88	0.88
$f_{3,3}^{Zn}$	4.04	0.40
$f_{4,4}^{Zn}$	4.03	0.45
$f_{5,3}^{Zn}$	68.75	2.93
$f_{3,5}^{Zn}$	2.61	0.35
$f_{5,4}^{Zn}$	18.37	2.51
$f_{4,5}^{Zn}$	1.74	0.37
$f_{6,4}^{Zn}$	15.03	2.51
$f_{4,6}^{Zn}$	0.60	0.42
$y_{w,01}^{Zn}$	3.50	0.25
$y_{w,02}^{Zn}$	8.40	0.27
$y_{w,03}^{Zn}$	8.09	0.29
$y_{w,04}^{Zn}$	2.82	0.29
$y_{w,05}^{Zn}$	4.36	0.35
$y_{w,06}^{Zn}$	0.60	0.35
$y_{p,05}^{Zn}$	78.41	5.93
$y_{p,06}^{Zn}$	13.83	2.93

The general triple-bottom-line-based sustainability quantification approach introduced in Eqs. 5.3 through 5.11 is applied in this case study, and the conceptual sustainability cube is used to demonstrate the situation of the surface finishing centered industrial system. In simplicity, the economic indicator, environmental indicator, and social indicator of the studied system are all specified as only one single sub-indicator:

(i) Economic indicator: narrowly defined total profit

$$G_{sys}^{eco} = \sum \text{revenue from product} - \sum \text{cost of raw material} - \sum \text{cost of waste treatment} \tag{5.26}$$

(ii) Environmental indicator: mass intensity

$$G_{sys}^{env} = \frac{\sum \text{product}}{\sum \text{raw material}} \tag{5.27}$$

(iii) Social indicator: collaboration through recycle and reuse

$$G_{sys}^{socl} = \sum \text{mass recycle and reuse} \tag{5.28}$$

With these triple-bottom-line indicators and the zone state data, the overall sustainability of the interested system (which can be the whole surface finishing centered industrial system or any of the six plants within it) at any interested time stage is able to be quantified by using Eq. 5.4 and displayed in the sustainability cube. For instance, with the current zone state data in table 5.1, the current sustainability of the whole surface finishing centered industrial system and the six plants are obtained and listed in Table 5.2.

The effort options in this case study are the investment on the four types of potential technology modifications at the current time stage marked as:

$$u^i(t_0), \quad i = 1, \cdots, 4 \tag{5.29}$$

where $u^1(t_0)$ is the investment on improving the internal zinc recycle capabilities ($f_{3,3}^{Zn}$)

of plating shops 1, $u^2(t_0)$ is the investment on improving the internal zinc recycle capabilities ($f_{4,4}^{Zn}$) of plating shops 2, $u^3(t_0)$ is the investment on improving the zinc recycle ($f_{3,5}^{Zn}$ and $f_{4,5}^{Zn}$) of OEM 1 back to both plating companies, and $u^4(t_0)$ is the investment on reducing waste generation ($y_{w,3}^{Zn}$) of chemical supplier 2.

Table 5.2. Current sustainability
of the surface finishing centered industrial system.

Interested System	$G_{sys}^{eco}(t_0)$	$G_{sys}^{env}(t_0)$	$G_{sys}^{socl}(t_0)$	$G_{sys}(t_0)$
Z	0.877	0.769	0.592	0.755
H_1	0.835	0.930	0	0.722
H_2	0.784	0.880	0	0.681
H_3	0.857	0.850	0.505	0.753
H_4	0.873	0.830	0.668	0.759
H_5	0.847	0.900	0.685	0.816
H_6	0.656	0.920	0.882	0.828

Furthermore, all these four effort options are assumed to have the following logarithmic effect at the end time stage, t_e :

$$\Delta f_{3,3}^{Zn,1}(t_e) = log\left(\frac{9u^1(t_0)}{\left(u^1(t_0)\right)_{max}} + 1\right)\left(\Delta f_{3,3}^{Zn,1}(t_e)\right)_{max} \tag{5.30}$$

$$\Delta f_{4,4}^{Zn,2}(t_e) = log\left(\frac{9u^2(t_0)}{\left(u^2(t_0)\right)_{max}} + 1\right)\left(\Delta f_{4,4}^{Zn,2}(t_e)\right)_{max} \tag{5.31}$$

$$\Delta f_{3,5}^{Zn,3}(t_e) = log\left(\frac{9u^3(t_0)}{\left(u^3(t_0)\right)_{max}} + 1\right)\left(\Delta f_{3,5}^{Zn,3}(t_e)\right)_{max} \tag{5.32}$$

$$\Delta f_{4,5}^{Zn,3}(t_e) = log\left(\frac{9u^3(t_0)}{\left(u^3(t_0)\right)_{max}} + 1\right)\left(\Delta f_{4,5}^{Zn,3}(t_e)\right)_{max} \quad (5.33)$$

$$\Delta y_{w,2}^{Zn,4}(t_e) = log\left(\frac{9u^4(t_0)}{\left(u^4(t_0)\right)_{max}} + 1\right)\left(\Delta y_{w,2}^{Zn,4}(t_e)\right)_{max} \quad (5.34)$$

where $\left(\Delta f_{3,3}^{Zn,1}(t_e)\right)_{max}$ = 4×10^3 lbs/yr, $\left(\Delta f_{4,4}^{Zn,2}(t_e)\right)_{max}$ = 4×10^3 lbs/yr, $\left(\Delta f_{3,5}^{Zn,3}(t_e)\right)_{max}$ = 1.2×10^3 lbs/yr, $\left(\Delta f_{4,5}^{Zn,3}(t_e)\right)_{max}$ = 0.8×10^3 lbs/yr, and $\left(\Delta y_{w,2}^{Zn,4}(t_e)\right)_{max}$ = 4.2×10^3 lbs/yr are the technology upper limits corresponding to each option's improving effect, and $\left(u^1(t_0)\right)_{max}$ = \$500 K, $\left(u^2(t_0)\right)_{max}$ = \$750 K, $\left(u^3(t_0)\right)_{max}$ = \$900 K, and $\left(u^4(t_0)\right)_{max}$ = \$1000 K thousand are the investments needed on each option for obtaining the maximum technology improving effects.

Equations 5.30 through 5.34 provide the quantitative relations between each effort option and its effect(s) to the directly affected zone states (which is generally defined in Eq. 5.13). Based on the mass balance principle, their effects to the indirectly affected zone states (see, Eq. 5.14) can be determined. Furthermore, the new zone states can be obtained by using Eq. 5.12, and finally, the new sustainability of the whole surface finishing centered industrial system or any of the six plants within it are able to be quantified by using Eqs. 5.16 and 5.26 through 5.28.

5.2.1 System optimization

Knowing the system information and the potential modification options, the proposed methodology can help the manager of such the surface finishing centered industrial system achieve the best possible future sustainability under certain amount of budget limits. For instance, if the total available budget for applying four effort options is half million dollars, then the following system optimization can be designed according to the general expression given in Eqs. 5.17 to 5.21.

$$J = \underset{u^i(t_0),\, i=1,\cdots,4}{Max} \; G_{zone}(t_e) \tag{5.35}$$

$$s.t. \quad \sum_{i=1}^{4} u^i(t_0) \le 5\times10^5 \tag{5.36}$$

$$0 \le u^1(t_0) \le 5\times10^5,\ \ 0 \le u^2(t_0) \le 7.5\times10^5,\ \ 0 \le u^3(t_0) \le 9\times10^5,$$

$$0 \le u^4(t_0) \le 1\times10^6 \tag{5.37}$$

$$G_{zone}^{eco}(t_e) \ge 0.877, \quad G_{zone}^{env}(t_e) \ge 0.769, \quad G_{zone}^{socl}(t_e) \ge 0.592 \tag{5.38}$$

$$\begin{aligned}
&G_1^{eco}(t_e) \ge 0.835, \quad G_1^{env}(t_e) \ge 0.930, \quad G_1^{socl}(t_e) \ge 0, \\
&G_2^{eco}(t_e) \ge 0.784, \quad G_2^{env}(t_e) \ge 0.880, \quad G_2^{socl}(t_e) \ge 0, \\
&G_3^{eco}(t_e) \ge 0.857, \quad G_3^{env}(t_e) \ge 0.850, \quad G_3^{socl}(t_e) \ge 0.505, \\
&G_4^{eco}(t_e) \ge 0.873, \quad G_4^{env}(t_e) \ge 0.830, \quad G_4^{socl}(t_e) \ge 0.668, \\
&G_5^{eco}(t_e) \ge 0.847, \quad G_5^{env}(t_e) \ge 0.900, \quad G_5^{socl}(t_e) \ge 0.685, \\
&G_6^{eco}(t_e) \ge 0.656, \quad G_6^{env}(t_e) \ge 0.920, \quad G_6^{socl}(t_e) \ge 0.882
\end{aligned} \tag{5.39}$$

In the above optimization, the objective function (see, Eq. 5.35) is to find the maximum sustainability of the entire industrial zone in the future (note that each aspect of the triple-bottom-lines has an equal emphasis here), and the adjustable variables are the budget spent on four potential options. Moreover, the total available budget and the budget applicable on each individual option are all limited (see, Eqs. 5.36 and 5.37). On the other hand, the future sustainability in terms of the triple-bottom-lines should be better or at least equal to the current situation for not only the whole industrial zone (see, Eq. 5.38), but also each of the six plants (see, Eq. 5.39).

To solve this non-linear programming, the Genetic Algorithm is applied which takes 100 total generations in each operation and 100 populations in each generation. Finally, 10 local optimal cases (i.e., $N_{GA}=10$ in Eq. 5.22) are obtained and their optimal value set information corresponding to Eq. 5.22 are all given in Table 5.3.

Table 5.3. System optimization results solved by using Genetic Algorithm.

Case	Optimal Budget Distribution ($\times 10^3$ \$)				Future Sustainability			
	$u^{1*}(t_0)$	$u^{2*}(t_0)$	$u^{3*}(t_0)$	$u^{4*}(t_0)$	$G_{zone}^{eco*}(t_e)$	$G_{zone}^{env*}(t_e)$	$G_{zone}^{socl*}(t_e)$	$G_{zone}^{*}(t_e)$
1	133	35	127	205	0.922	0.802	0.705	0.815
2	98	179	168	54	0.921	0.800	0.762	0.831
3	155	3.2	51	290	0.920	0.801	0.670	0.803
4	205	51	47	197	0.923	0.802	0.709	0.816
5	235	3.3	26	236	0.918	0.799	0.672	0.802
6	94	260	86	60	0.924	0.801	0.767	0.833
7	67	28	41	364	0.924	0.803	0.673	0.807
8	156	141	60	143	0.927	0.805	0.745	0.829
9	51	189	157	80	0.923	0.802	0.755	0.830
10	167	3.3	162	167	0.916	0.798	0.690	0.807

Since those local optimal results all have great sustainability improvement compared with the current situation, and satisfy both the budget limits and SD improvement requirements, they will all be recorded as decision candidates and output from the system optimization step for further uncertainty analysis in the next Monte Carlo based simulation.

5.2.2 Monte Carlo based simulation

Ten local optimal SD decisions after system optimization are obtained without considering uncertainties. In order to make the SD decision-making study more consistent with the real, uncertainties will be further introduced into the system and Monte Carlo based simulation will be applied to recheck the sustainability performance of each candidate under the introduced uncertainties. In detail, eight system uncertainties about the future zone planning are introduced to study the SD case of the surface finishing centered industrial system, which the first two are the uncertain cost of the raw materials (see, z_{10}^{Zn} and z_{10}^{Zn} in Fig. 5.4), the 3rd and 4th are uncertain price of the product (see, $y_{p,05}^{Zn}$ and $y_{p,06}^{Zn}$ in Fig. 5.4), and the last four are uncertain efficiency on technologies improvements (see, $\left(u^i(t_0)\right)_{max}$, $i=1,\cdots,4$ in Eqs. 5.30 through 5.34). The four-step procedure for implementing Monte Carlo based simulation is given as follows:

Step 1. Define domains of possible parameter values. The system parameters related to the eight uncertainties are changed from constants to the domains of possible values. Their domains of possible parameter values are defined as follows:

(i) the cost of raw material z_{10}^{Zn} is changed from 0.58 \$/lb to an uncertain value within the domain from 0.56 \$/lb to 0.60 \$/lb.

(ii) the cost of raw material z_{20}^{Zn} is changed from 0.55 \$/lb to an uncertain value within the domain from 0.53 \$/lb to 0.57 \$/lb.

(iii) the price of product $y_{p,05}^{Zn}$ is changed from 5.93 \$/lb to an uncertain value within the domain from 5.75 \$/lb to 6.11 \$/lb.

(iv) the price of product $y_{p,06}^{Zn}$ is changed from 2.93 \$/lb to an uncertain value within the domain from 2.84 \$/lb to 3.02 \$/lb.

(v) the investment parameter $\left(u^1(t_0)\right)_{max}$ is changed from \$500 K to an uncertain value within the domain from \$475 K to \$525 K.

(vi) the investment parameter $\left(u^2(t_0)\right)_{max}$ is changed from \$750 K to an uncertain value within the domain from \$712 K to \$788 K.

(vii) the investment parameter $\left(u^3(t_0)\right)_{max}$ is changed from \$900 K to an uncertain value within the domain from \$855 K to \$945 K.

(viii) the investment parameter $\left(u^4(t_0)\right)_{max}$ is changed from \$1000 K to an uncertain value within the domain from \$950 K to \$1050 K.

Step 2. Generate parameter values randomly from the domains, and perform a deterministic computation to obtain the total sustainability for each decision candidates recorded in system optimization. For instance, one set of parameter values generated randomly from the domains are:

$$z_{10}^{Zn} = 0.59 \text{ \$/lb}, \quad z_{20}^{Zn} = 0.54 \text{ \$/lb} \tag{5.40}$$

$$y^{Zn}_{p,05} = 6.01 \text{ \$/lb}, \quad y^{Zn}_{p,06} = 2.90 \text{ \$/lb} \tag{5.41}$$

$$\left(u^1(t_0)\right)_{max} = \$508 \text{ K}, \quad \left(u^2(t_0)\right)_{max} = \$725 \text{ K},$$

$$\left(u^3(t_0)\right)_{max} = \$866 \text{ K, and } \left(u^4(t_0)\right)_{max} = \$1000 \text{ K} \tag{5.42}$$

and the total sustainability for each decision candidates are obtained in Table 5.4 with these parameter values through a deterministic computation.

Table 5.4. Zone sustainability and ranking results of one random Monte Carlo sample.

Case	Optimal Budget Distribution ($\times 10^3$ \$)				$G^{*sample}_{zone}(t_e)$	Rank
	$u^{1*}(t_0)$	$u^{2*}(t_0)$	$u^{3*}(t_0)$	$u^{4*}(t_0)$		
1	133	35	127	205	0.821	5
2	98	179	168	54	0.834	1
3	155	3.2	51	290	0.809	7
4	205	51	47	197	0.813	6
5	235	3.3	26	236	0.806	9
6	94	260	86	60	0.832	3
7	67	28	41	364	0.805	10
8	156	141	60	143	0.833	2
9	51	189	157	80	0.830	4
10	167	3.3	162	167	0.808	8

Step 3. Sort the decision candidates based on their total sustainability status. For instance, the computation results in *Step 2* are further sorted in the last column of Table 5.4. In this case study, *Step 2* and *3* are repeated for 1000 random samples.

Step 4. Aggregate the results of the individual computations for a result according to the sorting. In this case study, the sorting results are aggregated by calculated a value of “Credit” for each decision candidate. The rule for such “Credit” calculation is defined as follows:

(i) if a decision candidate is in the 1st , 2nd , or 3rd rank out of the 10 candidates for a single sort, then a 10, 6, or 2 credits will be given to this candidate, respectively.

(ii) if a decision candidate is in the 4th or even lower rank out of the 10 candidates for a single sort, then no credits will be given to this candidate.

Table 5.5. Monte Carlo simulation results (1,000 random samples).

Case	Optimal Budget Distribution ($\times 10^3$ \$)				$\overline{G}^*_{zone}(t_e)$	Credit#
	$u^{1*}(t_0)$	$u^{2*}(t_0)$	$u^{3*}(t_0)$	$u^{4*}(t_0)$		
1	133	35	127	205	0.815	0
2	98	179	168	54	0.831	4520
3	155	3.2	51	290	0.803	0
4	205	51	47	197	0.816	0
5	235	3.3	26	236	0.803	0
6	94	260	86	60	0.833	7392
7	67	28	41	364	0.807	0
8	156	141	60	143	0.829	2762
9	51	189	157	80	0.830	3326
10	167	3.3	162	167	0.807	0

$\#\text{Credit} = 10\times(1^{st} \text{ rank times}) + 6\times(2^{nd} \text{ rank times}) + 2\times(3^{rd} \text{ rank times})$

By following this credit rule, the final aggregated results of total 1000 individual computations are obtained and shown in Table 5.5. Since case 6 has the best Credit among the 10 local optimal cases, it is finally selected as the best possible SD decisions for the surface finishing centered industrial system. That is, the half million budget should be distributed in \$94 K, \$260 K, \$86 K and \$60 K to technology modification 1 though 4, respectively, and the best possible future obtained with certain budget distribution will be 0.923, 0.801, 0.767 and 0.833 on zone based economic, environmental, social and total sustainability, which has 5.2%, 4.2%, 29.6% and 10.3%

improvements from the current value, respectively. Moreover, detailed analysis on the budget efficiency is given in Table 5.6, which provides more information to the decision-maker, and the zone based sustainability improvement is demonstrated visually in the sustainability cube, see, Fig. 5.5.

Table 5.6. Analysis on the budget efficiency.

Technology Modification Option	Budget Need ($\times 10^3$ \$)	Technology efficiency	Optimal Budget Distribution ($\times 10^3$ \$)
1	0	0	N/A
	N/A	26%	94
	1,000	100%	N/A
2	0	0	N/A
	N/A	61%	260
	750	100%	N/A
3	0	0	N/A
	N/A	27%	86
	900	100%	N/A
4	0	0	N/A
	N/A	31%	60
	500	100%	N/A

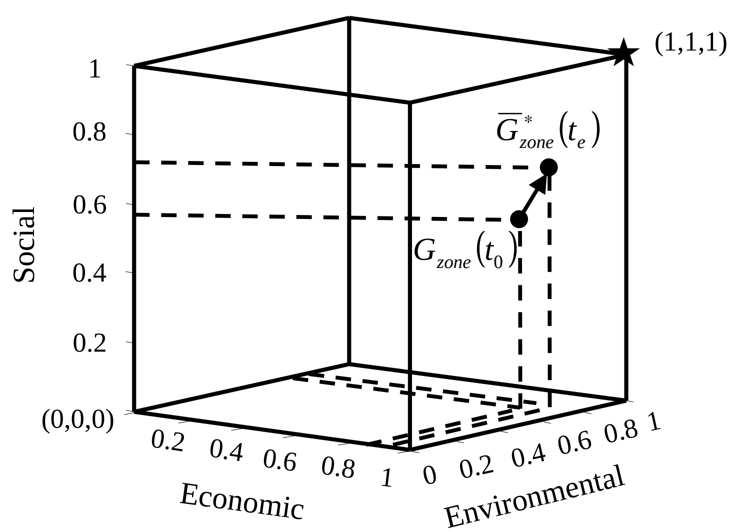


Figure 5.5. Sustainability evaluation of the zone before and after tech. modification.

5.2.3 Decision making with non-equal weights on triple bottom lines

The case study on sustainability improvement decision-making of a surface finishing centered industrial system demonstrated in 4.2.2.1 and 4.2.2.2 shows the efficacy of proposed SD decision-making methodology via Monte Carlo based simulation and system optimization. In its system optimization step, an equal emphasis was given on each aspect of the triple-bottom-lines, which corresponds to the objective function of Eqs. 5.4 and 5.24. However, it's also possible that an SD decision maker may prefer more benefits on one (or two) aspect of the triple-bottom-lines than the rest of others. Thus, the decision-making method with non-equal emphasis on the triple-bottom-lines is applied below to illustrate its efficacy in studying the same surface finishing centered industrial system.

According to the non-equal emphasis decision-making methodology introduced before, the objective function should be considered in the form of Eq. 5.25. Supposedly, given the same half million budget and four potential technology modification options, an SD decision maker selects $\alpha = 5$, $\beta = 2$ and $\gamma = 1$ in Eq. 5.25 to purse more economic and environmental benefits than the social benefits in the future. In this case, the system optimization can still be expressed by Eqs. 5.35 through 5.39. However, the objective function in finding the maximum sustainability of the entire industrial zone in the future has non-equal emphasis on the triple-bottom-lines:

$$G_{zone}(t_e) = \frac{1}{\sqrt{3}}\left(5\left(\overline{G}_{zone}^{eco}\right)^2 + 2\left(\overline{G}_{zone}^{env}\right)^2 + \left(\overline{G}_{zone}^{socl}\right)^2\right)^{\frac{1}{2}} \tag{5.43}$$

As the same in the equal emphasis decision-making analysis, this non-linear optimization will be solved by using Genetic Algorithm, then the local optimal cases obtained are recorded as decision candidates and output from the system optimization step for further uncertainty analysis in the next Monte Carlo based simulation. In Monte Carlo based simulation, eight system uncertainties about the future zone planning are introduced and 1000 random samples are taken to recheck the sustainability performance of these decision candidates. Finally, the computation results of the individual sample are aggregated for a result according to the sorting. The information of final best possible SD decision, which has the best Credit among the local optimal cases, is given in Table 5.7.

Table 5.7. Best possible decision solutions for equal and non-equal emphasis on each aspect of the triple-bottom-lines.

	Optimal Budget Distribution ($\times 10^3$ \$)				Future Sustainability		
	$u^{1*}(t_0)$	$u^{2*}(t_0)$	$u^{3*}(t_0)$	$u^{4*}(t_0)$	$\overline{G}_{zone}^{eco*}(t_e)$	$\overline{G}_{zone}^{env*}(t_e)$	$\overline{G}_{zone}^{socl*}(t_e)$
With equal emphasis	94	260	86	60	0.923	0.801	0.767
With non-equal emphasis	52	230	33	185	0.931	0.807	0.713

The comparison of future sustainability with equal and non-equal emphasis on the triple-bottom-lines shows that the non-equal decision has better zone based economic and environmental performances than the equal decision results in the future, which satisfies the preference of the SD decision maker. However, the zone based social performance obtained by the non-equal decision is quite lower than the equal decision results in the future.

5.2.4 Target driven decision making

Besides the effort oriented decision-making studies, the target-driven decision-making methodology is also applied to the same surface finishing centered industrial system. According to the introduced methodology, the target-driven decision-making analysis via Monte Carlo based simulation and system optimization is implemented in the following procedure.

Step 1. Set the future sustainability goal of the entire industrial zone. In this case study, a 10% improvement on the zone based total sustainability (i.e., from 0.755 to 0.831) is set as the SD goal for the surface finishing centered industrial system under the same four potential technology modifications. Note that the acceptable region of such the goal is defined within 0.830 to 0.832, and the equal emphasis is given to the triple-bottom-lines.

Step 2. Make a guess on the total effort, and use it to fulfill the system optimization and Monte Carlo based simulation. The initial guess on the total budget is made by the decision-maker as half million, which is the same number in the basic case study given before. Then the system optimization and Monte Carlo based simulation are implemented as the same shown in 4.3 and 4.4, which gives the best possible future sustainability of the whole industrial zone under uncertainties, and the budget distribution on each option as the same as Case 6 in Table 5.6.

Step 3. Since the best possible future sustainability obtained in *Step 2* (0.833) is higher than the future sustainability goal set in *Step 1* (0.831), the total budget guess is changed to a lower value, \$450 K. With this new total budget, *Step 2* is repeated, and a 0.829 best possible future sustainability is obtained, which is lower than the desired value. Therefore, the total budget guess is further changed to \$460 K, and *Step 2* is repeated again to obtain a 0.830 best possible future sustainability.

Since this best possible future sustainability is within the pre-set acceptable region, the final total budget guess, \$460 K, and its corresponding budget distribution is selected as the 10% target-driven decision solutions for the surface finishing centered industrial system. The detailed budget distribution is to spend \$91 K, \$257 K, \$68 K and \$51 K to technology modification 1 though 4, respectively, and the best possible future obtained with certain budget distribution will be 0.925, 0.803, 0.756 and 0.830 on zone based economic, environmental, social and total sustainability, which has 5.5%, 4.4%, 27.7% and 9.9% improvements from the current value, respectively.

5.2.5 Discussion on application potentials

The methodology proposed in this chapter is general for applying to many types of SD decision-making analysis. First, given various effort options, this methodology can help decision-makers determine the optimal effort distribution on each given effort option for achieving the best possible future sustainability under uncertainties. The efforts implemented to the industrial zone system can be substantial (for instance, investment) or non-substantial (for instance, new policy force). In the case study on sustainability improvement decision-making of a surface finishing centered industrial system, the efforts are the budget on four types of technology modification options. Similarly, one can design an SD decision-making problem about the product manufacturing plan selection under uncertainties, where an industrial zone decision-maker wants to determine the optimal way of distributing limited total investment on several types of product manufacturing plans, so that the whole industrial zone can have the best possible sustainability performance in the future. In this problem, the efforts are the required investment on several types of product manufacturing plans, and the objective is to find the best possible zone based sustainability in the future by optimally distributing limited total investment on those product manufacturing plans under uncertainties.

Second, the proposed methodology can be applied to the material, energy, and even information flow analysis. In Eq. 5.1, an industrial zone is defined as basic elements of input-output flow analysis. In general, the definition of those flows can be extended as all types of numerically/symbolically quantifiable flows, which are about material, energy, and policy information. Therefore, the SD decision-making analysis can be employed for not only material related industrial zone systems, but also energy or policy related industrial zone systems, or even the most complex industrial zone systems that are material, energy, and policy related together.

Finally, the proposed methodology can be used for both the single-time-stage and multi-time-stage SD decision-making analysis. Note that the previous methodology and case study are all talking about the single stage analysis. However, with direct repeat, i.e., implementing the proposed methodology for the current time stage, after obtaining the SD decision-making solutions, setting them as the initial conditions of the next time stage and implementing the proposed methodology again. In this way, one can analyze the SD decision-making problem of a given industrial zone system for many time stages, however, since the future system information becomes more and more uncertain when the time stages increasing, the decision solutions obtained will be more and more less confident.

5.3 Chapter Summary

Industrial sustainability is pursued by people to achieve the long-term sustainable development (SD) of a given industrial zone. In practice, decisions and strategies for sustainable development must be made, reviewed, and assessed by industrial planners, business leaders, and involving communities from time to time. However, industrial sustainability problems are always difficult to be fully investigated and further optimized, because of the large size and scope that carries highly complexness, and inevitable uncertainties that are associated with data, information, and knowledge. Therefore, most known studies on sustainability decision-making are scenario based which heavily relies on the identified scenarios, and is always heuristic. Moreover, no uncertainty is being considered in making decisions, which is inconsistent with the real situation.

In this section, an approach consisting of both the system optimization and Monte Carlo based simulation is introduced to guide the decision-making process for more effectively identifying solutions of sustainability improvement. First, the Extended EIO-based SD decision-analysis is borrowed to obtain the potential modification options. After that, an industrial sustainability is described as a system optimization problem, and a Genetic Algorithm approach is implemented to solve it. The local optimal solutions obtained from Genetic Algorithm approach will be recorded as candidates for further uncertainty analysis. Next, uncertainties are introduced into the system and Monte Carlo simulation is applied to recheck the sustainability performance of each candidate under the introduced uncertainties. Finally, the best possible decisions will be readily identified from the candidate solutions through aggregating the results of each individual Monte Carlo sample for a result.

The main advantage of this approach is its capability of identifying optimal choice effectively with the consideration of system uncertainties. The proposed approach is fully illustrated through analyzing the sustainability issues and developing strategies for enhancing the sustainability of a component-based electroplating industrial zone, and the potential applications by using the proposed methodology are further discussed.

CHAPTER 6

ISEE: A COMPUTATIONAL TOOL FOR INDUSTRIAL SUSTAINABILITY EVALUATION AND ENHANCEMENT

In the study on industrial sustainability, a major challenge is how to conduct effective sustainability assessment and decision making for industrial systems towards high efficiency of material and energy utilization, minimum waste generation, assured safety, high-level social responsibility, etc. Such a sustainability assessment and decision making is a multi-objective and interdisciplinary task, which has been greatly challenged due to the inherent complexity and uncertainty carried by the industrial sustainability essential.

Over the past decade, varieties of sustainability metrics have been introduced for sustainability assessment, but with various challenges for being applied on industrial practices. The key issue is that how to well address specific industrial sustainability assessment and decision making problems by using those general sustainability metrics, especially how to evaluate the multi-objective sustainability requests in a systematic, but also convincing and practical way. For decision-making on industrial sustainability enhancement, it is highly desirable that solutions can be identified in a holistic way, which requires the solution approach should be capable of assessing the state of short- to long-term sustainability of an industrial system and the identification of superior solutions for improving system's sustainability (Liu *et al.*, 2009). Therefore, it becomes clear that the industry needs urgently practical tools that can be used to conduct convincing systematic sustainability assessment on existing processes and/or new designs, and further to obtain decision support for necessary system enhancement or selection of design alternatives (Othman *et al*., 2010).

To facilitate industrial practice on engineering sustainability, a computational tool, namely ISEE (Industrial Sustainability Evaluation and Enhancement), has been designed and presented in this chapter, where comprehensive sustainability principles are embedded in a systems approach for sustainability assessment and decision support. The tool is featured by its capability of processing system data and information, assessing sustainability status quo and predicting its future performance, and evaluating design alternatives using various sustainability metrics. Based on the assessment, the tool is capable of identifying the most desirable design for sustainability improvement. The efficacy of the developed tool was demonstrated by applications of a sustainability assessment of biodiesel manufacturing technologies and a short- to long-term enhancement strategy development for a metal-finishing-centered industrial zone.

6.1 Tool Development

The developed computational tool, ISEE, has two functional modes, namely, the general sustainability assessment and the decision support of industrial sustainability enhancement. The welcome page of the tool is shown in Fig. 6.1 where these two functional modes can be selected on the bottom of it. The user can run each mode independently. Detailed methodologies and design structures of each tool mode are given in the following sections.

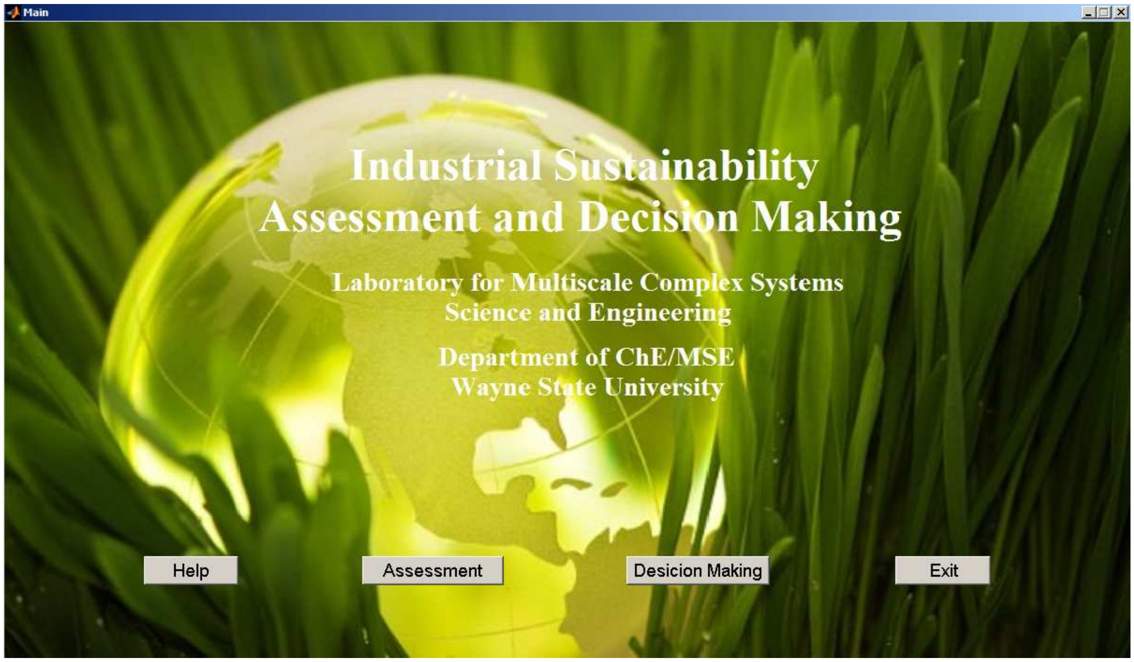


Figure 6.1. Welcome page of the computational tool, ISEE.

6.1.1 A double-layered sustainability assessment methodology

The most widely utilized sustainability metrics by the chemical and allied industry, i.e., the IChemE (IChemE, 2002) and AIChE (Cobb *et al*., 2009) sustainability metrics, are adopted in the tool to conduct the multi-objective sustainability assessment requests. These metrics are grouped for assessing economic, environmental, and social sustainability (so called the triple-bottom-lines of sustainability), and in each of these three categories, different numbers of indicators are assigned for the representation of various evaluating aspects. To assess the sustainability of a system systematically by using those general metrics, a double-layered sustainability assessment is proposed as follows, where the top and the bottom layer are well designed for conducting two different tasks towards the ultimate assessment goal.

Top layer. The task of this layer is to derive the composite economic, environmental, and social sustainability. For the sustainability assessment of an industrial system named P, we assume that a set of sustainability metrics, namely set S, has been defined or selected by the user. The metrics system is denoted as:

$$S = \{E,\ V,\ L\}, \tag{6.1}$$

where

$E = \{E_i \mid i = 1, 2, \cdots, F\}$, the set of economic sustainability indices,

$V = \{V_i \mid i = 1, 2, \cdots, G\}$, the set of environmental sustainability indices,

$L = \{L_i \mid i = 1, 2, \cdots, H\}$, the set of social sustainability indices.

By using the above-defined indices, the composite economic, environmental, and social sustainability of system P can be assessed in the following three steps: (i) dimensional data specification, (ii) data normalization, and (iii) composite sustainability calculation.

The first step is to specify dimensional data for each selected economic, environmental, and social sustainability indicator. Note that different indicators have different units usually. Therefore, they must be normalized in order to be combined into a single composite sustainability value.

In the second step for conducting normalization, the dimensional data of each indicator should be transferred into a value in the range between 0 and 1, with "0" as the lowest state of sustainability, and "1" as the highest state of sustainability. In detail, if the engineering meaning of one indicator for system P, $I(P)$, shows that a large value is more preferable from the sustainability point of view, then the normalized indicator, $\bar{I}(P)$, can be derived using Eq. 6.2.

$$\bar{I}(P)=\frac{I(P)-I_{min}(P)}{I_{max}(P)-I_{min}(P)}, \tag{6.2}$$

where I can be any indicator of E_i, V_i, or L_i, and $I_{min}(P)$ and $I_{max}(P)$ are the lower and upper bound values of $I(P)$, respectively. Details about how to identify boundaries depend on the user's preference, which will be discussed later. On the contrary, if the engineering meaning of one indicator, $I(P)$, shows that a small value is more preferable from the sustainability point of view, then Eq. 6.3 should be used to derive the normalized indicator, $\bar{I}(P)$.

$$\bar{I}(P)=\frac{I_{max}(P)-I(P)}{I_{max}(P)-I_{min}(P)}, \tag{6.3}$$

The last step of the top layer is to calculate the composite economic, environmental, and social sustainability for system P. This can be conducted by combining the normalized indicators in the same sustainability category with assigned weights, i.e.,

$$E(P)=\frac{\sum_{i=1}^{F} a_i \bar{E}_i(P)}{\sum_{i=1}^{F} a_i}, \tag{6.4}$$

$$V(P) = \frac{\sum_{i=1}^{G} b_i \overline{V}_i(P)}{\sum_{i=1}^{G} b_i}, \tag{6.5}$$

$$L(P) = \frac{\sum_{i=1}^{H} c_i \overline{L}_i(P)}{\sum_{i=1}^{H} c_i}, \tag{6.6}$$

where a_i, b_i, and $c_i \in [1, 10]$ are the weighting factors associated with the corresponding indices, reflecting the relative importance of the individual indices in overall assessment.

Bottom layer. The task of this layer is to obtain the overall sustainability. To achieve that, the cube-based sustainability state representation proposed by Piluso *et al*. (2010) is adopted and illustrated as follows. The proposed concept of a sustainability cube is shown in Fig. 6.2, where the three coordinates represent the composite economic index, the composite environmental index, and the composite social index. Each composite index is set to have a value between 0 (meaning no sustainability) and 1 (meaning complete sustainability). With this representation, the corner coordinate of (0, 0, 0) represents the system's status of no sustainability, while the opposite corner having the coordinate (1, 1, 1) indicates complete sustainability. In the figure, the point, $S(P)$, represents the overall sustainability status of system P, which can be evaluated using the composite indices, $E(P)$, $V(P)$, and $L(P)$, with the weighting factors assigned again by the user, i.e.,

$$S(P) = \frac{\left\| \left(\alpha E(P), \quad \beta V(P), \quad \gamma L(P) \right) \right\|}{\left\| \left(\alpha, \quad \beta, \quad \gamma \right) \right\|}, \tag{6.7}$$

where α, β, and γ each has a value of 1 (default). Naturally, $S(P)$ is still normalized.

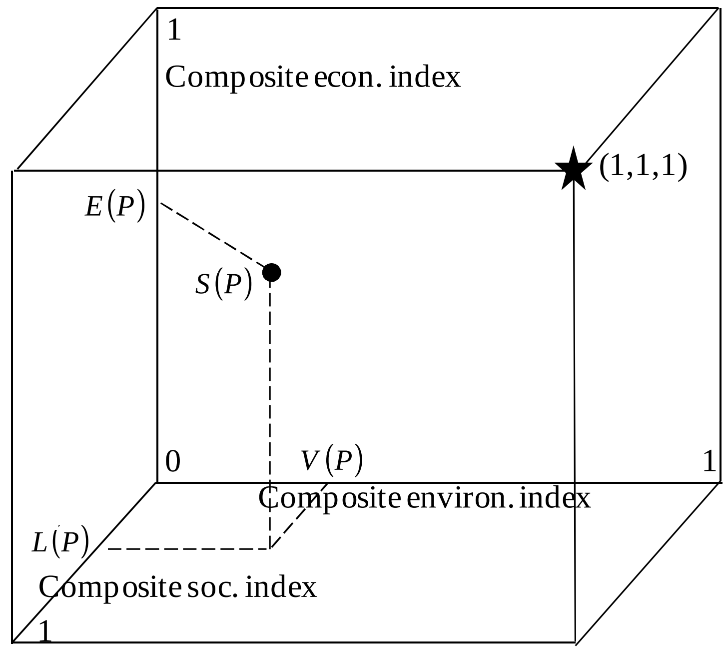


Figure 6.2. Cube-based sustainability evaluation.

6.1.2 Designed tool structure for sustainability assessment

The double-layered sustainability assessment methodology proposed above is implemented in the development of a user-friendly tool mode of ISEE, which allows the user to conduct the sustainability assessment for various industrial systems of interest. In this regard, the computational tool was designed in a unique assessment framework given in Fig. 6.3, which contains nine sequential stages described as follows.

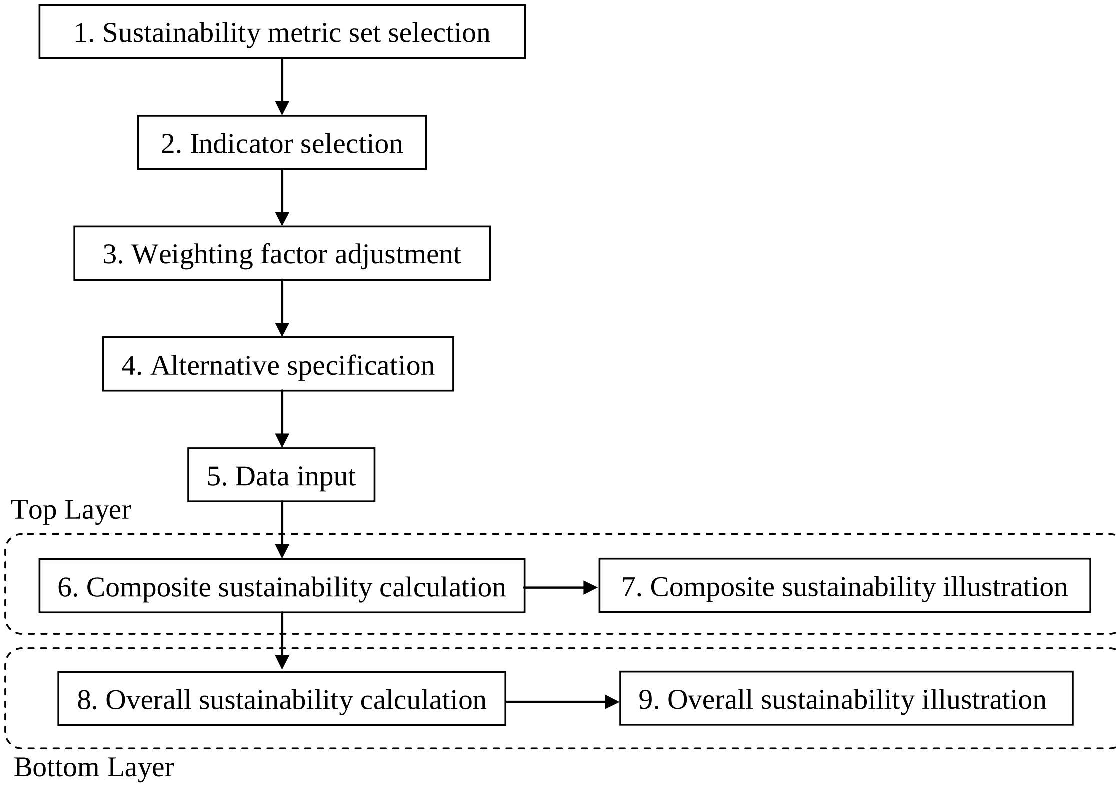


Figure 6.3. Flowchart of the double-layered sustainability evaluation framework.

Based on individual preference, the user is first able to select one of the widely utilized sustainability metric sets among the IChemE (IChemE, 2002), AIChE (Cobb *et al*., 2009), and several other sustainability metrics on the page shown as Fig. 6.4. When the metric set was selected, all the triple-bottom-line indicators associated with this set will be shown (see Fig. 6.5 as an example). Note that not all those available indicators are suitable for the assessment of various types of industrial systems. Therefore, the user is allowed to remove those irrelevant indicators to the assessment problem being studied by making their state buttons unselected. When this step is done, the total numbers of economic, environmental, and social sustainability indicators in Eq. 6.1 are set, and only those selected indicators will be editable shown in the following assessment procedures.

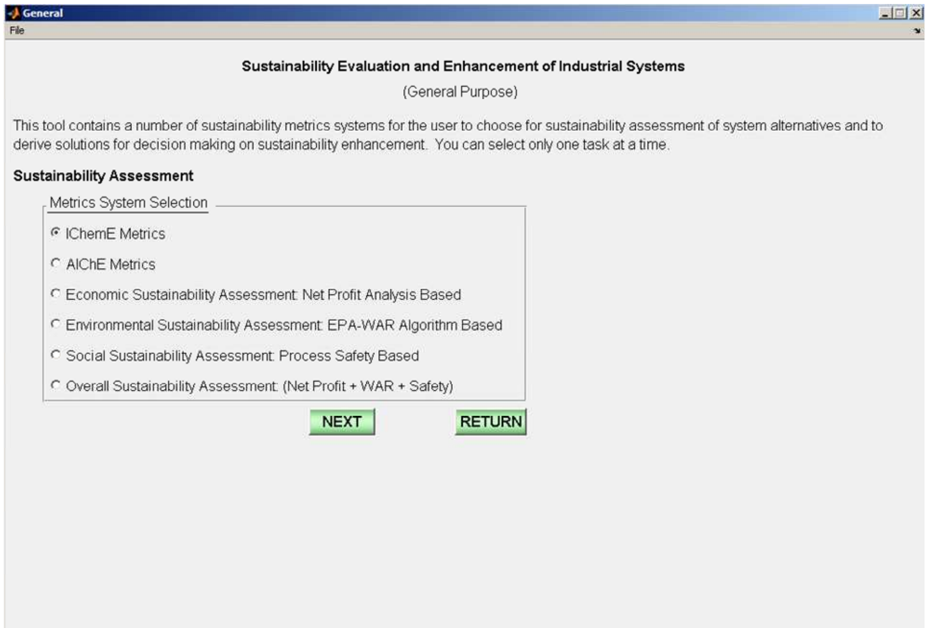


Figure 6.4. Page design for sustainability assessment: metric set selection.

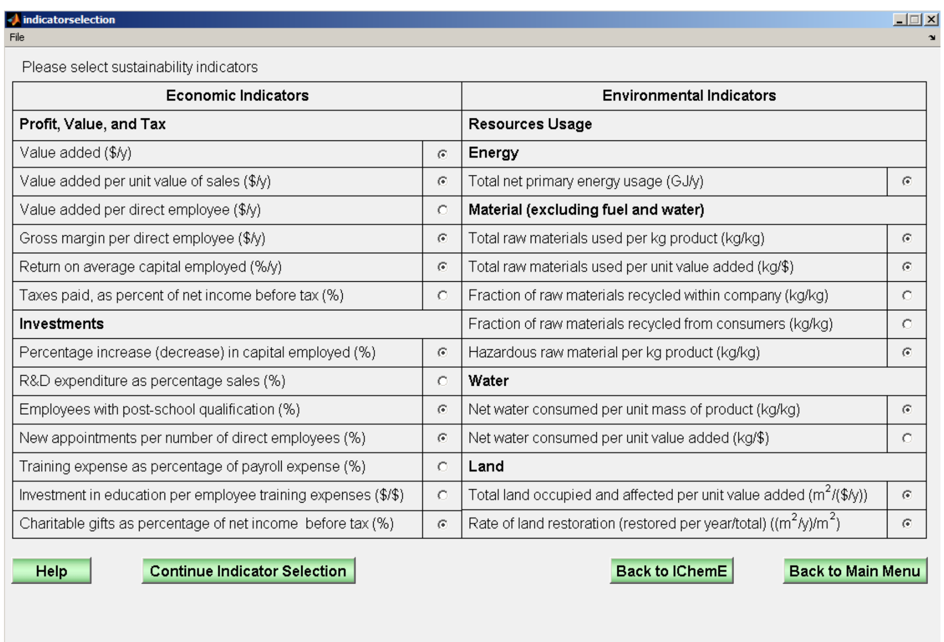


Figure 6.5. Page design for sustainability assessment: indicator selection.

Next, the user is able to adjust the weighting factors corresponding to each selected indicator (see Fig. 6.6 as an example). Adjusted weighting factors will be recorded and used for calculating composite sustainability index given in Eqs. 6.4 to 6.6. For the convenience of comparing different industrial processes and/or design scenarios, the tool is capable to conduct assessment for up to five design alternatives simultaneously. In this regards, the total number of design alternatives to be involved is asked on in the page shown in Fig. 6.7. Then, the pages of data input are posted (see Fig. 6.8 as an example), where the selected triple-bottom-line indicators are listed as rows and those design alternatives specified by the user are organized as columns (five design alternatives in this case, named from A to E).

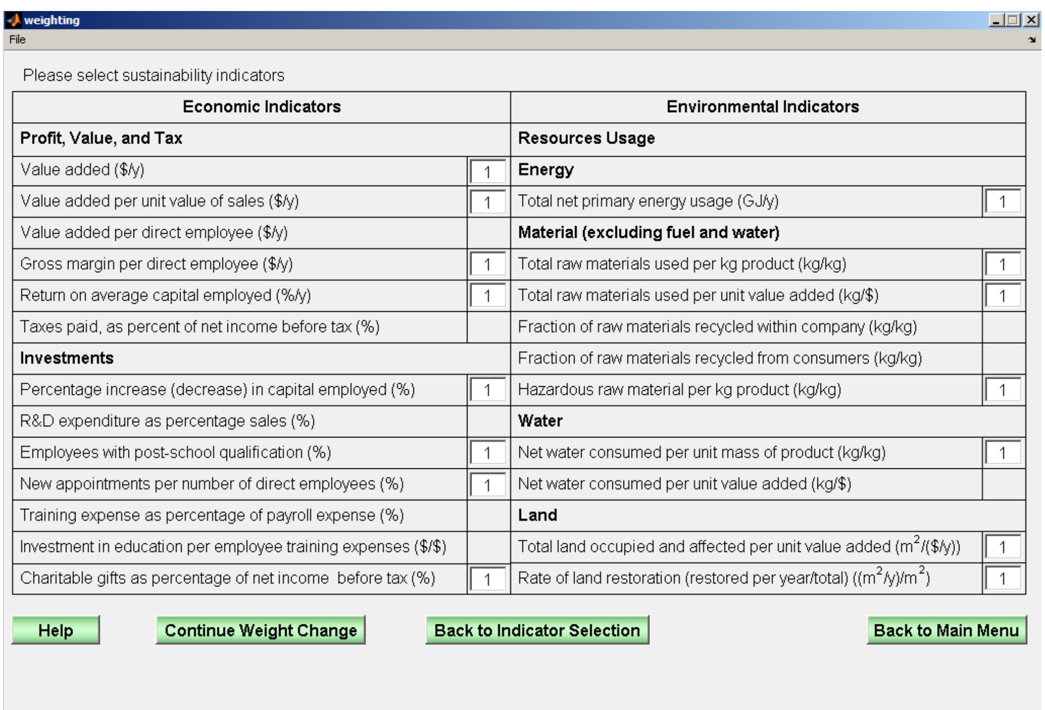


Figure 6.6. Page design for sustainability assessment: weighting factor adjustment.

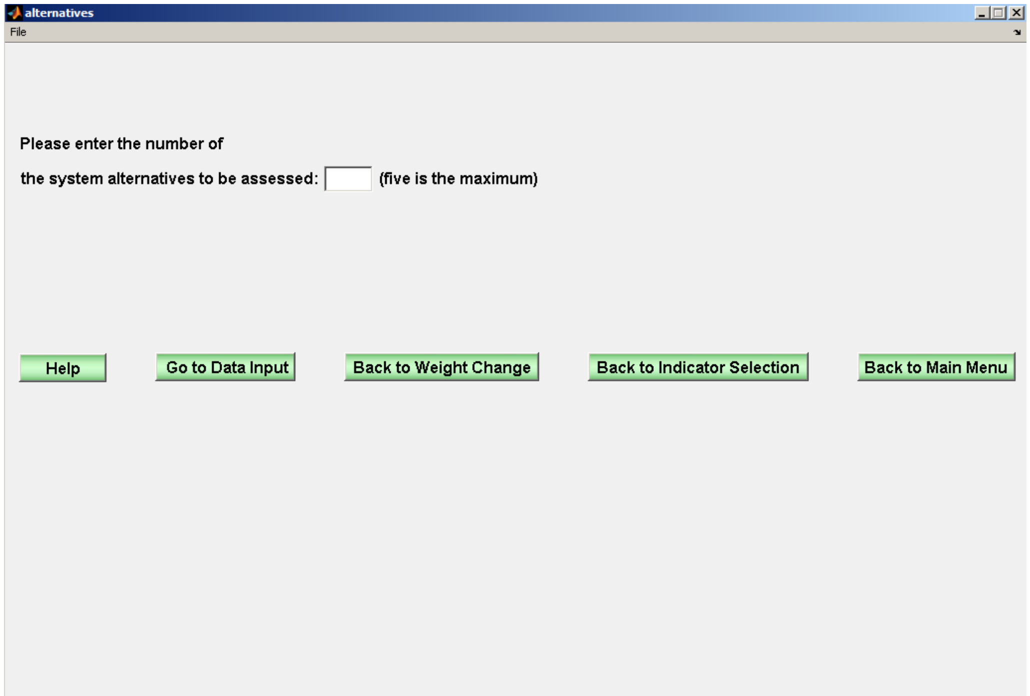


Figure 6.7. Page design for sustainability assessment: total number of design alternative specification.

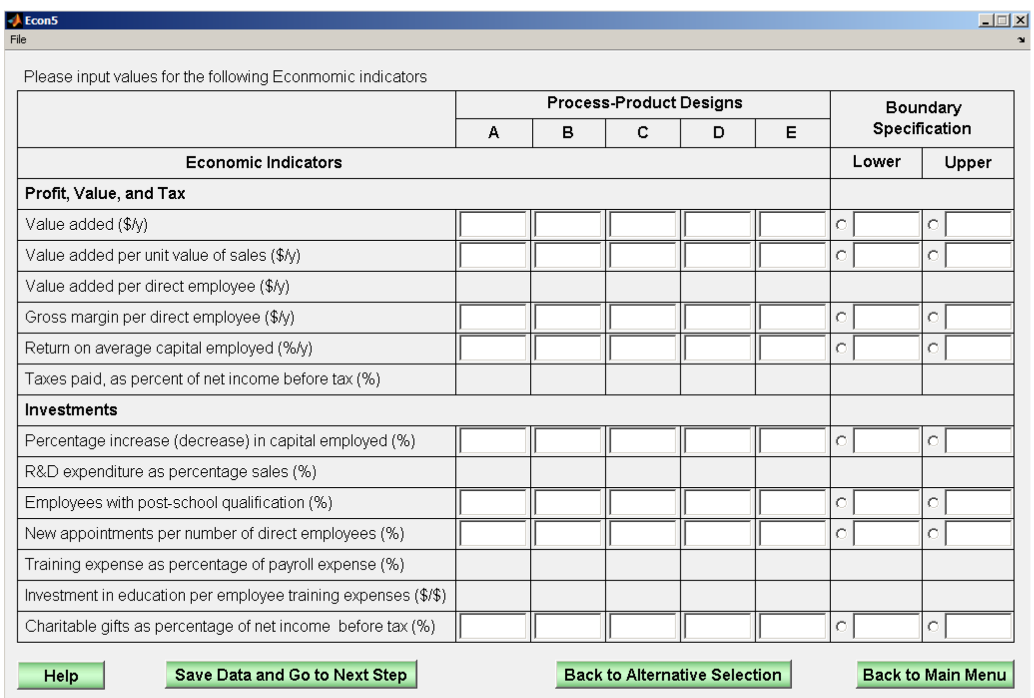


Figure 6.8. Page design for sustainability assessment: data input.

On each page of data input, the user should give a valid number in each data cell corresponding to each selected indicator and each design alternative. Those input values will be recorded and used for calculating composite sustainability given in Eqs. 6.4 to 6.6. Note that the lower and upper boundaries used in Eqs. 6.2 and 6.3 for indicator normalization can be specified in the two columns for boundary specification located on the right of this page. In detail, when a value is given in each of these two cells on the row of indicator $I(P)$, it will be recorded as $I_{min}(P)$ or $I_{max}(P)$ and used in Eqs. 6.2 or 6.3. Note that, the user may choose to specify one of these two boundaries, or even leave both of them unspecified. Under this situation, the $I_{min}(P)$ and/or $I_{max}(P)$ undefined by the user will be automatically assigned by the tool under the following algorithm.

$$I_{min}(P) = min\{I_i(P)\},\ i = 1, 2, ..., \text{up to } 5 \tag{6.8}$$

$$I_{max}(P) = max\{I_i(P)\},\ i = 1, 2, ..., \text{up to } 5 \tag{6.9}$$

where i is the total number of design alternatives, and $I_i(P)$ is the value of the i-th alternative of this indicator.

After the user inputs data for all the selected triple-bottom-line indicators of each design alternative, the calculation of composite sustainability (top layer) and overall sustainability (bottom layer) given in Eqs. 6.4 through 6.7 will be automatically conducted by the tool. The assessment results then will be demonstrated on the following two tool pages. First, three spider-charts will be illustrated for the representation of indicator-based economic, environmental, and social sustainability on the page given in Fig. 6.9. On each spider-chart, legs with numbers represent those selected indicators, where on each of them has normalized values marked in different colors for each design alternative. By checking the charts, the user can easily compare the sustainability performance between design alternatives by any indicator. To view the overall sustainability, the page given in Fig. 6.10 can be called, where the table-based composite and overall sustainability assessment results are given on the left, and the same assessment results are visually illustrated in the cube-based (3-D rotatable) figure on the right. With that, the user can easily compare design alternatives and choose the best one as decisions.

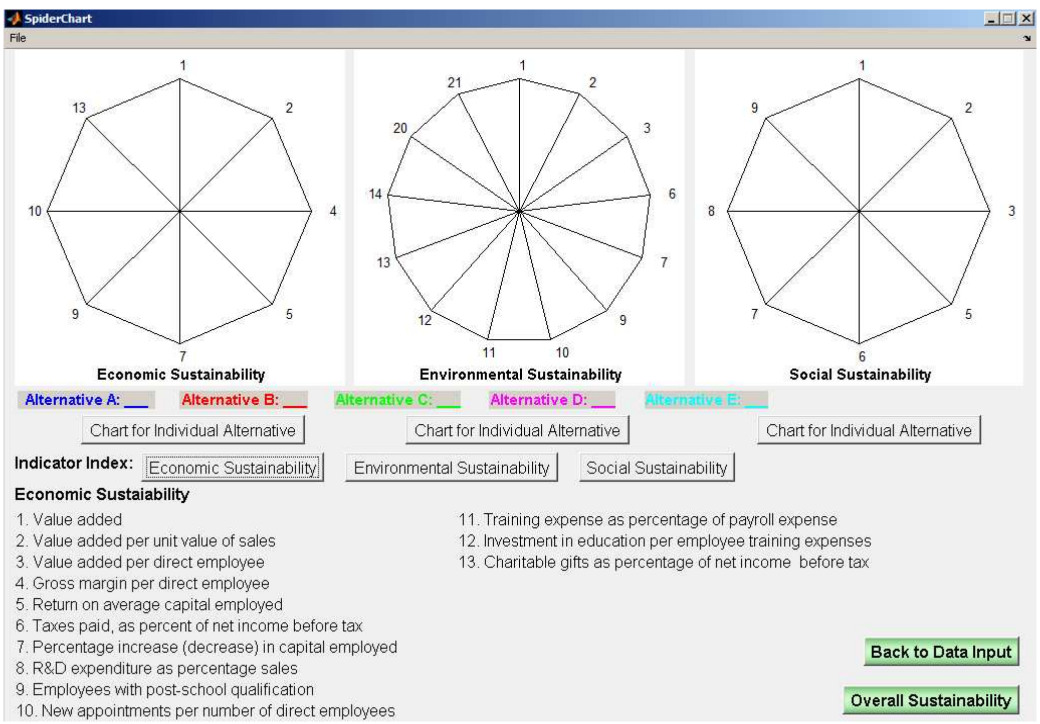


Figure 6.9. Page design for demonstration of sustainability assessment results: indicator-based spider-charts.

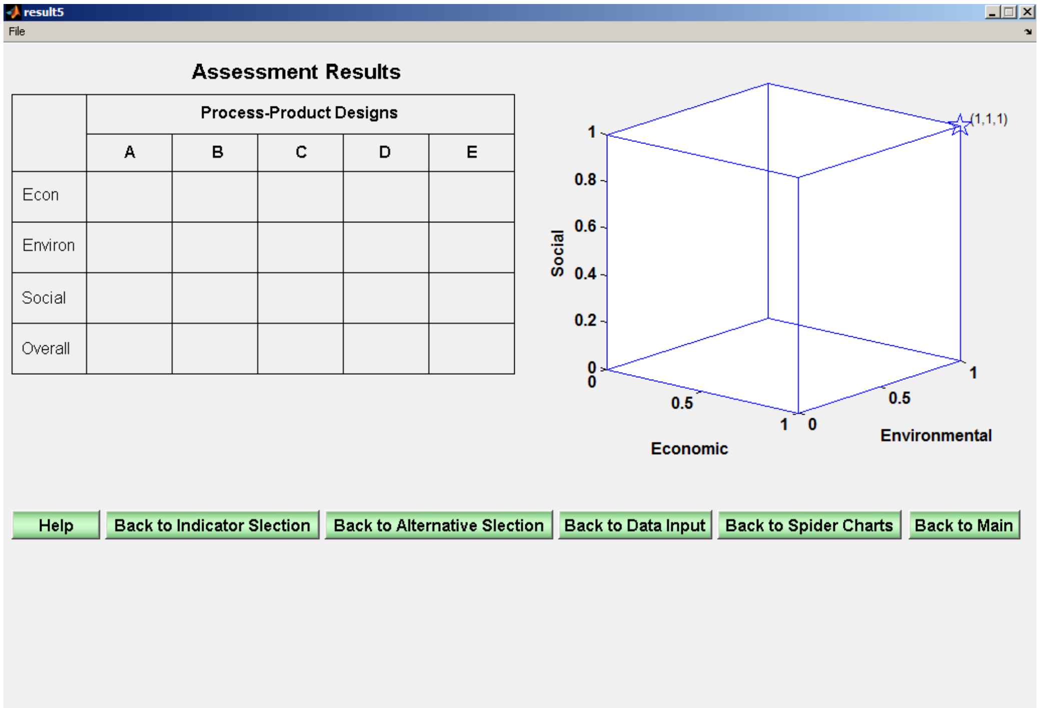


Figure 6.10. Page design for demonstration of sustainability assessment results: composite and overall sustainability.

Note that the whole assessment framework described above is designed extremely flexible: the user can go back to any previous stages at any assessment stage, which allows him to modify the assessment scheme or data in the most convenience. In addition, there are functional menus are buttons designed on each page for the user to directly view help information, save the assessment file, and print the page out.

6.1.3 Methodology of decision support on industrial sustainability enhancement

The second functional mode of the tool is the decision support on industrial sustainability enhancement. Using this mode, the solutions of industrial sustainability enhancement can be identified in a holistic way, which the solution approach is capable of assessing the state of short- to long-term sustainability of an industrial system and the identification of superior solutions for improving system's sustainability.

To assess the state of short- to long-term sustainability of an industrial system, there are three tasks: (i) sustainability evaluation of the current system, (ii) system analysis and short- to long-term enhancement strategy proposal, and (iii) short- to long-term sustainability prediction of enhancement plans.

The first task is actually a single sustainability assessment of an industrial system. Therefore, the double-layered assessment methodology proposed before can be directly applied. The second task is to identify the causes of the unsatisfied sustainability state, and then propose corresponding short- to long-term enhancement strategies by focusing on them. To identify the causes, the decision maker has to specify composite economic, environmental, and social development goals, namely:

$E^{sp}(P)$ = the economic sustainability goal for system P,

$V^{sp}(P)$ = the environmental sustainability goal for system P,

$L^{sp}(P)$ = the social sustainability goal for system P.

In addition, the decision maker should set satisfaction levels about the system performance by giving the maximum acceptable deviations of the system sustainability performance from the pre-set goals, namely, η_E, η_V, and η_L. They could be set to, for example, 5% each. If any of the following inequalities holds, this composite sustainability category will be considered as a cause for further enhancement:

$$E(P;0) < (1-\eta_E)E^{sp}(P), \tag{6.10}$$

$$V(P;0) < (1-\eta_V)V^{sp}(P), \tag{6.11}$$

$$L(P;0) < (1-\eta_L)L^{sp}(P), \tag{6.12}$$

where $E(P;0)$, $V(P;0)$, and $L(P;0)$ is the calculated composite sustainability of the current industrial system; $(1-\eta_E)E^{sp}(P)$, $(1-\eta_V)V^{sp}(P)$, and $(1-\eta_L)L^{sp}(P)$ represents the minimum acceptance of each composite sustainability state, respectively. Then, different short- to long-term enhancement strategies can be proposed by focusing on those identified causes, which surely will give effective sustainability improvement. Note that the decision maker may need various technical approaches for the proposal of potential enhancement strategies, i.e., empirical judgments, brainstorming, discussion, optimization, etc., and the details of using them, however, are out of the range in this chapter. The last task is again the sustainability assessment of industrial systems, which can be conducted by using the double-layered sustainability assessment methodology.

6.1.4 Designed tool structure of decision support on industrial sustainability enhancement

A user-friendly computational tool mode was developed in ISEE by implementing the enhancement methodology proposed above. The designed decision support framework by the tool is given in Fig. 6.11, which contains seven sequential stages as follows.

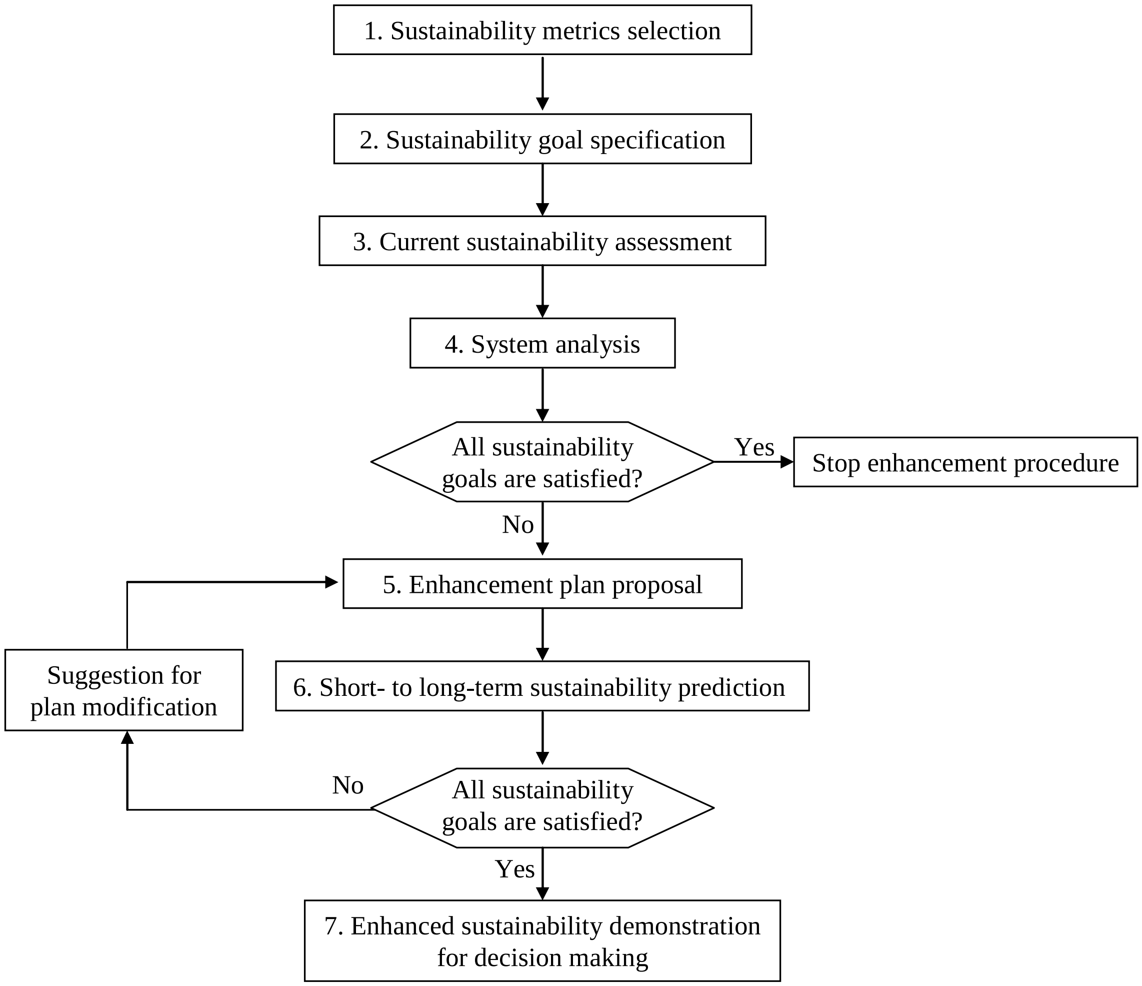


Figure 6.11. Flowchart of the sustainability enhancement framework.

At the first stage, desired triple-bottom-line indicators are required to be selected for sustainability assessment. After that, the user is asked to specify sustainability goals and deviation parameters, namely, $E^{sp}(P)$, $V^{sp}(P)$, $L^{sp}(P)$, η_E, η_V, and η_L, see Fig. 6.12. Then, the user should give data of each assessment indicator of the current industrial system, and the current sustainability state will be evaluated. Next, conditions of Eqs. 6.10 to 6.12 will be inspected. If all the minimum acceptances of sustainability goals are already satisfied, recommendation of stop the enhancement procedure will be given to the user. Otherwise, the causes of the unsatisfied sustainability state will be highlighted, which can help the decision maker to propose short- to long-term enhancement strategies.

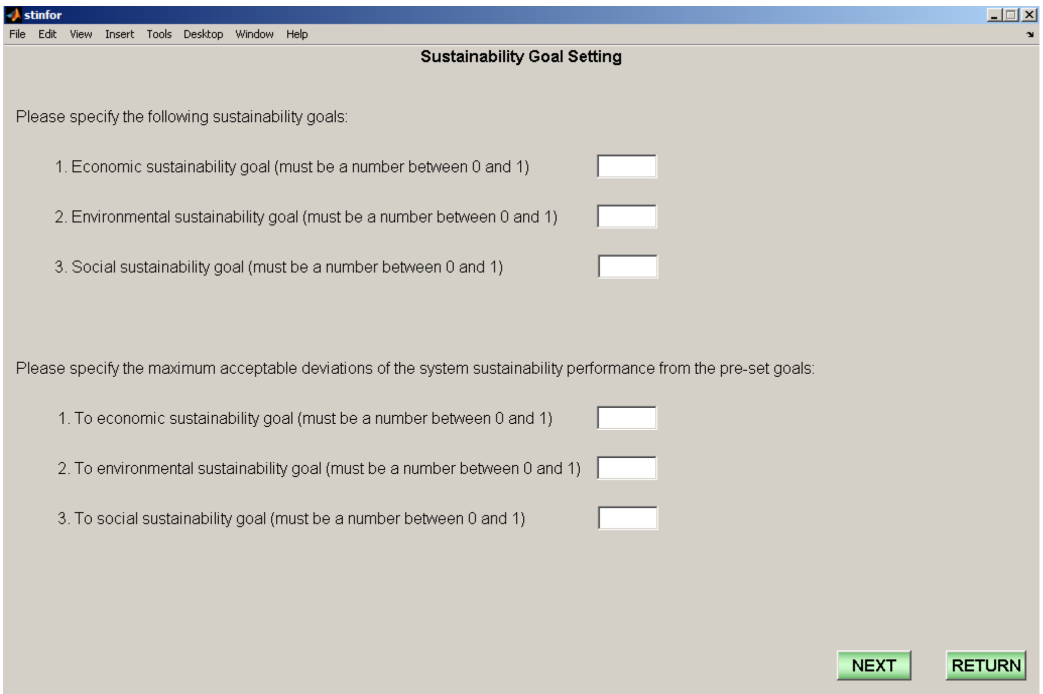


Figure 6.12. Page design for sustainability enhancement decision support: sustainability goal setting.

The user should then specify the total number of enhancement plans (up to three) and active time stages being interested among the available short, mid, and long terms for sustainability prediction, see, Fig. 6.13. New data of each triple-bottom-line indicator after implementing each enhancement plan will be input at selected time stages by the user, and the enhanced sustainability states will be calculated. The sustainability states of the current system, minimum acceptance, and the enhanced states by each plan at each time stage will be given in a table. By comparing those values, the satisfaction of each sustainability goal after implementing each plan can be easily judged. In addition, the development paths of enhancement plans will be demonstrated in the cube-based (3-D rotatable) figure for decision-making (see, Fig. 6.14 as an example having three enhancement plans and three time stages in short- to long-term). With that, the decision maker should be able to identify the best suitable enhancement strategy. Note that if the user wants to modify any enhancement plan after running this entire procedure, especially when some plans cannot satisfy all sustainability goals, he can go back to the previous pages to make changes directly.

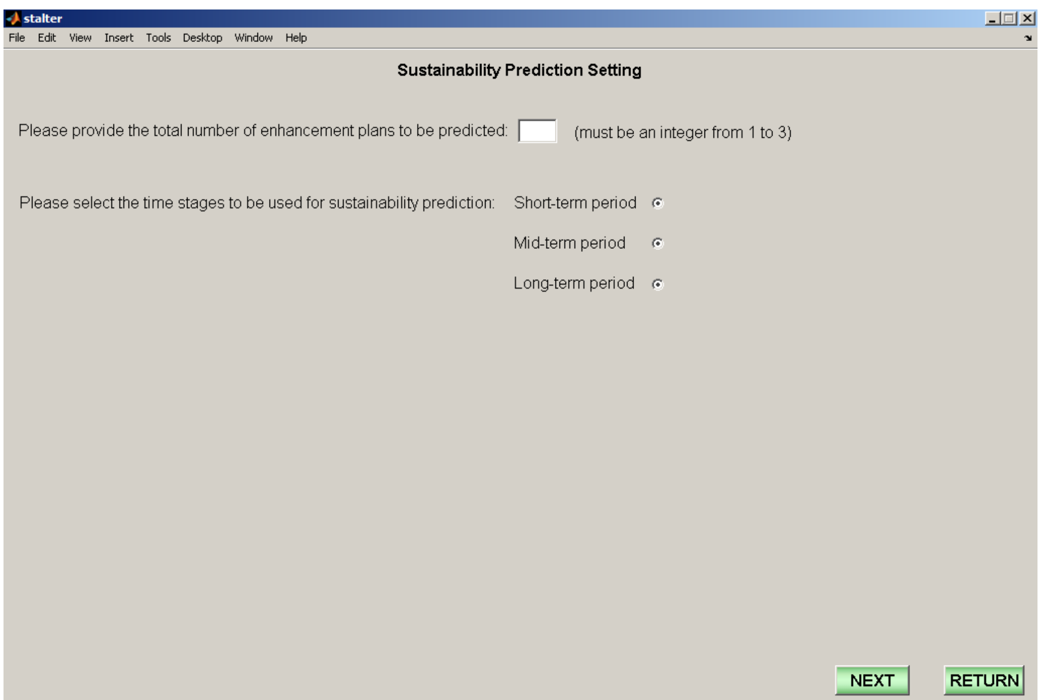


Figure 6.13. Page design for sustainability enhancement decision support: total number of plans and term stage specification.

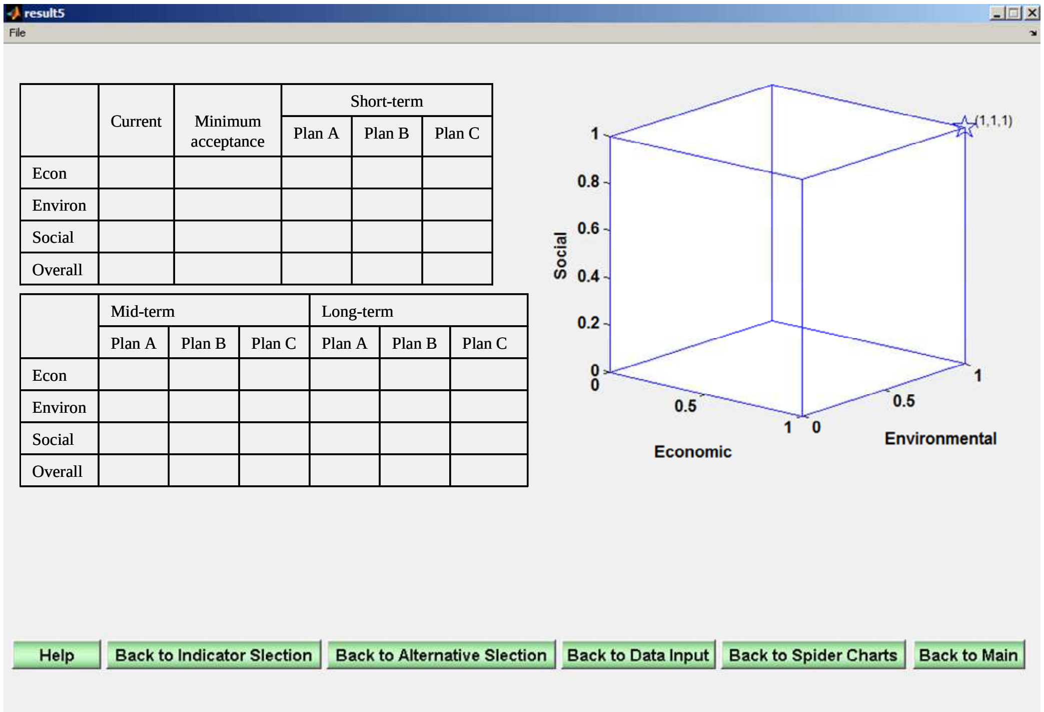


Figure 6.14. Page design for sustainability enhancement decision support: enhanced sustainability and development path demonstration.

Similar to the design of assessment tool mode, the user can go back to any previous stages at any step when conducting the sustainability enhancement. Moreover, the user can view help information, save files, and print data by using designed functional menus and buttons on each page.

6.2 Tool Applications

The developed ISEE tool has been tested by quite many industrial problems successfully. Among them, two applications are demonstrated in this section to show its efficacy. The first one is a sustainability assessment of biodiesel manufacturing technologies, and the second one is a short- to mid-term enhancement plan development for a metal-finishing-centered industrial zone.

6.2.1 Sustainability assessment of biodiesel manufacturing technologies

In this application, the sustainability performance of three biodiesel manufacturing technologies at the fixed production capacity of 50,000 tons/year was evaluated by using the tool mode of general sustainability assessment. Those three technologies are briefly introduced as follows, which each shows some potential advantages and disadvantages from the sustainability point of view. Therefore, the sustainability performance of each technology use must be carefully evaluated in order to compare them comprehensively.

Technology A: Acid-catalyzed process. This process can generate biodiesel by using waste cooking oil as the feedstock, which has a much cheaper price than the traditional feedstock, vegetable oil. Acid catalyst is needed by this technology, which will cause solid waste generation. More importantly, this process is not sensitive to both water and free fatty acids in the feedstock (Zhang *et al.*, 2003).

Technology B: Alkali-catalyzed process. This process requires virgin vegetable oil as feedstock for the production of biodiesel. Alkali catalyst is needed by this technology, which will cause solid waste generation. The limit of this process is the sensitivity of the system to both water and free fatty acids in the feedstock, which must be will operated in order to ensure smooth production (West *et al.*, 2008; Apostolakou *et* *al.*, 2009).

Technology C: Non-catalyzed process. This process requires vegetable oil as the feedstock for the production of biodiesel. However, no catalyst is needed by this technology, which will cause no solid waste generation. Instead, this process requires a super-critical condition of methanol for the transesterificaiton reaction to happen, which corresponds to a high temperature and pressure, and indicates great energy consumption and potential safety issues (Santana *et al.*, 2009; Glisic and Skala, 2009).

In using the developed tool mode for this sustainability assessment, the IChemE (IChemE, 2002) sustainability metric set was selected, which contains 14 economic indicators, 24 environmental indicators, and 11 social indicators. Considering their relevance to this application, eight economic indicators, 15 environmental indicators, and seven social indicators were picked up among those available indicators for conducting the assessment. The default-weighting factor, namely, "1" was assigned to each selected indicator and the total number of design alternatives was specified as "3", which tells the tool to assess those three biodiesel manufacturing technologies simultaneously. Then, data of each selected indicator are input for each design alternative and the boundaries of each indicator were specified as well, where the details are listed in Table 6.1 through 6.3.

Table 6.1. Data of economic indicators for biodiesel manufacturing technologies.

Economic Indicator	Technology			Boundary Specification	
	A	B	C	Lower	Upper
Value added (M$/yr)	1.388	1.556	1.445	1.000	N/A
Value added per unit value of sale ($/yr)	0.16	0.18	0.17	0.10	N/A
Gross margin per direct employee (M$/yr)	0.216	0.222	0.224	0.150	N/A
Return on average capital employed (%/yr)	3.10	3.23	3.01	2.00	N/A
Taxes paid, as percent of net income before tax (%)	50	50	50	N/A	N/A
Percentage increase (decrease) in capital employed (%)	0	0	0	N/A	N/A
R&D expenditure as percentage sales (%)	3.20	3.03	3.24	3.00	3.50
Investment in education per employee training expense ($/$)	88330	88330	88330	0	100000

Table 6.2a. Data of environmental indicators for biodiesel manufacturing technologies.

Environmental Indicator	Technology			Boundary Specification	
	A	B	C	Lower	Upper
Total net primary energy usage (GJ/yr)	62246	72246	82463	N/A	80000
Total raw materials used per kg product (kg/kg)	1.09	1.22	1.06	N/A	1.50
Total raw materials used per unit value added (kg/$)	6.65	6.66	6.49	N/A	9.00
Fraction of raw materials recycled within company (kg/kg)	0	0	0	0	N/A
Hazardous raw materials per kg product (kg/kg)	0.22	0.24	0.10	N/A	0.50
Net water consumed per unit mass of product (kg/kg)	181.0	250.7	230.9	N/A	400.0
Net water consumed per unit value added (kg/$)	0.16	0.27	0.25	N/A	0.30
Total land occupied and affected per unit value added (m^2/($/yr))	0.042	0.050	0.039	N/A	0.500

Table 6.2b. Data of environmental indicators for biodiesel manufacturing technologies (cont'd).

Environmental Indicator	Technology			Boundary Specification	
	A	B	C	Lower	Upper
Atmospheric acidification burden per unit value added (t/$)	0	0	0	N/A	N/A
Global warming burden per unit value added (t/$)	0	0	0	N/A	N/A
Human health burden per unit value added (t/$)	0	0	0	N/A	N/A
Ozone depletion burden per unit value added (t/$)	0	0	0	N/A	N/A
Photochemical ozone burden per unit value added (10^{-3}t/$)	0.010	0.116	0.006	N/A	0.589
Hazardous solid waste per unit value added (10^{-3}t/$)	0.086	1.65	0	N/A	4.3
Non-hazardous solid waste per unit value added (10^{-3}t/$)	0	0	0	N/A	N/A

Table 6.3. Data of social indicators for biodiesel manufacturing technologies.

Social Indicator	Technology			Boundary Specification	
	A	B	C	Lower	Upper
Benefits as percentage of payroll expense (%)	55.76	55.76	55.76	0	N/A
Employee turnover per number employed (%)	7.14	7.34	7.54	0	8.00
Working hours lost as percent of total hours worked (%)	11.51	11.51	12.33	0	15.00
Expenditure of illness & accident prevention per payroll expense ($/$)	0.86	0.60	0.70	0	1.00
Number of stakeholder meetings per unit value added (10^{-6}/$)	3.80	3.59	3.57	0	4.00
Number of complaints per unit value added (10^{-3}/$)	0.010	0.019	0.020	0	0.025

Using the data, the tool calculated the composite sustainability (top layer) and overall sustainability (bottom layer), where the pages for result demonstration are captured and illustrated in Fig. 6.15. Figure 6.15 shows three spider-charts demonstrating indicator-based economic, environmental, and social sustainability results in different colors for each design alternative. It is clear that alternative B (acid-catalyzed technology) is better than the other two technologies in terms of most economic indicators, and alternative A (alkali-catalyzed technology) is the best in terms of most environmental and social indicators.

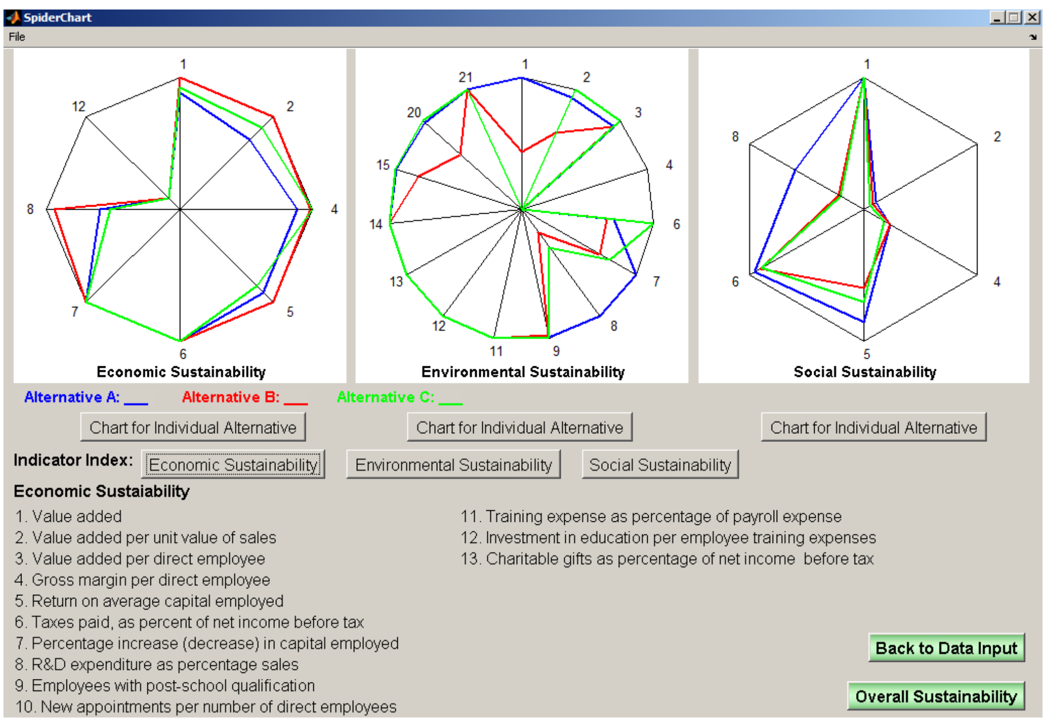


Figure 6.15. Sustainability assessment results of biodiesel manufacturing technologies: indicator-based spider-charts.

Figure 6.16 gives the table-based assessment results of composite and overall sustainability and the cube-based result visualization, where the best categorized sustainability states can be directly read as alternative B for composite economic sustainability (0.880), and alternative A for composite environmental sustainability (0.902), composite social sustainability (0.625), and overall sustainability (0.773), respectively. With that, we can easily compare these three biodiesel manufacturing technologies with different aspects for making decisions. For instance, the alkali-catalyzed technology (alternative A) is the best choice for pursuing the overall sustainability, and the acid-catalyzed technology (alternative B) and the non-catalyzed technology (alternative C) have nearly the same social and overall sustainability, while the acid-catalyzed technology is better than the non-catalyzed technology in terms of economic sustainability, but worse in terms of environmental sustainability.

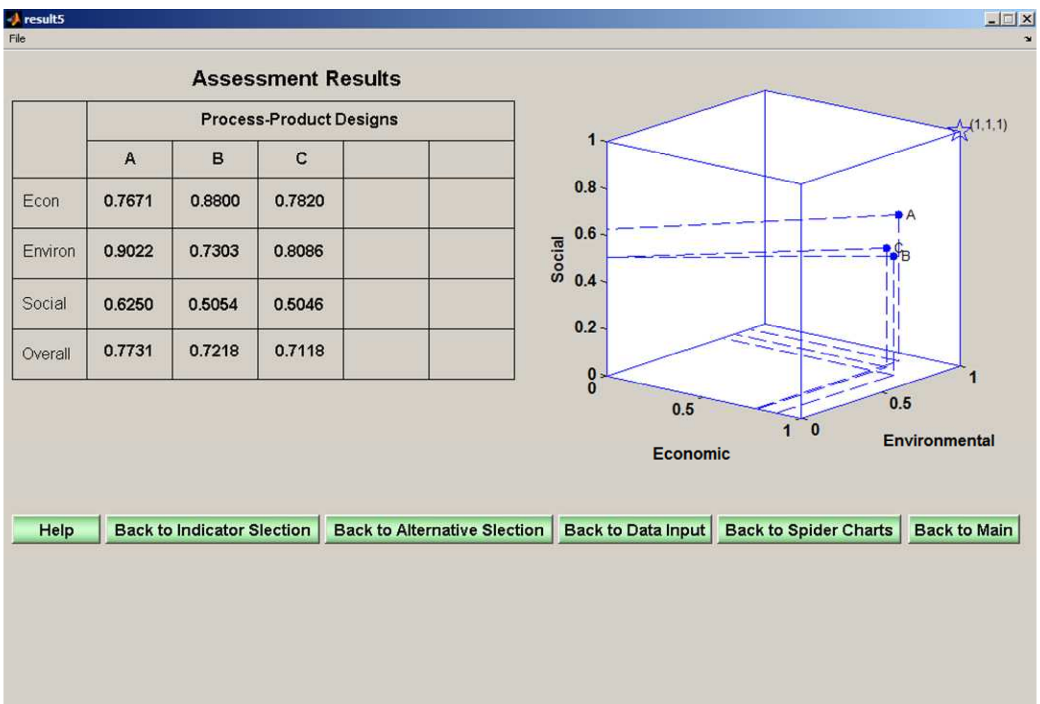


Figure 6.16. Sustainability assessment results of biodiesel manufacturing technologies: composite and overall sustainability.

6.2.2 Short- to mid-term enhancement plan development for a metal finishing centered industrial zone

A short- to mid-term enhancement plan development for a metal-finishing-centered industrial zone by Piluso *et al*. (2010) was adopted and applied by using the developed tool mode of industrial sustainability enhancement.

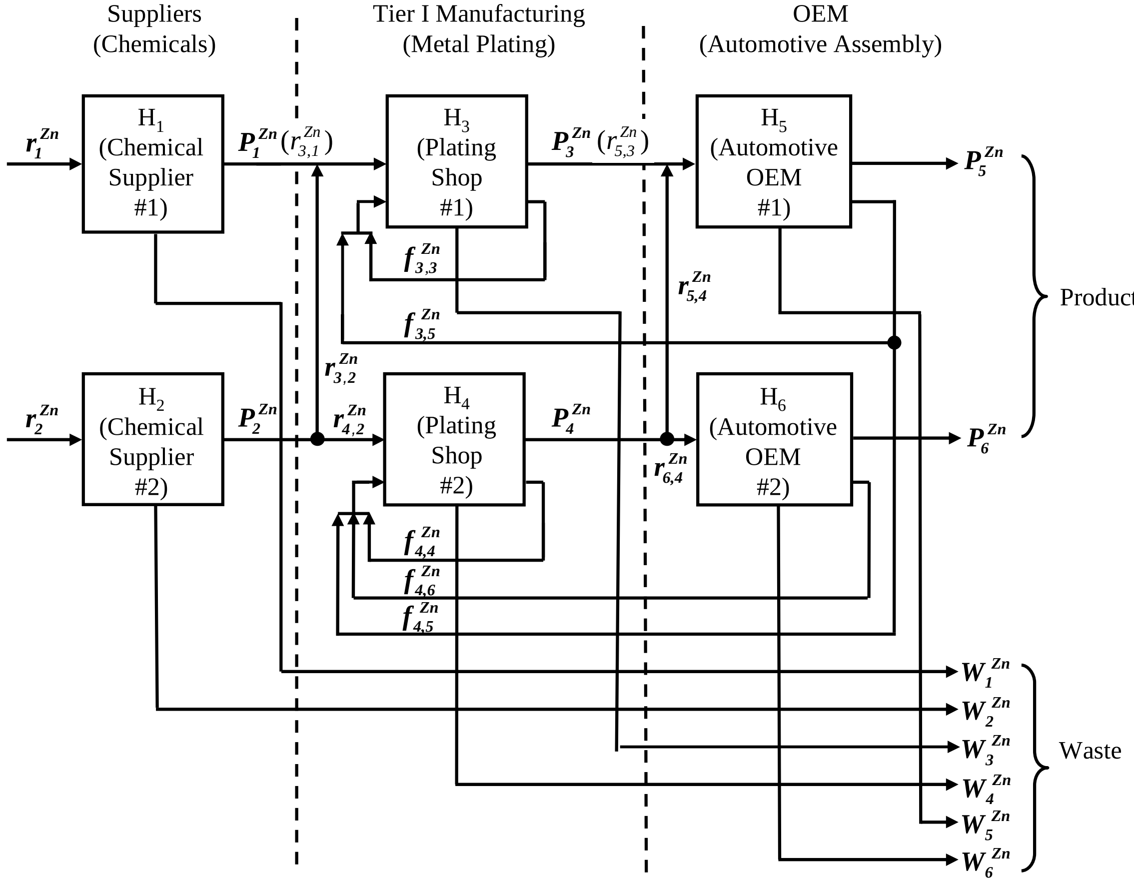


Figure 6.17. Surface finishing industrial region.

Problem Description. The industrial zone under study is sketched in Fig. 6.17.

This industrial zone consists of two chemical suppliers to the electroplating plants (H1 and H2), two electroplating shops (H3 and H4), two end users, in this case, two original equipment manufacturers (OEM) for the automotive industry (H5 and H6) and a regional wastewater treatment facility (WWTF). The WWTF is charged with cleaning the waste streams, from each of the component plants, to a level that is environmentally satisfactory for discharge into the local river and environment. This study is to investigate the sustainability level of the industrial zone, and then to develop and compare effective plans for sustainability enhancement.

Sustainability metrics selection. A subset of 11 indicators of the IChemE's sustainable development progress metrics has been selected as follows for conducting sustainability assessment.

(a) For economic sustainability assessment, the selected indicators are: (1) Value added ($x_{e,1}$), which is defined as the difference of the sales and the total cost of goods, raw materials (including energy), and services purchased, (2) Gross margin per direct employee ($x_{e,2}$), which is defined as the ratio of the difference between the sales and all the variable costs and the number of direct employees, (3) Return on average capital employed ($x_{e,3}$), and (4) Taxes paid as a percentage of net income before tax ($x_{e,4}$).

(b) In the environmental sustainability category, four indicators are selected: (1) Total raw materials used per lb. product produced ($x_{v,1}$), which is the ratio between the pounds of raw material used and the pounds of product produced, (2) Fraction of raw materials recycled within a company ($x_{v,2}$), (3) Fraction of raw materials recycled from consumers ($x_{v,3}$), and (4) Hazardous solid waste per unit value added ($x_{v,4}$).

(c) In the social sustainability assessment category, the suitable indicators are: (1) Lost time accident frequency ($x_{l,1}$), (2) Number of stakeholder meetings per unit value added ($x_{l,2}$), and (3) Number of complaints per unit value added ($x_{l,3}$).

Sustainability goal specification. For this tool application, the economic, environmental, and social development goals, i.e., $E^{sp}(P)$, $V^{sp}(P)$, and $L^{sp}(P)$ are specified as 0.55, 0.35, and 0.55, respectively. In addition, the maximum acceptable deviations of the system sustainability performance from the pre-set goals, namely, η_E, η_V, and η_L are set as 5% each. Note that the minimum acceptances can then be calculated as 0.523, 0.33, and 0.523 for economic, environmental, and social sustainability category, respectively.

Sustainability assessment. Data of of each assessment indicator of the current zone are input in the tool. Then, the tool calculates the current sustainability states, where the results are collected and listed in Table 6.4. It shows the current composite economic, environmental, and social sustainability of the zone is 0.570, 0.147, and 0.342, respectively.

System Analysis. With the current sustainability results, the sustainability goals, and the maximum acceptable deviations, the inequalities in Eqs. 6.11 and 6.12 hold. Therefore, the composite environmental and social sustainability categories will be treated as the causes of the current system for further enhancement.

Table 6.4. Sustainability assessment of the current zone (at Year 0).

ECON indicators	Input data (dimensional)	Normalized value	Weighting factor	Categorized Sustainability, $E(P;0)$	Overall sustainability, $S(P;0)$
$x_{e,1}$	10.0	0.833	0.10	0.570	0.393
$x_{e,2}$	690.0	0.690	0.30		
$x_{e,3}$	25.0	0.250	0.30		
$x_{e,4}$	32.0	0.681	0.30		
ENV indicators	Input data (dimensional)	Normalized value	Weighting factor	Categorized Sustainability, $V(P;0)$	
$x_{v,1}$	1.06	0.116	0.15	0.147	
$x_{v,2}$	0.08	0.080	0.35		
$x_{v,3}$	0.02	0.020	0.35		
$x_{v,4}$	3.70	0.630	0.15		
SOC indicators	Input data (dimensional)	Normalized value	Weighting factor	Categorized Sustainability, $L(P;0)$	
$x_{l,1}$	11.4	0.430	0.30	0.342	
$x_{l,2}$	2.2	0.220	0.35		
$x_{l,3}$	30.6	0.388	0.35		

Enhancement strategy proposal. The results of the system analysis are useful in identifying areas that require improvement and provide aid in future zone planning decisions for sustainability enhancement. For this case, the strategy for sustainable development must follow the form where economic sustainability will achieve a steady improvement, while the environmental and social sustainability aspects should be significantly enhanced. In order to achieve this outcome, two improvement plans are proposed in Table 6.5 (where the data provided is the dimensional input data for each scenario at two time stages of interests, namely, the short- term from year 1 to 3, and the mid-term from year 4 to 6).

Table 6.5. Sustainability enhancement Plan A and B.

Improvement Focus	Current (Year 0)	Short-term (Year 3)	Mid-term (Year 6)
Plan A			
Main plan for environmental sustainability improvement			
• Fraction of raw materials recycled within a company ($x_{v,2}$)	0.08	0.22	0.30
• Fraction of raw materials recycled from consumers ($x_{v,3}$)	0.02	0.15	0.25
• Hazardous solid waste per unit value added ($x_{v,4}$)	3.7	1.5	1.4
Main plan for social sustainability improvement			
• Lost time accident frequency ($x_{l,1}$)	11.4	7.0	6.2
• Number of complaints per unit value added ($x_{l,3}$)	30.6	17	12
Plan B			
Main plan for environmental sustainability improvement			
• Fraction of raw materials recycled within a company ($x_{v,2}$)	0.08	0.15	0.35
• Fraction of raw materials recycled from consumers ($x_{v,3}$)	0.02	0.10	0.32
• Hazardous solid waste per unit value added ($x_{v,4}$)	3.7	3.2	1.2
Main plan for social sustainability improvement			
• Lost time accident frequency ($x_{l,1}$)	11.4	9.8	3.0
• Number of stakeholder meetings per unit value added ($x_{l,2}$)	2.2	2.2	5.4
• Number of complaints per unit value added ($x_{l,3}$)	30.6	25	6

The two plans are very similar, with the exception of one additional improvement area for social sustainability in Plan B; however, the stage-wise goals of the two plans are quite different. Plan A emphasizes its major efforts on the short-term period, and more passively maintains the industrial zone without any major investment over the mid-term period. On the contrary, Plan B focuses on incorporating small improvements throughout the short-term period and will make major investment over the mid-term period. Note that the two plans are developed based on different business development strategies; this is not discussed here as it is out of scope of this work.

Short- to mid-term sustainability prediction. New data of the industrial zone after implementing enhancement Plan A and B at both the short and mid-term stages are input in the tool for sustainability prediction. Then, the sustainability states at those time stages are calculated and presented in the tool, where the screenshot is shown in Fig. 6.18. This prediction clearly shows that Plan A and B will both keep a good economic sustainability over the short- to mid-term period. For environmental and social sustainability, Plan A can provide a faster improvement than Plan B over the short-term period. However, when the industrial zone goes to the mid-term period, the environmental and social sustainability improvement by Plan B will have a significant improvement, while the improvement by Plan A will become slow. By the consideration of the entire six year along the short- to mid-term period, the composite economic, environmental, and social sustainability after implementing Plan A will be 0.603, 0.344, and 0.578, respectively, and the same composite sustainability after implementing Plan B will be 0.601, 0.399, and 0.752, respectively. Note that both plans satisfy the pre-set minimum acceptances of sustainability goals, i.e., 0.523, 0.33, and 0.523, which indicates that no plan modification is needed.

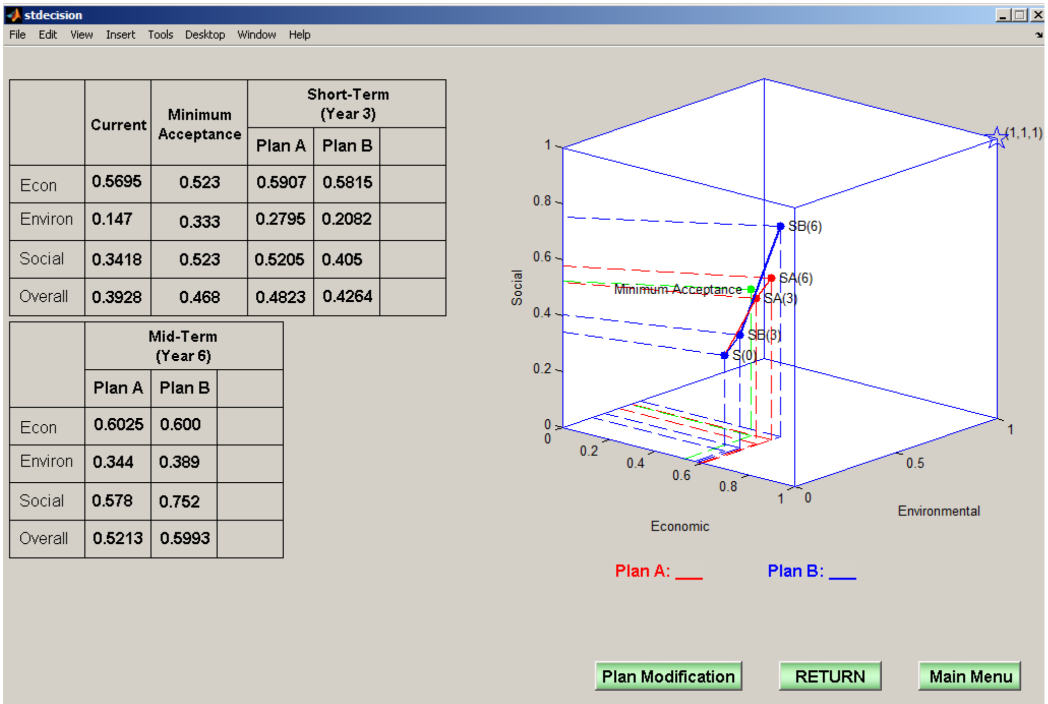


Figure 6.18. Short- to mid-term sustainability prediction of the industrial zone after implementing Plan A and B.

The overall sustainability by Plan A and B will be 0.512 and 0.599, respectively. In the same screenshot by Fig. 6.18, such the development path of Plan A and B are depicted in the sustainability cube, which visually demonstrates the different enhancement effects of each plan at each term stage. With these prediction results and comparisons, decisions can be easily made for the identification of the best suitable enhancement strategy: if short-term performance is the primary concern, Plan A would be more desirable; however, if the zone's planner focuses on a mid-term performance goal, Plan B would be more advantageous.

6.3 Future Works

Two types of future works are being considered to further improve this computational tool. First, a considerable and important need is to provide the tool a capability of handling data and information uncertainty. In reality, data and information uncertainty is one of the most challenging issues in sustainability assessment and decision making for industrial systems. For example, the price of raw materials and products, forthcoming environmental regulation, future market demand, etc., are frequently uncertain, and much information need for sustainability assessment are always incomplete and imprecise, like the potential environmental impact of untraditional chemicals.

Among those available mathematical techniques, and computer and cognitive science based methods for handling uncertainties, interval parameter based approaches has been proposed and proven for effectively handling data and information uncertainties in sustainability studies (Liu *et al.*, 2011), which treat uncertainties as intervals with known lower and upper bounds, and apply interactive algorithm to obtain numerical solutions resulting in the same interval format (Li *et al.*, 2006). Therefore, it is highly desirable to further integrate the interval parameter based approaches into the current methodology and update the tool. Moreover, since the methodology framework and tool interfaces can be almost kept the same, there is no big effort needed for implementing this methodology and tool update.

Another considerable future work is to introduce optimization-based decision support for sustainability enhancement. The current decision support of the tool is based on comparisons between scenarios of enhancement plans, which is well used in industrial societies. However, the quality of the solutions derived by this method highly depends on the plans proposed, and no optimal solutions can be addressed. In order to derive optimal solutions, this comparison-based method must be replaced by the optimization-based method, which should be able to conduct sustainability assessment using models of system variables instead of specified data, and derives solutions by handling system optimizations instead of simple comparisons. Such a change requests great efforts in developing new methodology and designing new tool interfaces.

6.4 Chapter Summary

To facilitate industrial practice on engineering sustainability, a computational tool, namely ISEE (Industrial Sustainability Evaluation and Enhancement), has been designed and presented in this chapter, where comprehensive sustainability principles are embedded in a systems approach for sustainability assessment and decision support. The developed ISEE tool is featured by its capability of processing system data and information, assessing sustainability status quo and predicting its future performance, and evaluating design alternatives using various sustainability metrics. Based on the assessment, the tool is also capable of identifying the most desirable design for short- to long-term sustainability enhancement. Using this tool, people without knowing the complex sustainability theories and calculations, can easily evaluate the sustainability status of industrial and energy systems of interest, compare different design alternatives, identify the best design for decision-making, and acquire suggestions on potential system improvements.

This tool is developed in a flexible structure, which allows the user to modify either the assessment or the enhancement schemes in the most convenience. The tool interfaces are developed user-friendly with menus and buttons for help review, file saving, page print, etc. The efficacy of the developed tool was demonstrated by applications of a sustainability assessment of biodiesel manufacturing technologies and a short-to-long-term enhancement strategy development for a metal-finishing-centered industrial zone. In summary, this computational tool, ISEE will greatly facilitate the academic and industrial practices on the study of sustainability, as the only one available to the public so far.

CHAPTER 7

INTRODUCTION OF EXERGY ANALYSIS AND ITS APPLICATION IN INDUSTRIAL SUSTAINABILITY RESEARCH

Industrial sustainability is a major branch of sustainability research focusing on how to pursue the short- to long-term sustainable development of an industrial or energy system, where material and energy efficiencies, waste reduction, safety, synergies among the systems, etc., are among the major concerns (Piluso *et al.*, 2010). For a given industrial or energy system, there are three types of elements carrying all the information of it, namely, material flows, energy flows, and operation units. Sustainable system methodologies introduced in Chapter 2 to 5 are all suitable for dealing with those three types of elements, while the most fundamental material and energy balance are applied.

In the recent years, the concept so called Exergy has been paid more and more attentions in the study of industrial sustainability. Since exergy represents the chemical and physical properties of material and energy flows in a unique way, its application in sustainability gives raise to new views and understanding compared with the traditional material and energy balance based approaches, while at the same time, there are still some unclear issues for using this concept. In this chapter, we will give a brief introduction about the concept of exergy and exergy based process analysis, and then develop an exergy based IOA method for industrial sustainability analysis. Detailed discussion about the advantages and disadvantages by using exergy analysis will be given at the end of this chapter.

7.1 Concept of Exergy

In thermodynamics, the exergy of a system is the maximum useful work possible during a process that brings the system into equilibrium with a heat reservoir. When the surroundings are the reservoir, exergy is the potential of a system to cause a change as it achieves equilibrium with its environment. By this concept, we can say that exergy is the energy that is available to be used, which represents the quality property of energy.

Excluding nuclear, magnetic, electrical, and interfacial effects, the exergy of a stream of substance can be divided into four components: (i) kinetic exergy, (ii) potential exergy, (iii) physical exergy, and (iv) chemical exergy. However, the first two components are always very small, so that we can neglect them in the normal exergy analysis.

The physical exergy and chemical exergy of a stream can be calculated using the following two equations (Kotas, 1985):

$$E_{physical} = H - T_0 S \tag{7.1}$$

$$E_{physical} = \sum_{k=1}^{K} n_k \tilde{\varepsilon}_k^{0} + (T - T_0) \sum_{k=1}^{K} x_k \tilde{c}_{P,k}^{\varepsilon} \tag{7.2}$$

$$E = E_{physical} + E_{chemical} \tag{7.3}$$

where $E_{phycial}$, $E_{chemical}$, and E are the physical, chemical, and total exergy of the stream, respectively; H and S are the enthalpy and entropy of the stream, respectively; K is the total number of chemical components in the stream; n_k is the molar amount of component K; $\tilde{\varepsilon}_k^0$ is the chemical exergy of component K in its reference state (environment); x_k is the flow rate of the k-th component per mole of mixture; and $\tilde{c}_{P,k}^{\varepsilon}$ is the mean isobaric exergy capacity of component K. As can be seen in such an exergy calculation, the environment of the system must be specified as a reference state in order to conduct the exergy calculation.

First law of thermodynamics shows that energy is never destroyed during a process; it changes from one form to another. In contrast, the physical exergy accounts for the irreversibility of a process due to increase in entropy (see second law of thermodynamics). Physical exergy is always destroyed when a process involves an entropy change. This destruction is proportional to the entropy increase of the system together with its surroundings. For a simple chemical reaction system (see, Fig. 7.1), its physical exergy change between the inlet flow and outlet flow can be calculated by Eq. 7.4.

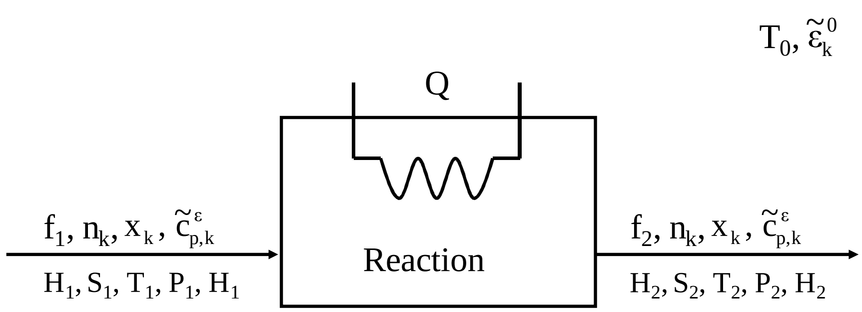


Figure 7.1. A simple chemical reaction system for illustration of exergy change.

$$E_{2,physical} - E_{1,physical} = H_2 - H_1 - T_0(S_2 - S_1) \tag{7.4}$$

where $E_{1,phycial}$ and $E_{2,physical}$ are the physical exergy of the inlet and outlet flow, respectively; H_1 and H_2 are the enthalpy of the inlet and outlet flow, respectively; T_0 is the temperature of the environment; and S_1 and S_2 are the entropy of the inlet and outlet flow, respectively.

For such a system described in Fig. 7.1, there is also chemical exergy change due to the reaction, where the chemical exergy change between the inlet flow and outlet flow can be calculated by Eq. 7.5.

$$E_{2,chemical} - E_{1,chemical} = \sum_{k=1}^{k_2} n_k \tilde{\varepsilon}_k^0 + (T_2 - T_0)\sum_{k=1}^{k_1} x_k \tilde{c}_{P,k}^{\varepsilon} - \sum_{k=1}^{k_1} n_k \tilde{\varepsilon}_k^0 - (T_1 - T_0)\sum_{k=1}^{k_1} x_k \tilde{c}_{P,k}^{\varepsilon} \tag{7.5}$$

where k_1 and k_2 are the total number of chemical components in the inlet and outlet flow, respectively; n_k is the molar amount of component K; $\tilde{\varepsilon}_k^0$ is the chemical exergy of component K in its reference state (environment); x_k is the flow rate of the k-th component per mole of mixture; and $\tilde{c}_{P,k}^{\varepsilon}$ is the mean isobaric exergy capacity of component K.

Adding Eqs. 7.4 and 7.5 together, the total exergy loss between the inlet flow and outlet flow is given Eq. 7.6, which is also called anergy.

$$\begin{aligned} E_2 - E_1 = {} & H_2 - H_1 - T_0(S_2 - S_1) + \sum_{k=1}^{k_2} n_k \tilde{\varepsilon}_k^0 + (T_2 - T_0)\sum_{k=1}^{k_1} x_k \tilde{c}_{P,k}^{\varepsilon} - \sum_{k=1}^{k_1} n_k \tilde{\varepsilon}_k^0 \\ & - (T_1 - T_0)\sum_{k=1}^{k_1} x_k \tilde{c}_{P,k}^{\varepsilon} \end{aligned} \tag{7.6}$$

7.2 Exergy based IOA

In this section, an exergy based input-output analysis method is proposed for the study of industrial systems. Since exergy has no conservation as neither the mass nor the energy, the traditional input-output analysis of mass and energy system was modified to suit the exergy analysis, where the general principle can be illustrated using Fig. 7.2.

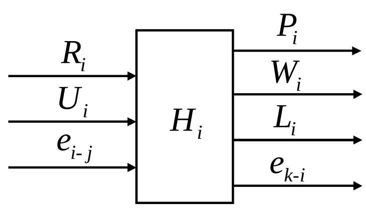


Figure 7.2. Exergy based IOA for one system entity.

In this figure, H_i represents the i-th entity of the system under study; R_i is the exergy inflow carried by raw materials from the environment to H_i; U_i is the exergy inflow carried by fuels from the environment to H_i; e_{i-j} is the internal exergy flow from H_j to H_i; P_i is the exergy outflow carried by products from H_i to the environment; W_i is the exergy outflow carried by wastes from H_i to the environment; and L_i is the exergy loss in H_i. For a system contains multiple entities, the internal exergy flows of each entity need to be connected, which will give a complete exergy IOA structure.

The exergy of R_i, U_i, e_{i-j}, P_i, W_i, and e_{k-i}, can be calculated using Eqs. 7.1 through 7.3, while the exergy loss, L_i, should be quantified by Eq. 7.6. With that, the exergy efficiency of that entity can be conducted using the following equation.

$$EE_i = \frac{P_i + e_{k-i}}{R_i + U_i + e_{i-j}} \tag{7.7}$$

where EE_i stands for the exergy efficiency of the i-th entity. Note that the same exergy efficiency can be calculated for a sector or the whole system.

The chief aim of this exergy analysis is to detect and to evaluate quantitatively the causes of the thermodynamic imperfection of the process under consideration. Exergy analysis can, therefore, indicate the possibilities of thermodynamic improvement of the process under consideration.

7.2.1 Case study

As an example for efficacy demonstration, the proposed exergy based IOA is applied to an automotive manufacturing centered industrial region. The goal of this study is to evaluate the current exergy efficiency of the system and identify effective strategies for the system's enhancement.

The exergy based IOA flow sheet of this automotive manufacturing centered industrial region is given in Fig. 7.3, which contains six entities defined in the way of Fig. 7.2. To quantify the current exergy efficiency of the system, the exergy of each stream is calculated using Eqs. 7.1 through 7.3, where the results are demonstrated visually in Fig. 7.4. Note that in this figure, the summation of two exergy inflows (R_1 *and* R_2) carried by the raw materials from the environment to the system is defined as the reference amount, and all other exergy streams are normalized as a percentage compared to this reference amount. For instance, the exergy of P_5 is 28.4% to the exergy of R_1+R_2.

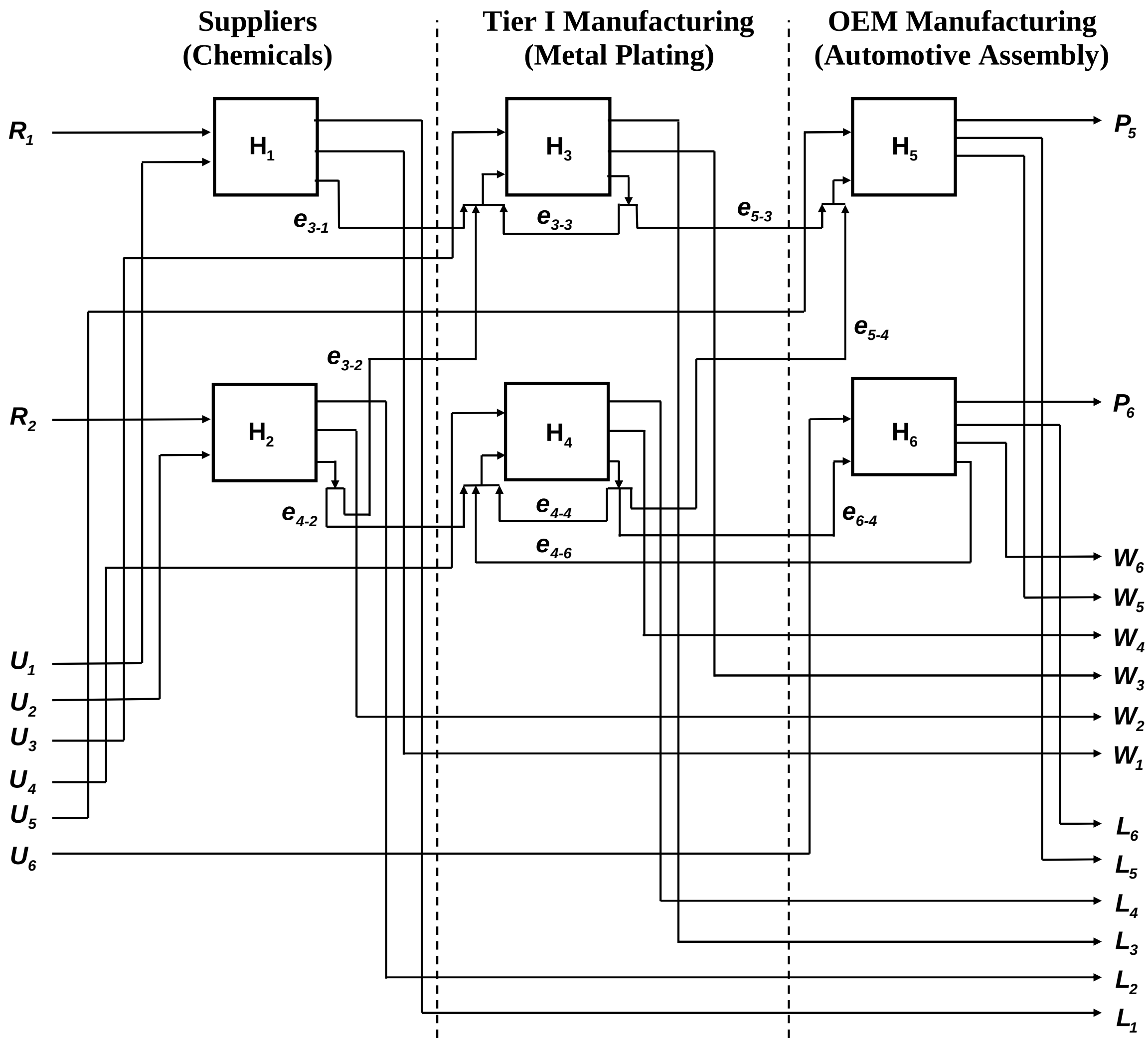


Figure 7.3. Exergy based IOA flow sheet
of the current automotive manufacturing centered industrial region.

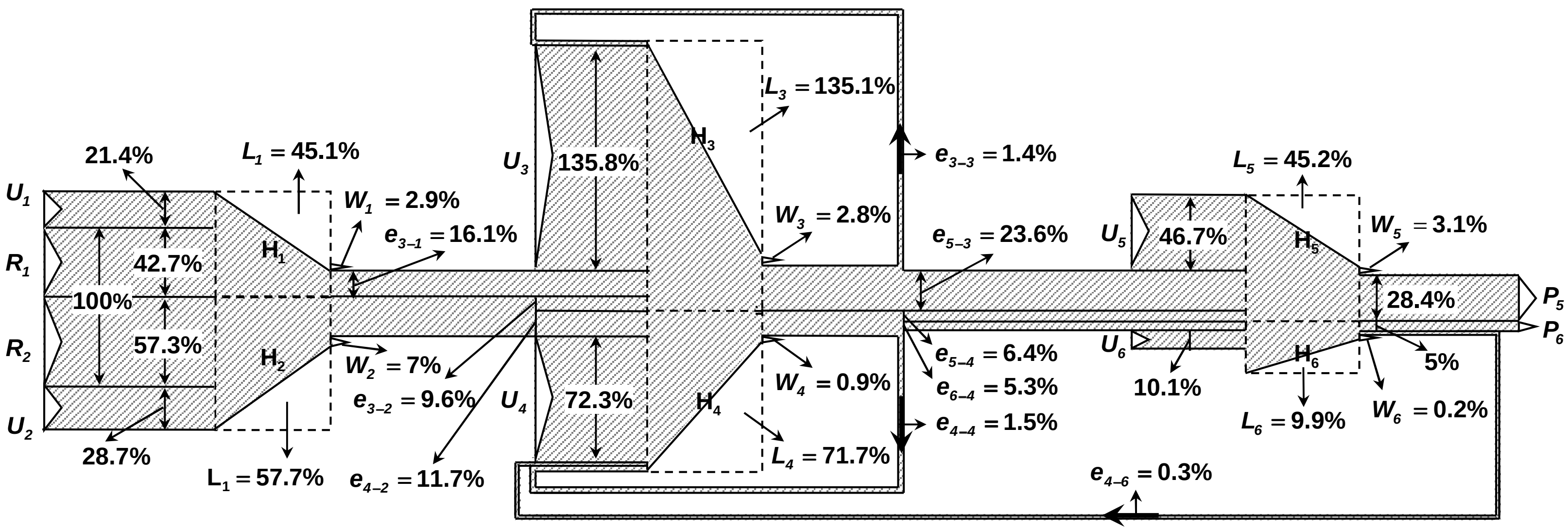


Figure 7.4. Exergy flow diagram of the current system.

With that, the exergy efficiency of the six plants can be calculated using Eq. 7.7, where the results are given as follows:

$$EE_1 = \frac{e_{3-1}}{R_1+U_1} = \frac{16.1\%}{42.7\%+21.4\%} = 25.12\% \quad (7.8)$$

$$EE_2 = \frac{e_{3-2}+e_{4-2}}{R_2+U_2} = \frac{9.6\%+11.7\%}{57.3\%+28.7\%} = 24.77\% \quad (7.9)$$

$$EE_3 = \frac{e_{3-3}+e_{5-3}}{U_3+e_{3-1}+e_{3-2}+e_{3-3}} = \frac{1.4\%+23.6\%}{135.8\%+16.1\%+9.6\%+1.4\%} = 15.35\% \quad (7.10)$$

$$EE_4 = \frac{e_{4-4}+e_{5-4}+e_{6-4}}{U_4+e_{4-2}+e_{4-4}+e_{4-6}} = \frac{1.5\%+6.4\%+5.3\%}{72.3\%+11.7\%+1.5\%+0.3\%} = 15.38\% \quad (7.11)$$

$$EE_5 = \frac{P_5}{U_5+e_{5-3}+e_{5-4}} = \frac{28.4\%}{46.7\%+23.6\%+6.4\%} = 37.03\% \quad (7.12)$$

$$EE_6 = \frac{P_6+e_{4-6}}{U_6+e_{6-4}} = \frac{5\%+0.3\%}{10.1\%+5.3\%} = 34.42\% \quad (7.13)$$

Moreover, the exergy efficiency of the three sectors, i.e., Suppliers, Tier Manufacturing, and OEM, are calculated using Eq. 7.7, and the results are given as follows:

$$EE_{suppliers} = \frac{e_{3-1}+e_{3-3}+e_{4-2}}{R_1+U_1+R_2+U_2} = \frac{16.1\%+9.6\%+11.7\%}{42.7\%+21.4\%+57.3\%+28.7\%} = 24.92\% \quad (7.14)$$

$$EE_{Tier\ Manu} = \frac{e_{3-3}+e_{5-3}+e_{4-4}+e_{5-4}+e_{6-4}}{U_3+e_{3-1}+e_{3-2}+e_{3-3}+U_4+e_{4-2}+e_{4-4}+e_{4-6}}$$
$$= \frac{1.4\%+23.6\%+1.5\%+6.4\%+5.3\%}{135.8\%+16.1\%+9.6\%+1.4\%+72.3\%+11.7\%+1.5\%+0.3\%} \quad (7.15)$$
$$= 15.36\%$$

$$EE_{OEM} = \frac{P_5 + P_6 + e_{4-6}}{U_5 + e_{5-3} + e_{5-4} + U_6 + e_{6-4}} \qquad (7.16)$$
$$= \frac{28.4\% + 5\% + 0.3\%}{46.7\% + 23.7\% + 6.4\% + 10.1\% + 5.3\%} = 36.56\%$$

Finally, the exergy efficiency of the whole system is:

$$EE_{zone} = \frac{P_5 + P_6}{R_1 + U_1 + R_2 + U_2 + U_3 + U_4 + U_5 + U_6}$$
$$= \frac{28.4\% + 5\%}{42.7\% + 21.4\% + 57.3\% + 28.7\% + 135.8\% + 72.3\% + 46.7\% + 10.1\%} \qquad (7.17)$$

$$= 8.05\%$$

The above exergy analysis results of the current system shows that the overall exergy efficiency is only 8.05%, which should be improved. Thus, two feasible system modification strategies are proposed: (i) to introduce recycle from H_5 to both plating plants, i.e., H_3 and H_4, which can decrease 45% of the waste generated by H_5, and (ii) to replace the water heating source of both plating plants, i.e., H_3 and H_4, from electricity to liquid fuel, which can increase the exergy efficiency significantly.

The exergy based IOA flow sheet of the modified industrial region is given in Fig. 7.5. Then, the exergy of each stream is re-calculated using Eqs. 7.1 through 7.3, where the results are demonstrated visually in Fig. 7.6.

For this modified industrial zone, the exergy efficiency of the six plants can be re-calculated using Eq. 7.7, where the results are given as follows:

$$EE_1 = \frac{e_{3-1}}{R_1 + U_1} = \frac{16.1\%}{42.7\% + 21.4\%} = 25.12\% \qquad (7.18)$$

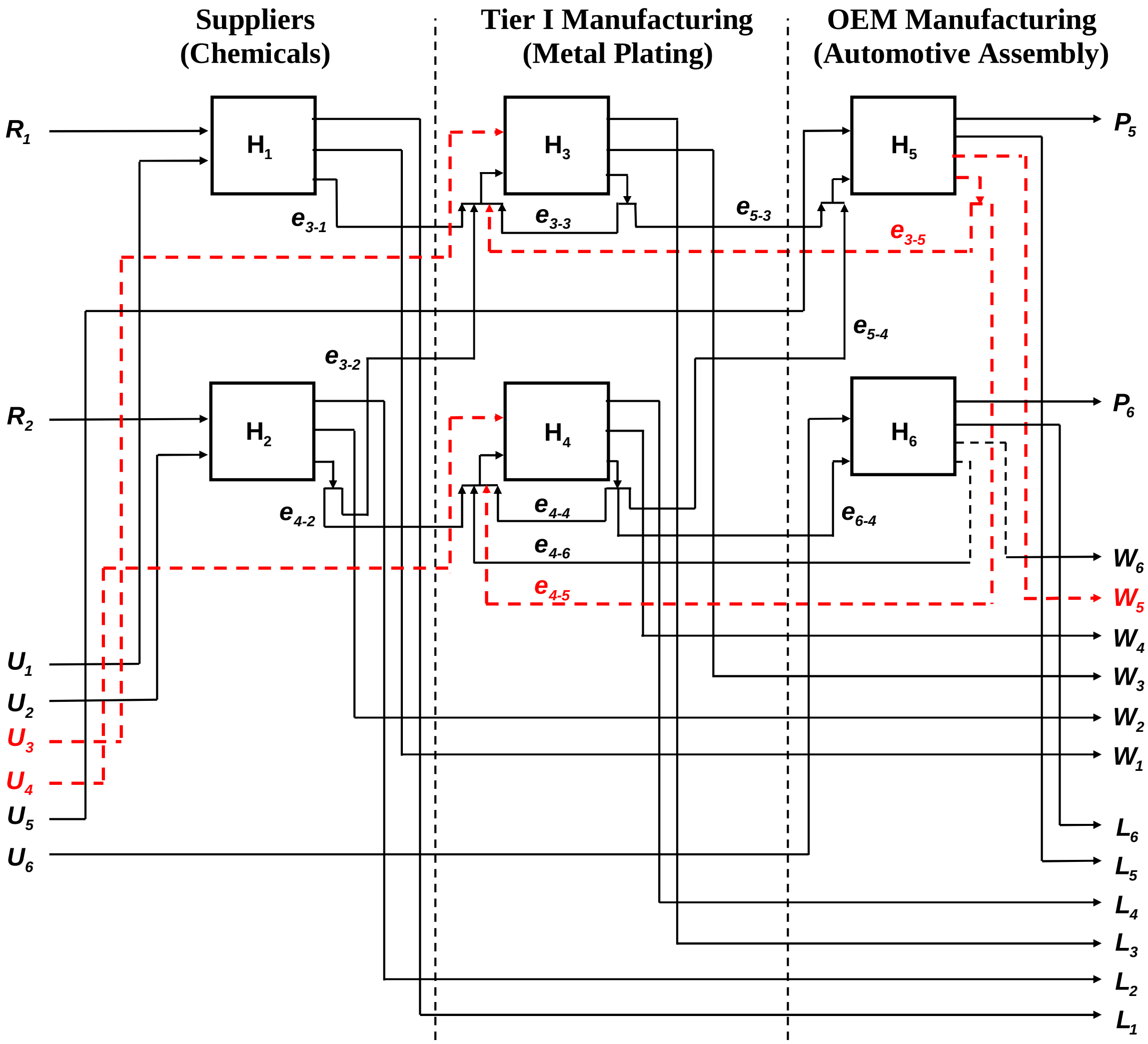


Figure 7.5. Exergy based IOA flow sheet
of the modified automotive manufacturing centered industrial region.

$$EE_2 = \frac{e_{3-2} + e_{4-2}}{R_2 + U_2} = \frac{9.6\% + 11.7\%}{57.3\% + 28.7\%} = 24.77\% \tag{7.19}$$

$$EE_3 = \frac{e_{3-3} + e_{5-3}}{U_3 + e_{3-1} + e_{3-2} + e_{3-3} + e_{3-5}} = \frac{1.4\% + 23.6\%}{105.8\% + 16.1\% + 9.6\% + 1.4\% + 0.9\%} \tag{7.20}$$

$$= 18.68\%$$

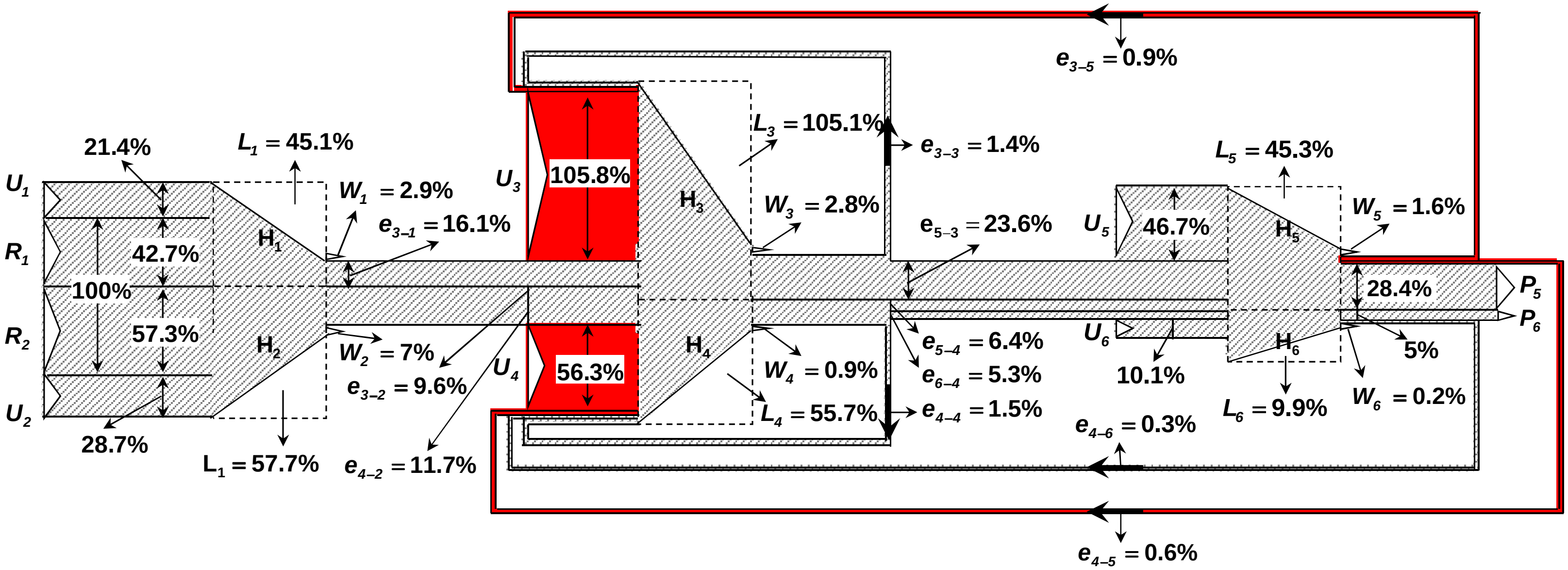


Figure 7.6. Exergy flow diagram of the modified system.

$$EE_4 = \frac{e_{4-4}+e_{5-4}+e_{6-4}}{U_4+e_{4-2}+e_{4-4}+e_{4-5}+e_{4-6}} = \frac{1.5\%+6.4\%+5.3\%}{56.3\%+11.7\%+1.5\%+0.6\%+0.3\%}$$
$$= 18.75\% \quad (7.21)$$

$$EE_5 = \frac{P_5+e_{3-5}+e_{4-5}}{U_5+e_{5-3}+e_{5-4}} = \frac{28.4\%+0.9\%+0.6\%}{46.7\%+23.6\%+6.4\%} = 38.98\% \quad (7.22)$$

$$EE_6 = \frac{P_6+e_{4-6}}{U_6+e_{6-4}} = \frac{5\%+0.3\%}{10.1\%+5.3\%} = 34.42\% \quad (7.23)$$

Moreover, the exergy efficiency of the three sectors, i.e., Suppliers, Tier Manufacturing, and OEM, are calculated using Eq. 7.7, and the results are given below:

$$EE_{suppliers} = \frac{e_{3-1}+e_{3-3}+e_{4-2}}{R_1+U_1+R_2+U_2} = \frac{16.1\%+9.6\%+11.7\%}{42.7\%+21.4\%+57.3\%+28.7\%} = 24.92\% \quad (7.24)$$

$$EE_{Tier\ Manu} = \frac{e_{3-3}+e_{5-3}+e_{4-4}+e_{5-4}+e_{6-4}}{U_3+e_{3-1}+e_{3-2}+e_{3-3}+e_{3-3}+U_4+e_{4-2}+e_{4-4}+e_{4-5}+e_{4-6}}$$
$$= \frac{1.4\%+23.6\%+1.5\%+6.4\%+5.3\%}{105.8\%+16.1\%+9.6\%+1.4\%+0.9\%+56.3\%+11.7\%+1.5\%+0.6\%+0.3\%} \quad (7.25)$$
$$= 18.7\%$$

$$EE_{OEM} = \frac{P_5+P_6+e_{3-5}+e_{4-5}+e_{4-6}}{U_5+e_{5-3}+e_{5-4}+U_6+e_{6-4}}$$
$$= \frac{28.4\%+5\%+0.9\%+0.6\%+0.3\%}{46.7\%+23.7\%+6.4\%+10.1\%+5.3\%} = 38.18\% \quad (7.26)$$

Finally, the exergy efficiency of the whole system is:

$$EE_{zone} = \frac{P_5+P_6}{R_1+U_1+R_2+U_2+U_3+U_4+U_5+U_6}$$
$$= \frac{28.4\%+5\%}{42.7\%+21.4\%+57.3\%+28.7\%+105.8\%+56.3\%+46.7\%+10.1\%} \quad (7.27)$$
$$= 9.05\%$$

The exergy analysis shows that after implementing the modified strategies, the system's overall exergy efficiency can be increased from 8.05% to 9.05%, which denotes a 12.42% improvement. To further improve the exergy efficiency of the system, other enhancement strategies should be proposed, and the same exergy based IOA needs to be re-applied to demonstrate the enhancement performance.

7.2.2 Discussion on exergy analysis in sustainability research

Since exergy represents the chemical and physical properties of material and energy flows in a unique way, its application in sustainability gives raise to new views and understanding compared with the traditional material and energy balance based approaches. Advantages of exergy analysis can be highlighted as follows: (i) exergy represents the quality property of energy, which indicates the possibilities of thermodynamic improvement of the process under consideration, and (ii) exergy combines both the material and energy aspects of a system into one property, which can be used to represent the total impact of the system to the environment.

However, exergy has not been well accepted in the study of industrial problems due to the following two concerns. First, as a traditional and practical concept, energy has been used and well accepted by industry over hundreds of years. Almost all the real life and research accomplishment are described in the format of energy, especially for the cost of energy usage., people already got use to using "$/energy amount" as the common basis. Second, the exergy-based analysis is not consisted with energy-based analysis, and there is no existing system to related exergy usage to the cost.

Therefore, exergy based analysis cannot be simply used in sustainability research for the replacement of energy based analysis. The best role of it could be a complement out of the current material and energy based sustainability study. In detail, exergy efficiency can be used as one of the assessment indicators of sustainability, which uniquely indicates the quality property of energy, and helps for the identification of possibilities of thermodynamic improvement of the system in necessary.

7.3 Chapter Summary

In the recent years, the concept so called Exergy has been paid more and more attentions in the study of industrial sustainability. Since exergy represents the chemical and physical properties of material and energy flows in a different way, its application in sustainability gives raise to new views and understanding compared with the traditional material and energy balance based approaches, while at the same time, there are still some unclear issues for using this concept.

In this chapter, a brief introduction about the concept of exergy and exergy based process analysis is given. After that, an exergy based IOA method is proposed for industrial sustainability analysis, and a detailed case study is given to demonstrate the efficacy of the proposed method. Finally, the advantages and disadvantages by using exergy-based analysis are discussed at the end of this chapter.

CHAPTER 8

CONCLUSIONS AND FUTURE WORK

The major developments and significant contributions of this dissertation are summarized in the first part of this chapter, which is followed by a set of recommendations for future work.

8.1 Conclusions

The research leading to this dissertation has yielded a series of methodologies for the study of sustainability problems of industrial and energy systems under various types of complexity and uncertainty. Such methodologies have three major features: (i) effective approaches that can address the sustainability principles, (ii) system approaches that can handle great complexity and identify optimal solutions, and (iii) practical approaches that can be implemented under various types of uncertainty. Beyond that, a computational tool is being designed, which provides functions on both the industrial sustainability assessment and decision-making through several convenient and interactive steps of computer operation.

Part I: Methodology development. The first part of this dissertation (Chapters 2 to 5) is focused on the development of sustainability design and decision making methodologies under various types of uncertainties. As stated, sustainability design and decision making of industrial and energy systems is a multi-objective and interdisciplinary task, which has great challenges due to the inherent complexity and uncertainty. Through imbedded uncertainty handling approaches into systems approaches, sustainable systems methodologies developed in those chapters are able to perform sustainability assessment, design and decision making under various types of uncertainties and great complexity, where solutions obtained can help decision makers to identify desired manufacturing strategies and/or system enhancement decisions for industrial practices.

The first two chapters introduce interval parameter based sustainability decision-making methodologies, where the interval parameter based approach is used to handle epistemic and alearoty uncertainties. Dealing with sustainability enhancement on any existing industrial systems, Chapter 2 introduces a simple approach for systematic sustainability assessment of industrial systems and technologies, and effective system sustainability enhancement under uncertainty. The methodology is able to derive efficiently the most suitable solutions for identification of superior sustainability technologies under uncertainty, and can be generally applied to the sustainability enhancement problems of any size and scope.

Chapter 3 focus on sustainability oriented strategy making on new (non-existing) energy systems. A systematic sustainability assessment based decision-making methodology is proposed in this chapter for conducting strategic planning of biodiesel manufacturing in regions. By this methodology, the best strategy for biodiesel manufacturing in regions can be identified through conducting a series procedure in several functional modules. The key feature of the methodology is its system analysis and decision making under uncertainty. The methodology is general and systematic to apply for the strategic plans of biodiesel and other types of industrial manufacturing in any region as states and countries. The case study on strategies identification for biodiesel manufacturing in the state of Michigan over next ten years has clearly shown the efficacy of the methodology. The solutions obtained can help decision makers to identify desired manufacturing strategies with maximized sustainability performance under uncertain data and information.

Chapter 4 introduces a Fuzzy Logic based Triple-A template for deriving the optimal sustainability enhancement strategies under subjective uncertainties, where the Fuzzy Logic theory is imbedding with systems approaches to handling both the complexity and uncertainty associated with the sustainability study. The problem solving procedure, through system assessment, analysis, and action, can characterize the system thoroughly, identify root causes deeply, and derive solutions conveniently and reasonably. The methodological efficacy has been successfully demonstrated through studying a complicated industrial zone problem. This methodology can be further enhanced by integrating more domain and heuristic knowledge.

Compared to the first three chapters all dealing with epistemic and aleatory uncertainties, an approach consisting of both the system optimization and Monte Carlo based simulation is introduced in Chapter 5 for effectively identifying the best possible solutions of sustainability improvement under only alearoty uncertainty in stochastic formats. By this method, the extended EIO-based SD decision-analysis is first borrowed to obtain the potential modification options. After that, an industrial sustainability is described as a system optimization problem, and a Genetic Algorithm approach is implemented to solve it. The local optimal solutions obtained from Genetic Algorithm approach will be recorded as candidates for further uncertainty analysis. Next, uncertainties are introduced into the system and Monte Carlo simulation is applied to recheck the sustainability performance of each candidate under the introduced uncertainties. Finally, the best possible decisions will be readily identified from the candidate solutions through aggregating the results of each individual Monte Carlo sample for a result. The main advantage of this approach is its capability of identifying optimal choice effectively with the consideration of system uncertainties. The proposed approach is fully illustrated through analyzing the sustainability issues and developing strategies for enhancing the sustainability of a component-based electroplating industrial zone, and the potential applications by using the proposed methodology are further discussed.

Part II: Other sustainability research. The second part of this dissertation contains Chapter 6 and 7, which introduce two other types of work on sustainable systems engineering. In Chapter 6, a computational tool is designed to provide functions on both the industrial sustainability assessment and decision-making through several convenient and interactive steps of computer operation. Using this tool, people without knowing the complex sustainability theories and calculations, can easily evaluate the sustainability status of industrial and energy systems of interest, compare different design alternatives, identify the best design for decision-making, and acquire suggestions on potential system improvements. This computational tool will greatly facilitate the academic and industrial practices on the study of sustainability, which is the only one available to the public so far.

In Chapter 7, a brief introduction about the concept of exergy and exergy based process analysis is given. After that, an exergy based IOA method is proposed for industrial sustainability analysis, and a detailed case study is given to demonstrate the efficacy of the proposed method. Although this exergy based analysis has not been well accepted in the current study on industrial problems, it has a promising role of being used as a complement of the current sustainability analysis, which is able to uniquely indicate the quality property of energy, and helps for the identification of possibilities of thermodynamic improvement of the system.

8.2 Future Work

This dissertation builds a solid basis from which additional and more in-depth investigations on sustainable systems approaches can be conducted for design and decision making of industrial and energy systems. This section discusses possible directions for future development.

Multi-stage decision-making. The sustainability design and decision making methodologies developed in this dissertation are essentially based on a single time stage, which provide solutions form the starting point of that stage directly to the end point of it. As stated in the introduction, however, the concept of sustainability indicates a short to long-term harmonious development. For a long-term problem, there are much likely multiple stages along the time scale, where the sustainability design and/or decision making need to be conducted at all those stages to achieve certain sustainability goals and meet various constraints at each stage.

To solve such a long-term problem with multiple stages, two ways can be applied. The first way is to simply decompose the multi-stage problem into several separated single-stage problems, and thus, the methodologies introduced in this dissertation can be directly applied on each single stage in sequence (from the first stage to the final stage) for deriving individual solutions, and the overall solutions for the multi-stage problem are the combination of all single-stage solutions. Note that although the best possible solutions for each time stage are achieved individually, the sustainability design and/or decision-making at the final stage may not be the best in terms of the overall problem, since the solutions of an earlier stage were made without considering the information from the later stages.

Another way is to consider the multi-stage problem as a whole task, and use the algorithm of dynamic programming (Lew and Mauch, 2007) to derive the best possible solutions backwards from the final stage to the first stage. Note that the solutions derived in this way can guarantee the best sustainability design and/or decision making at the final stage in terms of the overall problem, since the solutions of a later stage must be made in considering the information from the earlier stages. However, since that all the information should be transferred (especially when there are models with undefined variables) between stages, the dynamic programming will most likely result in a very complex format, which is impractical to be solved by traditional optimization approaches. Therefore, although the general methodology is clear, the details for solving some real applications by this way should be developed carefully.

Hierarchical decision-making. Industrial sustainability is always addressed in a large scale and scope, for instance, an industrial zone or even a nationwide sustainable development. In reality, such a large system, like a company or an industrial zone, is organized in a hierarchical structure, where different management focuses are required at different levels of the system. Figure 8.1 shows a sketch of the hierarchical structure of an industrial zone containing M functional sectors, where each sector has different numbers of plants. A desired sustainability design and decision making for this industrial zone must be made in each sector and each plant entity, and then coordinated over the entire system to ensure the best possible decisions.

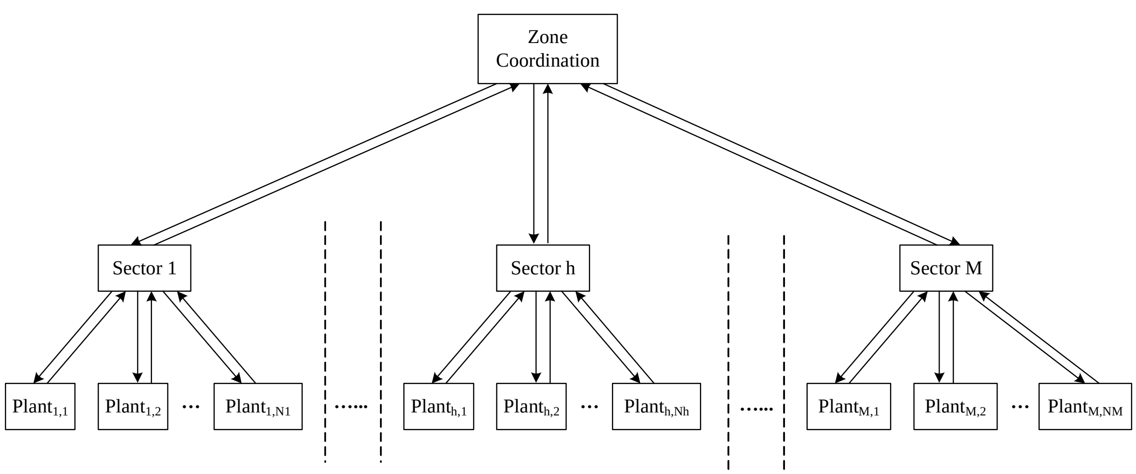


Figure 8.1. Hierarchical decision making of an industrial zone.

In detail, the sustainability on the top level, i.e., the zone coordinator should be studied first. Note that when conducting the study, the zone managers only possess the information of the next lower level, i.e., the sectors, where the information of the plant level is totally unknown. As the results, the best possible sustainable development decisions of the zone level in terms of budget distribution, predicted sustainability improvement, etc., are sent to each corresponding sector at the middle level of the system.

After that, each individual sector will conduct its own sustainability based decision making, with those information given by the zone and all individual plants in the same sector. Note that in this step, each sector works separately, where the information of the other sectors is unconnected. As the results, the best possible sustainable development decisions of each sector in terms of budget distribution, predicted sustainability improvement, etc., are sent to each corresponding plant at the bottom level of the system. Since those decisions were made without considering the connection with other sectors, there must be some contradictions in the decisions made by different sectors.

When the information reaches the bottom level of the system, each individual plant will conduct its own sustainability-based decision-making. Note that in this step, each plant works separately as well, where the information of the other plants is unconnected. As the results, the best possible sustainable development decisions of each plant in terms of desired budget, predicted sustainability improvement, etc., are generated. Since those decisions were made without considering the connection with other sectors, there must be some contradictions in the decisions made by different plants. On the other hand, since each plant prefers to pursue its own benefits, their decisions may not be consistence with those given by the upper sector.

After making the first round decisions in a top down direction at all levels, the decision information will be sent backwards from the plant level to the sector level. At the sector level, each sector will coordinate the information from different individual plants in the same sector, and then modify the previous sector decisions in order to achieve the best possible sustainability over the whole sector. Note that the coordination of plant decisions can only be conducted at the sector level, where the information of all plants is known. New decisions of each sector will then be sent down to each plant again. With that, plants will make their new decisions and send back to the sectors. In this way, the decisions by sectors and plants are cycled back and forth between the sector level and the plant level until there is no decision modification happened in the sector level.

After that, the decisions by each sector will be sent to the upper zone level to take the same kind of coordination cycle between the zone level and the sector level. Note that every time when the decisions at the sector level changed, the coordination cycle between the sector level and the plant level should be conducted once more.

In general, such a completely hierarchical decision-making procedure is tedious and complex to be handled manually. However, with the ability of modern computers, loop-based programming can realize it quite easily.

Finally, the hierarchical decision-making can be combined with the multi-stage decision-making discussed before, where the decision making at zone, sector, and plant level are always conducted over multiple time stages using the dynamic programming method. Such a multi-stage and hierarchical decision-making for industrial sustainability development is certainly the best way for deriving solutions; however, it is also the most complicated case in sustainability research.

Agent-based decision-making. The sustainable systems methodologies introduced in this dissertation are all in a top down structure, where the aim is to achieve the best possible sustainability performance over the entire system. In reality, it suits for those relatively small-scale systems, for instance, a company, where the overall manager of the system can directly control all the individual entities. For large-scale systems, as discussed before, the hierarchical decision-making may be more practical in reality, although the solutions derived may not be as good as the one derived by those pure top down methodologies introduced in this work. Beyond those two types of approaches, there is another way to conduct sustainability study in a bottom up structure, which is so called the agent-based decision-making.

An agent-based decision-making imitates the natural selection principle of the nature, which allows each individual agent (or so called as entity) within the system to make their own decisions freely, and then through the connection and/or competition between entities, achieve a good performance over the entire system (Bonabeau, 2002).

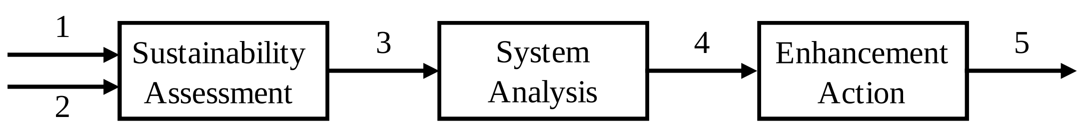
To run an agent-based decision-making, four types of models must be predefined: (i) information of each agent, (ii) information of a general environment embodies all agents, (iii) behavior algorithm of each agent when it receives new information from the environment, and (iv) evolving algorithm of the environment when new information is given from the agents. With those, the agent-based decision-making starts from agents, where each of them processes the information of the general environment using its behavior algorithm, and then obtains its decisions. Next, agents' decisions are sent to the environment, and the environment will then run its evolving algorithm with such information to obtain new environment information. Such new environment information will be sent back to each agent for another round of decision-making for each agent. When there is no change on each agent and the general environment, the agent-based decision-making is completed, where the final solutions are then obtained.

Note that the sustainability performance of the overall system derived by the agent-based decision-making are definitely not as good as the one derived by the first two approaches, since that the agent-based decision-making is essentially an unit approach (the opposition of the systems approach). Therefore, the agent-based decision-making was not widely accepted and practiced in the sustainability research area. However, agent-based decision-making is still worth for handling some particular cases, where free competition and self-evolution are the dominating principles of the systems.

Sustainability-oriented process retrofit design: gap closing. Among those sustainable systems methodologies developed in Chapter 2 to 5 of this dissertation, the fuzzy logic based methodology (Chapter 2), the simple interval parameter based methodology (Chapter 3), and the Monte Carlo based methodology (Chapter 5) are all for deriving sustainability enhancement strategies under uncertainties. Sustainability-oriented process retrofit design is surely one of the key branches in sustainability research area, since there are great many existing industrial or energy systems with unsatisfied sustainability performance, which request effective and efficient methods to help enhance their current sustainability.

Compared with the sustainability-oriented strategy making on new (non-existing) systems, sustainability-oriented process retrofit design is more difficult, the reasons are: (i) there are always restrictions on the change of existing equipments, connections, etc., and (ii) to achieve good retrofit design effects, design efforts must be put on the bottlenecks of the unsatisfied systems. Therefore, how to identify the feasible and effective retrofit design options becomes the most important part in the entire retrofit design procedure.

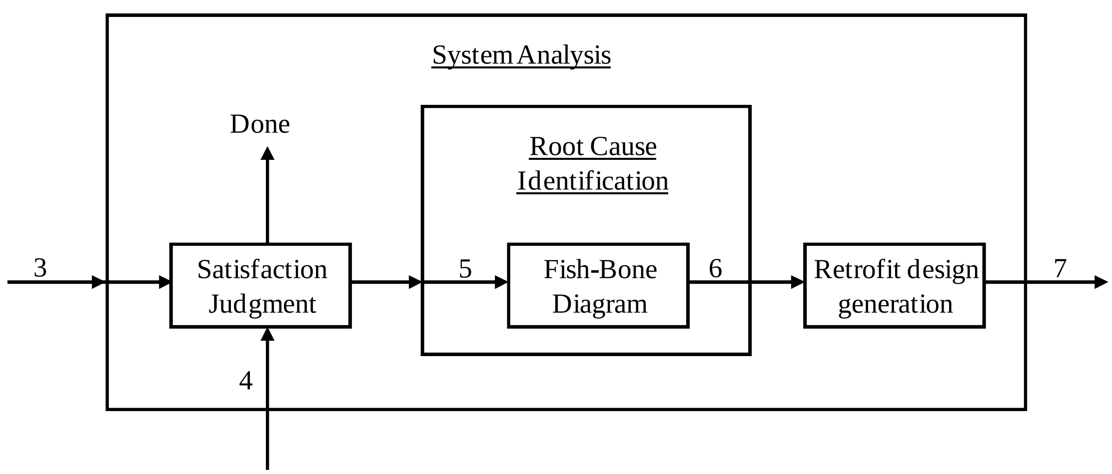
Sustainable systems methodologies developed in Chapter 2 to 5 can be summarized in Fig. 8.2 as a triple-A template for sustainability-oriented process retrofit design.



1. System data.
2. Well defined sustainability metrics.
3. Values of sustainability indicators.
4. Retrofit design options.
5. Best retrofit design strategies - decisions.

Figure 8.2. Triple-A template for sustainability-oriented process retrofit design.

According to Fig. 8.2, the task for identifying the feasible and effective retrofit design options should be done in the "System Analysis" functional block, where the details of it are extended in Fig. 8.3. Values of sustainability indicators will first be compared with the pre-set sustainability goals. If the current sustainability is within the satisfaction range, the retrofit design is done, otherwise, the values of sustainability indicators will be further sent to the root cause identification unit. In this unit, the fish-bone diagram (Ishikawa, 1990) is used to trace back from those sustainability indicators in low values to the potential system bottlenecks, where the details can be found in section 2.1.2. After that, the retrofit design options can be identified by brain storming or industrial experiences.



3. Values of sustainability indicators.
4. Sustainability goals.
5. Sustainability indicators in low values.
6. Potential system bottlenecks.
7. Retrofit design options.

Figure 8.3. Detailed steps for system analysis.

Actually, when the system under study is very complex, the identification of retrofit design options with known system bottlenecks are difficult by brain storming or industrial experiences. Therefore, there is a gap to be closed, where more scientific methods should be developed for the identification of retrofit design options.

To close this gap, Carvalho *et al.* (2008) proposed a sensitivity analysis based methodology, which through calculating 5 mass and 3 energy indicators (not sustainability goal related), identify potential process variables for modification (i.e., potential process bottlenecks). Next, a sensitivity analysis is conducted on each potential process variable to the sustainability of the entire system, where the results can give the process variables that have the potential to make significant improvements in the process (i.e., the process bottlenecks). After that, the traditional process design algorithm is applied to transfer those process variables to the potential operational variables directly indicating the feasibility of retrofit design. Finally, another sensitivity analysis is conducted on each potential operational variable to the sustainability of the entire system, where the results can give the final retrofit design options.

This methodology by Carvalho *et al.* (2008) has great advantages in the identification of feasible retrofit design options, since it successfully transfers the need of process variable modification to the need of operational variable modification. However, also due to this variable transformation, the retrofit design options may not be the most effective ones. Note that this methodology is the only one so far published for sustainability goal oriented process retrofit design. Therefore, there is still a research need to develop better methodologies to close the gap.

Improvement on the computational tool for sustainability assessment and decision-making. A computational tool is designed in Chapter 6 to provide functions on both the industrial sustainability assessment and decision-making. Using this tool, people without knowing the complex sustainability theories and calculations, can easily evaluate the sustainability status of industrial and energy systems of interest, compare different design alternatives, identify the best design for decision-making, and acquire suggestions on potential system improvements.

However, such a computational tool has no ability to deal with uncertainty, which is one of the key issues in sustainability research. Therefore, a considerable and urgent need for improving this computational tool is to add the uncertainty handling approach into it. Since the interval parameter based approach is straightest forward to be implemented, it should be considered first.

APPENDIX A

POTENTIAL ENVIRONMENTAL IMPACT (PEI) CALCULATION

The basic concept of PEI in the WAR algorithm is based on the traditional mass and energy equilibrium. Eight impact categories are then considered for quantifying PEI, namely global warming potential (GWP), ozone depletion potential (ODP), acidification potential (AP), photochemical oxidation or smog formation potential (PCOP), human toxicity potential by ingestion (HTPI), human toxicity potential by inhalation/dermal exposure (HTPE), aquatic toxicity potential (ATP) and terrestrial toxicity potential (TTP). For steady state conditions, the algorithm can be expressed by Eqs. A-1 and 3.9.

$$0 = I_{in}^{(cp)} + I_{in}^{(ep)} - I_{out}^{(cp)} - I_{out}^{(ep)} - I_{we}^{(cp)} - I_{we}^{(ep)} + I_{gen}^{(t)} \tag{A-1}$$

$$I_{we} = I_{we}^{(cp)} + I_{we}^{(ep)} \tag{3.9}$$

where $I_{in}^{(cp)}$ and $I_{out}^{(cp)}$ are the mass input and output rates of PEI to the chemical process. $I_{in}^{(ep)}$ and $I_{out}^{(ep)}$ are the input and output rates of PEI to the energy generation process. $I_{we}^{(cp)}$ and $I_{we}^{(ep)}$ are the outputs of PEI associates with the waste material and energy from the chemical process and the energy generation process, $I_{gen}^{(t)}$ is the rate of PEI inside the system and it represents the creation and consumption of PEI by chemical reactions, and I_{we} is the total rate of PEI output from the chemical process.

In Eq. 3.9, the PEI for mass and energy are calculated by counting the impact by all the components in either the waste mass streams or the consumed energy streams of a plant P_i, which can be expressed in Eqs. 3.10 and 3.11.

$$\bar{I}_{we}^{(cp)}(P_i) = \sum_{\alpha=1}^{8} \sum_{\beta=1}^{N_\beta} \sum_{\lambda=1}^{N_\lambda} A_\alpha c_\lambda \bar{a}_{\alpha,\lambda} \tag{3.10}$$

$$I_{we}^{(ep)}(P) = \sum_{\alpha=1}^{8} \sum_{\psi=1}^{N_\psi} G_\psi a_{\alpha,\psi} \tag{3.11}$$

$\bar{I}_{we,i}^{(cp)}(P_i)$ and $I_{we,i}^{(ep)}(P_i)$ are the mass and energy based PEI of the i-th plant, respectively; A_α (kg) is the amount of the α-th waste material stream, which is determined by the plant capacity, x_i; c_λ (kg/kg) is the mass-based chemical composition of the λ-th chemical component in the waste stream; $\bar{a}_{\alpha,\lambda}$ (PEI/kg) is the normalized value of the specific potential environment impact of the λ-th chemical component associated with impact category α; G_ψ (J) is the amount of the ψ-th energy stream consumed, which is determined by the plant capacity, x_i; $a_{\alpha,\psi}$ (PEI/J) is the normalized value of the specific potential environment impact of the ψ-th energy stream associated with impact category α; and N_β, N_λ, and N_ψ are the total number of the waste material streams, the chemical components, and the consumed energy streams, respectively. Note that for most of traditional chemicals, their specific potential environment impact values are defined by EPA as certain values. However, the specific potential environment impact value of some special chemicals (for instance, biodiesel) has not been well identified due to the incomplete data and information. For those chemicals, we define their PEI values in interval-based numbers.

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ABSTRACT

SUSTAINABLE DESIGN OF COMPLEX INDUSTRIAL AND ENERGY SYSTEMS UNDER UNCERTAINTY

by

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May 2012

Advisor: Dr. Yinlun Huang

Major: Chemical Engineering

Degree: Doctor of Philosophy

Depletion of natural resources, environmental pressure, economic globalization, etc., demand seriously industrial organizations to ensure that their manufacturing be sustainable. On the other hand, the efforts of pursing sustainability also give raise to potential opportunities for improvements and collaborations among various types of industries.

Owing to inherent complexity and uncertainty, however, sustainability problems of industrial and energy systems are always very difficult to deal with, which has made industrial practice mostly experience based. For existing research efforts on the study of industrial sustainability, although systems approaches have been applied in dealing with the challenge of system complexity, most of them are still lack in the ability of handling inherent uncertainty. To overcome this limit, there is a research need to develop a new generation of systems approaches by integrating techniques and methods for handling various types of uncertainties.

To achieve this objective, this research introduced series of holistic methodologies for sustainable design and decision-making of industrial and energy systems. The introduced methodologies are developed in a systems point of view with the functional components involved in, namely, modeling, assessment, analysis, and decision-making. For different methodologies, the interval-parameter-based, fuzzy-logic-based, and Monte Carlo based methods are selected and applied respectively for handling various types of uncertainties involved, and the optimality of solutions is guaranteed by thorough search or system optimization. The proposed methods are generally applicable for any types of industrial systems, and their efficacy had been successfully demonstrated by the given case studies.

Beyond that, a computational tool was designed, which provides functions on the industrial sustainability assessment and decision-making through several convenient and interactive steps of computer operation. This computational tool should be able to greatly facilitate the academic and industrial practices on the study of sustainability problems, and it is the first one available to the public.

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- Journal Referee: Chemical Engineering Journal, Computers & Chemical Engineering, Chemical Product and Process Modeling.

SELECTED PUBLICATIONS

1. **Liu, Z.**, J. Xiao, and Y. L. Huang, “Proactive Product Quality Control: An Integrated Product and Process Control Approach to MIMO Systems,” Chemical Engineering Journal, 149, 435-446, 2009.
2. **Liu, Z.**, C. Piluso, and Y. L. Huang, “Fuzzy Logic Based System Modification For Industrial Sustainability Enhancement, Chapter 81, in Design for Energy and the Environment, M. El-Halwagi and A. Linninger (Ed.), Taylor & Francis Group, NW, 2009.
3. Piluso, C., Huang J., **Liu Z.**, and Huang Y. L., “Sustainability Assessment of Industrial Systems under Uncertainty: A Fuzzy-Logic-Based Approach to Short-to-Mid-Term Predictions,” Ind. Eng. Chem. Res., 49(18), 8633-8643, 2010.
4. **Liu, Z.** and Y. L. Huang, “Technology Evaluation and Decision Making for Sustainability Enhancement of Industrial Systems under Uncertainty,” accepted, AIChE J., 2012.
5. **Liu, Z.** and Y. L. Huang, “Sustainable Strategic Planning for Regional Biodiesel Manufacturing under Uncertainty,” to be submitted.
6. **Liu, Z.** and Y. L. Huang, “Fuzzy-Logic-Based Triple-A Template for Industrial Sustainability Enhancement,” to be submitted.
7. **Liu, Z.** and Y. L. Huang, “Industrial Sustainability Decision Making via Monte Carlo Based Simulation and System Optimization,” to be submitted.
8. **Liu, Z.** and Y. L. Huang, “ISEE: A Computational Tool for Industrial Sustainability Evaluation and Enhancement,” to be submitted.