APPROACHING SUSTAINABILITY IN ENGINEERING DESIGN WITH MULTIPLE CRITERIA DECISION ANALYSIS

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APPROACHING SUSTAINABILITY IN

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- In memory of my father -

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NOMENCLATURE

a	Scalar alternative in a MADM
a	Vector alternative in a MADM, $\mathbf{a} = [a_1, a_2, \ldots, a_m]^T$
A or **A**	Alternative set in MODM, $A = \{a_1, a_2, \ldots, a_n\}$ and $\mathbf{A} = \{\mathbf{a}_1, \mathbf{a}_2, \ldots, \mathbf{a}_n\}$
C(a,b)	Concordance index for alternative pair {a,b}
C*	Concordance threshold
cv	Violation of a constraint
d	Distance function
d(i, j)	Distance between solution i and j
D(i, j)	Distance of ith solution to its jth closest neighbor
D(a, b)	Disconcordance index for the alternative pair {a,b}
D*	Disconcordance threshold
F	Feasible space
f	Objective function
f’	Altered objective function
f_p	Penalized objective function
f_a	Augmented objective function
g	Inequality constraint or generation number
h	Equality constraint
I	Environmental performance index
I	Infeasible space

i, j, or k	Ordinal numbers
l	Lower bound
m	Number of attributes (criteria)
n	Number of alternatives
nc	Niche count
nf	Number of objective functions
ng	Number of inequality constraints
nh	Number of equality constraints
nx	Number of dimensions of decision variables
n_{elite}	Number of elites
$n_{tournament}$	Number of individuals participating tournament
p	Individual in a population
Q(a,b)	Set of attributes for which a is at least as good as b
r	Reference point
$r_{\Omega F}$	Constrained-objective ranking
R	Binary relation on a set or ranking among a population
R(a,b)	Set of attributes for which b is strictly preferred to a
S	Search space
sh	Sharing function
u	Upper bound
v	Partial value function
V	Value function
w	Weight
x	Scalar solution to a MODM
x	Vector solution to a MODM, $\mathbf{x} = [x_1, x_2, \ldots, x_{nx}]^T$

x_{il}	Lower bound on x_i
x_{iu}	Upper bound on x_i
x^*	Preferred solution
z_j	A single attribute
$\mathbf{z}$	Attribute vector $\mathbf{z} = [z_1, z_2, \ldots, z_m]^T$
λ	Aggregation parameter
σ_{mating}	Mating restriction threshold
σ_{share}	Sharing threshold
Ω	Feasibility measure
Δ	Diversity measure
$\forall$	For all
$\exists$	At least one
$\in$	Is an element of
$\succ$	Strictly preference
$\succeq$	Week preference
$\sim$	Indifference
$\neg$	There does not exist

ACRONYMS

ACGIH	American Conference of Governmental Industrial Hygienists
ASCE	the American Society of Civil Engineers
AHP	Analytic Hierarchy Process
AICHE	The American Institute of Chemical Engineers
AR	Acid Rain
CO_2	Carbon Dioxide
COMOGA	Constrained Multi-Objective Optimization by Genetic Algorithm
CP	Compromise Programming
CWRT	Center for Waste Reduction Technology
DALYs	Disability-Adjusted Life Years
DM	Decision Maker(s)
DPSIR	Drive force-Pressure-State-Impact-Response
DSR	Driving force-State-Response
EAs	Evolutionary Algorithms
ECMOP	Equality Constrained Multiple Objective Programming
ELECTRE	Elimination and (et) choice translating algorithm(French translation)
EP	Evolutionary Programming
EPCRA	Emergency Planning and Community Right-to-Know Act
ES	Evolution Strategy
EU	European Union

FT	Fish Toxicity
GAs	Genetic Algorithms
GNP	Gross National Product
GP	Goal Programming
GPA	Grade Point Average
GRE	Graduate Record Examination
GW	Global Warming
HTP	Human Toxicity Potential
ICCA	International Council of Chemical Association
IChemE	The Institute of Chemical Engineer (British)
IISD	International Institute of Sustainable Development
MAVT	Multiple Attribute Value Theory
MAUT	Multiple Attribute Utility Theory
MCDA	Multiple Criteria Decision Analysis
MCDM	Multiple Criteria Decision Making
MIR	Maximum Incremental Reactivity
MOEA	Multiple Objective Evolutionary Algorithms
MODM	Multiple Objective Decision Making
MOGAs	Multiple Objective Genetic Algorithms
MOOP	Multiple Objective Optimization Problems
MOP	Multiple Objective Programming
MS	Management Science
NAE	National Academy of Engineering
NPGAs	Niche Pareto Genetic Algorithms
NSGAs	Non-Dominated Sorting Genetic Algorithms

NRC	National Research Council
OCED	Organization for Economic Cooperation and Development
OR	Operations Research
ORGA	Ordinal Ranking-based Genetic Algorithm
OSHA	Occupational Safety and Health Administration
PAES	Pareto Archived Evolution Strategy
PFD	Process Flow Diagram
POCP	Photochemical Ozone Creation Potential
PROMETHEE	Preference Ranking Organization for Enrichment Evaluation
PSIR	Pressure-State-Impact-Response
PSR	Pressure-State-Response
RDGAs	Rank-Density-based Genetic Algorithms
RIVM	Netherlands National Institute of Public Health and the Environment
SCMOP	Side-Constrained Multiple Objective Programming
SF	Smog Formation
SOP	Single Objective Programming
SPEAs	Strength Pareto Evolutionary Algorithms
SSEIW	Stress-Status-Effect-Integrality-Well-being
STEM	Step Method
TLV	Threshold Limit Value
TOEFL	The Test of English as a Foreign Language
TOPSIS	Technique for Order Preference by Similarity and Ideal Solutions
TRACI	The Tool for the Reduction and Assessment of Chemical and Other Environmental Impacts
TRI	Toxic Release Inventory

UCMOP	Unconstrained Multiple Objective Programming
UNCED	United Nations Conference on Environment and Development
UNCSD	United Nation Commission on Sustainable Development
UNEP	United National Environmental Programme
VEGA	Vector Evaluated Genetic Algorithm
VMP	Vector Maximization Problem
VOC	Volatile Organic Compound
WCED	World Commission on Environment and Development
WSSD	World Summit on Sustainable Development

CHAPTER 1

INTRODUCTION

Design is a human activity of configuring an artifact such that the performance of the resulting solution meets certain functional and other requirements (Sen & Yang, 1998). Biegler and coauthors (1997) depicted design as a creative process of discovering why, what, and how an expected system should be devised. Different design methods have been used at different times in history (Beder, 1993). Modern industrialization has catalyzed ever-increasing scientization and mathematization in design. For most engineering systems in particular, the steps and methods of executing a regular design have reached a high level of maturity (Suh, 2001; Bieglar et al., 1997).

Since the official emergence in 1987, the concept of "sustainable development" or "sustainability" has gone through a dramatic development in a broad variety of theoretical and practical contexts. In the recent 5-10 years, escalating demand surged in many industrial/business fields calling for tangible commitment towards sustainability. Engineers, along with other practitioners, have been urged to embrace and implement the concept of sustainability. However, two stumbling blocks exist, namely, conceptual ambiguity and scientific uncertainty, which, as introduced by Manion (2002), have severely hampered sustainability from being put into engineering practice.

Dissenting opinions exist among engineers in response to those difficulties. Some understand sustainability as a philosophical ideal to be aspired after and a radical part of engineering ethics to be apprehended, while the others insisted that sustainability should be fully operationalized and incorporated into daily nut-and-bolts practice rather than just being valued. Recent witnesses indicated that the later has gradually become a mainstream voice (Sikdar, 2003a; ASCE, 2004; Abraham, 2004). However, implementing sustainability is easier said than done (Frosch, 1999). As far as engineering design is concerned, few designers are assertive about what exactly needs to be done, or even where to start, to practically achieve sustainability. This can be partly attributed to the fact that the traditional engineering training and skills are inadequate to provide a successful solution to certain new challenges associated with sustainability.

Like many other design problems, three fundamental questions need to be first elaborated in this context, which, as just mentioned, are *why*, *what*, and h*ow* does one design for sustainability?

1.1 WHY DOES ONE DESIGN FOR SUSTAINABILITY?

Heightened anxiety about the "unsustainable" status quo and ubiquitous desire for a better living constitute major stimuli for people to take actions in pursuit of sustainability. However, limited by humans' cognitive horizon, it wasn't until the recent 20 years that the motive for sustainability was recognized by the public.

1.1.1 A Brief Retrospect

The report "Our Common Future," also known as the Brundtland Report, was often taken as a starting point of contemporary "sustainability" or "sustainable development." However, like any other ideological breakthrough, there were many conceptual precursors as well as landmark events in history that have led to the concept of sustainability today.

A wave of environmental movements starting from the 1960s greatly boosted the public awareness on the issues of ecosystem deterioration, global pollution, resource exhaustion, and so forth. Those pioneering efforts, represented by the seminal book "Silent Spring" by Rachel Carson (1962), culminated in 1972 with the historical United Nations Conference on Human Environment in Stockholm, Sweden. The Stockholm Conference initiated a global forum on the issues that link environmental concerns to economic development. More importantly, it marked a major step forward in the emergence of modern sustainability (Edwards, 2000). Almost at the same time, the Club of Rome consisting of a group of eminent scientists and concerned citizens issued a booked entitled "The Limit to Growth." It was concluded in this book that humanity is going to exceed most of the major ecological limits and exhaust the planet's carrying capacity in the next foreseeable decades to come (Byrne & Hoffman, 1996).

Numerous ideas and terminologies have evolved since the Stockholm Conference, which variously state a similar theme: the concurrency of preserving environment and improving life. Two conceptual breakthroughs emerged in the early 1980s. The

International Union for the Conservation of Nature and Natural Resources in its 1980 report "World Conservation Strategy" first brought up the issues about "living resource conservation for sustainable development," which transcended the traditional conservation of only materials (Mebratu, 1998). Another breakthrough was the landmark publication "Building a Sustainable Society" by Lester Brown (1981). This book further garnered wider public attention to the relevant issues and particularly to the term "sustainability." Picking up the ideas from the aforementioned cornerstone work, the World Commission on Environmental and Development (WCED, 1987) published its famous report "Our Common Future," in which the term "sustainable development" for the first time was explicitly stated and formalized.

1.1.2 Recent Trends

After the WCED, sustainability interest has quickly grown globally, attracting people's attention worldwide at all levels. Notably, the United Nations Conference on Environment and Development (UNCED) in Rio de Janeiro, Brazil and the World Summit on Sustainable Development (WSSD) in Johannesburg, South Africa were held in 1992 and 2002 respectively. These two international conferences, also referred to as the first and second Earth Summit, raised a great deal of issues (e.g. poverty alleviation, environmental preservation, economic growth, etc.) and produced a series of important documents and guidelines.

From the 1990s, driven by overwhelming public support, sustainability started to bounce beyond political prate and gained its momentum in a wide range of day-to-day human practices. As a result, many mainstream industrial/business activities were increasingly connected to sustainability, which include but are not limited to: performance reporting to both regulators and stakeholders; policy or investment analysis; technology innovation; risk management; propaganda and public relations; and employee training, and so forth (Jin & High, 2004a). As an example, according to KPMG (2002), 45% of the Global Fortune Top 250 companies published a separate corporate report on sustainability (environmental and social issues), while this number for the 100 top U.S. companies was 36% by 2002. The reporting rate in many process industry sectors, such as chemicals and synthetics, mining, pulp and paper, was 100%!

Chemical engineers, for instance, have been under enormous pressure to contribute to sustainability, because their practice, perhaps more than any other technical discipline, intensively involves such elements (e.g. natural resource and energy consumption, ecosystem impact) that are critical to making a reality of the notion of sustainability (Sikdar, 2003a; Hammond, 2000). The American Institute of Chemical Engineers has announced sustainability as one of its four strategic growth areas (AICHE, 2001) and launched the Institute of Sustainability to initiate and foster future discussion and research. As pointed out by Batterman (2003) who envisioned the challenges facing chemical engineering profession in the next 10 years, sustainability essentially "encourages us to do differently, instead of stopping us from doing." To achieve this goal, many issues need to be tackled. According to the International Council of Chemical Associations (ICCA, 2002), one of them is "to evaluate alternative products and manufacturing processes, and substituting more sustainable products where appropriate."

1.2 WHAT IS SUSTAINABILITY IN A DESIGN CONTEXT

What is sustainability? The answer to this long-standing question has never been easy. On the other hand, the same question remains perplexed in a design context. Then, what is sustainability in the context of a design?

1.2.1 The Concept of Sustainability

By 1992, only five years since the WCED, some seventy different definitions and interpretations of sustainability have circulated (Holmberg, 1992). In the years that follow, there was a huge diversity in defining sustainability (Mebratu, 1998; Edwards, 2000).

1.2.1.1 Different Views

Though a large number of disparate semantic explanations exist, various interpretations can be essentially sorted into three classes of views. The first view stresses on social justice and distributional equity, which advocates the fairly developed well-being of the human society, not only within a same generation (intra-generation) but also between different generations (inter-generation). The representing statement of this view is the oft-heard quote from the Brundtland Report, in which sustainable development is expressed as "the development that meets the needs of the present without compromising the ability of future generations to meet their own needs." A similar elaboration was adopted in (U.S. Presidential Council on Sustainability Development, 1994). McDaniels (1994) pointed out that this kind of effort that casts sustainability questions in terms of ethics and social justice are of limited help to operationalize sustainability, attributed to the complexity in determining what justice is and the habitual resistance of changing the status quo.

The other two views, as described by Farrell (Farrell, 1998), are the critical limits view and the competing objectives view. The former gives emphasis to the critical limits and/or constraints on development. Bossel (1999) stated four types of physical constraints, namely, 1) natural laws and logic rules; 2) global environment; 3) solar energy flow and material resource stocks; and 4) the planet's carrying capacity. These constraints define important "accessible space," only within which the successful development can be achieved. This view was adopted by (World Conservation Union, United Nations Environmental Programme, and Worldwide Fund for Nature, 1991).

The competing objective view has perhaps received the most support as far as implementation is concerned. This view specifically addresses the conflict arising from the high dimensionality of the concept, and is based on the fact that the simultaneous realization of a multitude of environmental, economic and social objectives can hardly be achieved in the real world. To this end, sustainability is sometimes referred to as solving a "trilemma." The Triple Bottom Line Theory (Elkington, 1997), as illustrated in Figure 1-1, presents a perfect elaboration on those competing goals in pursuit of a "sustainable" business in the 21st century.

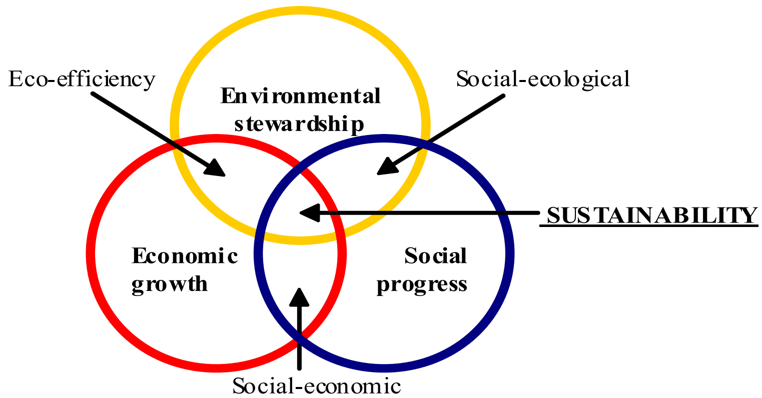


Figure 1-1 Triple Bottom Line of sustainability (revised from (Sikdar, 2003a, b))

1.2.1.2 Key Characteristics

Many have expressed growing frustration about divergent understandings and ceaseless debates on what sustainability is really about, to cite a few: "arguably overused catchword" (Graedel and Klee, 2002), "devalued concept and just a cliche" (Holmberg, 1992) and "bleeding ground for disagreement" (Daly, 1996). The incisive remarks presented in (Gladwin et al., 1995) pointed out that the concept of sustainability "will remain fuzzy, elusive, contestable, ideologically controversial for some time to come." It is true, given that new semantic interpretation often ends up with extra vagueness arising from the ambiguity associated with the diction applied. As a matter of fact, the growing consensus has gradually formed in the sustainability community, which, instead of trying to come up with a definition every one would agree on, tends to fully recognize those inherent difficulties/characteristics in interpreting and implementing the concept. As a consequence, it is more desired to develop the methods that are suited with accordance to those common characteristics, rather than any specific interpretation.

Therefore, some common characteristics that most affect the way in which people understand and handle sustainability are described below. They are concluded as vagueness, complexity, transdisciplinarity and flexibility, respectively.

Vagueness – Like “democracy” and “liberty,” the term "sustainability" was invented and constantly redefined as a means to fulfill certain linguistic needs. Thus, its meaning can never possibly catch up with the preciseness and comprehensiveness that are required by an ever-changing world. In this sense, the semantic uncertainty associated with sustainability will infinitely last. However, fuzziness has to be somehow reduced to the lowest extreme, where sustainability evolves from the “qualitative” to the “quantitative” regime.

Complexity – How many dimensions does sustainability have? The answer can be partly revealed by the number of different indicators applied, which, however, has exhibited dramatic variety. For instance, a set of sustainability metrics released by the Center of Waste Reduction Technology (CWRT) contains 10 metrics (CWRT, 2000), while 134 indicators are proposed in (UNCSD, 1996). Nevertheless, none of them is expected to be comprehensive. The sustainability concerns are so exhaustive that even experts could not perfectly enumerate them. More importantly, the spectrum of sustainability varies with one’s value judgement, knowledge horizon and individual perspective.

Transdisciplinarity – Mihelcic and coworkers (2003) portrayed the emergence of sustainability science and engineering as a new metadiscipline, which spans across multiple disciplines: physics, chemistry, economics, sociology, ecology and biology, to cite but a few. This has led to the vacancy of an accepted general theoretical foundation at least up until today. Researchers have explored statistics (e.g. fisher information, Cabezas, 2002) as well as thermodynamics (e.g. exergy and emergy) theories to work as an interdisciplinary platform for sustainability. However, no single theory has thus far worked satisfactorily over the full range of sustainability. Continuing to search for a general theory or giving respective consideration to each different dimension will form two distinct routes for studying sustainability in the next couple of years.

Flexibility – The above discussions naturally lead to the fourth characteristic: flexibility, which basically reflects the variety in answering the question "what does sustainability really mean?" Obviously, there is no unique correct answer, as sustainability could mean very different things to different people. Various parties whose interests and perspectives vary may choose to handle sustainability in their own manner. It is noted that flexibility, both ideologically and operationally, is embodied in “width” (what is concerned) and “depth” (how sophisticated a concern is).

1.2.2 Sustainability in a Design Context

As elaborated in Section 1.2.1, sustainability is such a concept that has broad appeal yet little specificity (Parris & Kates, 2003), wide acceptance yet diverse interpretations (Mebratu, 1998), and rich meanings yet scanty operational tools (Herkert et al., 1995).

This has given rise to significant confusion and inconsistency in linking the concept of sustainability to a specific design. An urgent question that needs to be first answered, as asked by Munda (2005), is “sustainability of what and whom?”

Let’s take chemical process design as an example. Depreciated by age, wear, market condition change, and new technology innovation, an industrial plant can only have a limited lifespan. Hence, a so-called “sustainable” design, to some extent, is misleading, as it does not really mean to keep the manufacturing activity last for a prolonged period of time. Instead, a process is said to be sustainable when it is designed in such a manner that certain “factors” essential to sustain the mankind as a whole will not be potentially harmed. But what are those “factors?”

1.2.2.1 Numerous Aspirations

Humans rely on many things to sustain their lives. A basic living requires air to breathe, water to drink, place to live, food to eat, clothes to wear, vehicle to travel, light to see, to cite just a few. It would cost even more to meliorate the living condition and maintain it at a high level. Figure 1-2 illustrates a possible list of specific concerns one may have in designing a sustainable chemical process. Obviously, some of these concerns are environment-related, while the others fall in either economic or social aspect.

Economic development Biodiversity Social walfare
Job creation Ozone depletion Smog Climate change
Renewable energy Poverty Ecosystem resilience
Water shortage Energy efficiency Eduction Landscape
Human health Global warming Population growth
Natural resources Acid rain Eutrophication Clean air

Figure 1-2 Possible concerns about sustainability in a design

It should be noted that the list in Figure 1-1 is not exhaustive. New issues may arise. As a matter of fact, sustainability has been in a persistent process of broadening its scope up until now. If such a tendency lasts, one possible aftermath could be “anything is sustainability.” This means that anyone does not even have to be farfetched to prove his/her work is actually sustainability-related. After all, there’s really not much left besides three fuzzily defined pillars of sustainability (i.e. environmental stewardship, economic prosperity, and social welfare).

1.2.2.2 A Pluralistic and Pragmatic Perspective

On the other hand, not all of concerns in Figure 1-2 are necessarily involved in a particular design. How many and what concerns are considered have to be determined on a case-by-case basis. Consider the following questions:

- A company developed a new product that has a bigger profit margin than the old product. Is this new product more sustainable?
- A professor invented a novel technology to generate energy from renewable sources. Is this invention more sustainable compared with those technologies using unrenewable fossil fuel?

- A manufacturing process recently reduced its toxic release by implementing some pollution prevention measures. Is the current process more sustainable?

At first glance, an intuitive answer seems to be "YES" to all three questions, as those (i.e. profitable business, renewable energy, and less environmental pollution) are exactly what people are talking about with respect to sustainability. However, a deliberative analysis could possibly overthrow the initial verdict, if the following alternative questions are asked:

- Is the profitable new product (or its production process) energy intensive?
- If the renewable technology (e.g. biomass- or solar-based) is applied in a large-scale, is it friendly to the surrounding ecosystem?
- Is the payoff of pollution prevention investment adequate and prompt?

From the above questions as well as the conceptual discussion in Section 1.2.1, it is clear that lots of issues may arise when sustainability is referred to in general. For different practitioners, sustainability means different things. However, people tend to interpret sustainability from a pluralistic perspective, rather than any one fold orientation. For instance, to qualify for being "sustainable," a chemical process needs to tally with multiple general criteria, which include:

- Meeting human needs and aspirations (prosperity, equity, health, security, etc.)
- Consuming less matters (minerals, forest, landscape, etc.)
- Consuming less energy (fossil fuel, solar, wind, nuclear, biomass etc.)
- Producing less impacts on natural systems (air, water, soil, ecosystem)

1.3 HOW DOES ONE DESIGN FOR SUSTAINABILITY?

Over the past years, engineering solutions to achieve sustainability have been flooded with all sorts of buzzwords, such as green chemistry, green engineering, cleaner production, industrial ecology, life cycle analysis, 3R (recycle, reuse, reduce), 4 or 10 factors, responsible care, waste minimization, eco-efficiency, eco-design, and a lot more. In literature, a myriad of techniques/methods/procedures/tools have been entitled "sustainable" by their inventers or supporters and claimed to be capable of leading to a somewhat "sustainable" design. However, are those techniques really sustainable? And what is the procedure for conducting a sustainable design?

1.3.1 Example "Sustainable" Techniques

Many techniques are worth a large discourse by themselves. Therefore, it is only possible in this subsection to present a glimpse of some representative techniques, which are selected from a huge body of existing techniques particularly in the area of chemical process design.

1.3.1.1 Measuring Sustainability Performance

Sustainability indicators/metrics is one of the most active research areas during the past 15 or so years. According to IIDS (2000), more than 500 different sets of sustainability indicators/metrics have been or are being developed. Parris and Kates (2003) and Azapagic and Perdan (2000) offered insightful overviews on characterizing and measuring sustainability. At process level, the American Institute of Chemical

Engineers (CWRT, 2000) and the (British) Institute of Chemical Engineers (IChemE, 2003) have each published a set of sustainability metrics, respectively. Similar endeavors have also been made extensively by industry, academia and governmental agencies, to cite just a few, ICI's environmental burden indices (Wright et al., 1997); BASF's eco-efficiency analysis (Sailing & Wall, 2002; Shonnard et al., 2003); USEPA's TRACI (Bare et al., 2003); sustainable process index by Narodoslawsky and Krotscheck (2000); and the sustainability metrics by BRIDGES to Sustainability (Beloff et al., 2002; Schwarz et al., 2002). Each of these metrics/indicators can be applied to measure the extent to which a target process performs in terms of one interested aspect of sustainability (e.g. profit, energy use, material use, land use, various environmental impacts etc).

1.3.1.2 Mitigating Environmental Impacts

By the end of the last century, chemical engineers' environmental commitments have evolved considerably, from the foremost dilution to end-of-the-pipe treatment, and further to source reduction. In process design, numerous "green" or "clean" techniques have been developed. Systematic reviews on different methods can be found in (Cano-Ruiz & McRae, 1998) and (Yang & Shi, 2000). Allen & Shonnard (2002) employed the title "green engineering" to refer to their collection of environmentally conscious design techniques. Tsoka and coworker (2004) more recently reported 10 valuable tools and 10 promising technologies for green chemical engineering identified by a panel of European senior industrialists. Some most recognized techniques in this respect include process synthesis for waste minimization (Douglas, 1992), green chemistry and reaction pathway design (Marteel et al., 2003), various pollution prevention measures for unit operations (Englehardt, 1993; Freeman, 1995), and process integration (Dunn & El-Halwagi, 2003).

1.3.1.3 Conserving Energy and Materials

Energy and material conservation is ranked the highest priority by many sustainability proponents (Hammond, 2000; Huesemann, 2003; Abraham, 2005). This is not only because they may be vulnerable to depletion, but also that a lower consumption level usually means the reduced expenditure and environmental damage associated with the given energy or material during its entire life cycle. For chemical process designers, energy and material conservation is achieved primarily by promoting efficiency (Arons et al., 2004; Hallale, 2001). In literature, enormous successful techniques have been reported, which vary from advanced unit operation technologies, such as highly selective catalyst (Choudhary & Mamman, 2000), membrane separation (Feng & Huang, 1997), pressure swing adsorption (Mersmanne et al., 2000), to novel process integration tools, such as heat/mass exchange networks (HENs/MENs) (Dunn & El-Halwagi, 2003; Hallale, 2001), and recycling/reuse (Lange, 2002). On the other hand, chemical engineers have made pioneering contribution to the development of renewable substitutes to the current nonrenewable sources of energy/material. A prominent instance is various technologies (combustion, pyrolysis, gasification, fermentation, or liquefaction) of converting biomass to energy (Arons et al., 2004; McKendry, 2002). The next immediate request would be to adopt renewable energy and materials in designs wherever available.

1.3.2 A Generic Design Process

Different goals have been in the spotlight of different design, such as design for profit, design for environment, and design for safety. However, a design, in its prototype, often falls short of the designer's expectation. Therefore, further assessment and improvement are always needed, sometime iteratively, to achieve a final design with desired performance. Figure 1-3 contains a simple flowchart illustrating such a procedure that is generic for a wide range of different designs.

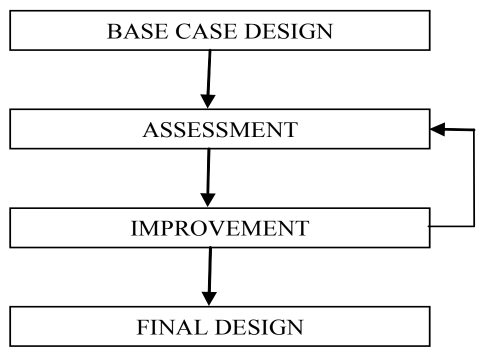


Figure 1-3 Flowchart of a generic design procedure

Both assessment and improvement techniques are of critical importance for the success of a design. Clearly, all the techniques introduced in 1.3.1 essentially offer various fulfillments to either assessment or improvement in the sustainability context. However, are those techniques sufficient to provide a sustainable design? or does the generic procedure shown in Figure 1-2 apply to a design for sustainability? Those questions will be further explored in Chapter 2.

CHAPTER 2

SUSTAINABLE DESIGN FRAMEWORK AND MULTIPLE CRITERIA DECISION ANALYSIS

2.1 SUSTAINABLE DESIGN FRAMEWORK

Implementing sustainability requires more than wishful thinking and rhetoric discourse (Bui, 2000). Today, practitioners sometimes find themselves in an embarrassing situation. On the one hand, various "sustainable" techniques abound, such as those reviewed in 1.3.1. However, adding up those techniques does not yields an appropriate design, because each of them essentially offers a piecemeal solution that is based on "individual conviction or motivational case examples" (Paramanathan et al., 2004). On the other hand, people are still anxiously searching for a methodological framework that could operationalize the concept of sustainability, particularly allowing for controversial interpretations and various multidisciplinary details. To this end, many authors have asserted that the biggest predicament for practicing sustainability lies in the absence of a widely accepted operational framework (Hall et al., 2000; Bakshi & Fiksel, 2003).

Figure 1-3 in Chapter 1 illustrated a typical design process from which a final design may result. However, the challenges raised by the complex nature of sustainability exceed just assessment and improvement. A more integrated design procedure is illustrated in Figure 2-1. Contrasted to Figure 1-3, this integrated procedure features two additional building blocks, namely, problem framing and decision making. Those two elements are critical parts of the overall infrastructure for achieving true sustainability. Unfortunately, they were often neglected or depreciated in the past.

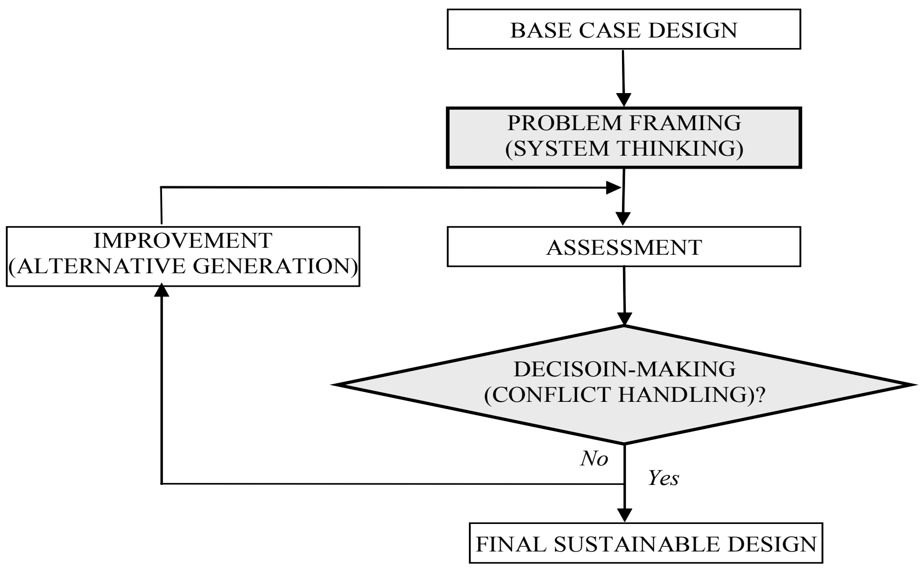


Figure 2-1 Flowchart of an integrated procedure for sustainable design

2.1.1 Problem Framing with Systems Thinking

Day-to-day experience shows that the worst frustration often occurs in the earlier stage of discovering the nature of a problem. For a sustainability-oriented design, serious efforts are needed to explore the complex nature of the concept of sustainability as well as reify the scope and objectives of the intended design. The key to a successful problem framing for sustainability is systems thinking, which, as opposed to reductionist thinking, has been increasingly heeded and endorsed by the sustainability community (Bakshi & Fiksel, 2003; Stigson, 1999; Fiksel, 2003; Cutcher-Gershenfelf et al., 2004; Cabezas et al, 2004; Kurzhanski, 2000). Systems thinking calls for a systems and holistic perspective to comprehend sustainability, which, at least, has twofold meanings in an engineering design context.

On the one hand, sustainability depicts a state of a broader system comprising the engineering system to be designed, rather than an inherent property of the isolated engineering system itself (Bakshi & Fiksel, 2003; Cabezas et al, 2004). This is not hard to understand, because many sustainability concerns are difficult to be interpreted as inherent properties of the engineering system. For instance, as pointed out by Sikdar (2003a) and Jenck and coworkers (2004), the social-political dimension cannot be achieved by technology alone. Furthermore, an environmental impact of an engineering system usually depends on not only its internal configuration, but also the external conditions of the ecosystem. To this end, sustainability should be understood as a characteristic of such an integrated system that consists of different subsystems (environmental, economic, and social). These subsystems contribute synergistically to one's value on sustainability as they are typically interconnected and inseparable from each other. For designers, their task is to devise and adjust the target engineering system such that the "sustainable" status of the encompassing bigger system can be achieved or approached.

On the other hand, though the parlance of sustainability is relatively recent, most of its backbone issues have been long-standing, such as environmental protection, energy conservation, social justice, etc. However, it wasn't until the emergence of sustainability concept that these different issues were brought together. This joining or bundling, in reverse, has greatly boosted the study of each of its elements. To this end, sustainability should not be equivalent to either environmental consciousness or energy efficiency. Holism constitutes the underpinning factor that defines sustainability. In this sense, sustainability is essentially an overarching goal sitting above specific objectives (Cutcher-Gershenfeld et al., 2004).

2.1.2. Decision Making via Conflict Handling

As just mentioned, sustainability is an overarching design goal, which, however, involves a broad collection of aspirations. In reality, the presence of different points of view always gives rise to some sort of conflict. This is particularly true for sustainability, as it would not even be an issue, if there is no conflict. For instance, industrialized civilization would have created more abundant substantial wealth, if natural resources can be consumed without abstention; or people today would have lived a more enjoyable life, if they don't have to worry about future generations. McDaniels (1994) stated that sustainability is conceptually challenging not because it is "logically flawed or lack public support, but because it involves trade offs." Cutcher-Gershenfeld and coworkers (2004) further discovered that the trade-offs existing between various facets of sustainability are "inherent and value-laden." In (Dovers & Handmer, 1993), the eight most obvious contradictions in sustainability were identified, based on their observation of the "deep-seated contradictions, paradoxes, conflict, and tensions."

More importantly, there is no absolute sustainability (Fiksel, 2003). Though people have portrayed a series of desired characteristics of a sustainable system, like zero emission and renewable energy supply, no convictive standard virtually exists that can ultimately distinguish "sustainable" from "unsustainable." Therefore, whether the overarching goal of sustainability is reached or not has to be always determined by human judgement, which, however, is complicated by the existence of inherent conflict.

In light of these evidences, this author argues that sustainability is essentially a multiplex state of an integrated system. The philosophical soul of achieving such a state essentially rests on a status of "reconciliation" among multiple (contradictory) interests, instead of unilateral pursuit of any individual acme. Accordingly, design for sustainability should not just pursue either most profit or least emission. On the contrary, it should provide a scientific process that is effective for reaching the highest harmony among variously defined objectives. In other words, "conflict handling" or "trade-offs resolution" stands central to the success of a sustainable design.

Given the above propositions, Multiple Criteria Decision Analysis (MCDA) immediately suggests itself as a logical and operational framework to handle the problems of this kind. Similar opinions have been expressed elsewhere (Herkert et al., 1995). Hobbs and Meier (2000) further specified six aspects in which MCDA can be of help. However, what is MCDA? To answer this question, another opt-seen and closely related term – Multiple Criteria Decision Making (MCDM) needs to be first elucidated. MCDM, in short, refers to a particular class of decision problems, which feature more than one criterion. Obviously, MCDM may consist of a huge collection of problems with various characteristics. On the other hand, decision analysis, according to (Hwang et al., 1995), is a merged discipline from decision theory and systems analysis. The purpose of decision analysis is not to replace judgement, but to help to organize the information and provide models which can lead to greater understanding of the situation (Seppala, 2003). Hence, the term "Multiple Criteria Decision Analysis" (MCDA) essentially stands for a process of using principles and knowledge from decision analysis to perceive, formulate, analyze, and finally solve a given MCDM problem. Since MCDA is a framework instead of a single technique, the significance of adopting MCDA is more ideological, which calls for explicit, scientific, and systematic efforts to deal with the complexity and conflict inherent in essentially all sustainability-oriented designs.

2.2 MULTIPLE CRITERIA DECISION ANALYSIS

Decision permeates life (French, 1986), though most day-to-day decisions are made in a rather routine and subconscious manner. For many years the only way to make a decision was selecting the best alternative with respect to a single figure of merit (Tabucanon, 1988). However, ever since there were decisions to be made people have recognized that most important decisions engage multiple values, which are ordinarily in conflict (von Winterfeldt & Edwards, 1986). Some even argued that decisions with single criterion should be considered a special case, given the prevalent existence of multiple criteria (Croce et al., 2002). A letter written by Benjamin Franklin back in 1772 witnessed the harassment that early time decision makers (DM) were confronted with under multiple criteria (Yoon & Hwang, 1995).

The presence of multiple conflicting criteria exponentially increases the difficulty associated with decision-making. Today, the problems of this type are widely known as

Multiple Criteria Decision Making (MCDM), though other names do exist. MCDM did not receive formal scientific articulation until the World War II (Zeleny, 1982), when the inception of the efficient vector concept was set forth by Koopmans (1951) and almost simultaneously by Kuhn and Tucker (1951). In 1972, the historic First International Conference on Multiple Criteria Decision Making was held at the University of South Carolina (Bana E Costa, et al., 1997; Martel & Price, 2000). From that point on, research on MCDM has undergone an explosive growth (Dyer et al., 1992), especially within the discipline of Operations Research/Management Science (OR/MS).

During the past 30 or so years, an impressive amount of literature has been published on various issues pertaining to MCDM, which has particularly calls for decisions to be made in a "rational" and "informed" fashion. In the past, two distinct routes of decision research existed. "Descriptive" studies aim to unveil how humans behave when making a decision, while "normative" theories/principles tend to capture the norms of such behaviors. Apparently, a scientific conjunction would be necessary to bridge those two. This is exactly where enormous efforts have been made under the banner of Multiple Criteria Decision Analysis (MCDA) (Keeney & Raiffa, 1976; von Winterfeldt & Edwards, 1986; Ballestero & Romero, 1998). Some good overview books on MCDA published in each decade are listed below in Table 2-1.

Table 2-1 MCDA overview books

Decades	Books
1970~1980	Keeney & Raiffa, 1976; Hwang & Masud, 1979
1980~1990	Hwnag & Yoon, 1981; Zeleny, 1982; Yu, 1985; Steuer, 1986
1990~2000	Roy, 1996; Miettinen, 1999, Gal et al., 1999
After 2000	Belton & Stewart, 2002; Ehrgott & Gandibleux, 2002; Figueira et al., 2005

2.2.1 Definitions and Terminology

A multitude of criteria bring unique properties and extra difficulties, both conceptually and technically, to decision-making problems (Croce, et al., 2002). However, a clear-cut description of defining characteristics was often hindered by the repletion of terms, which have been variously applied and mutually defined (Zeleny, 1982).

2.2.1.1 Components of a MCDM

This author adopted from (Yu, 1985) the four basic components of a general MCDM problem, however, expressed them somewhat differently in "standard" terminology. These four constituents are elaborated below.

- A set of alternatives

Alternatives, also seen as actions, courses of action, states, feasible solutions, and so forth, constitute the candidate set over which decisions are to be made. Alternatives are represented in this work by $A = \{a_1, a_2, \ldots, a_n\}$, if they are explicitly known by the DM and the number of alternatives n is countable. It is also likely that alternatives are implicitly characterized by depicting a set of requirements (e.g. mathematical programming) without specifying any individual. In this case, an alternative can be denoted by $\mathbf{x} \in \mathbf{F}$ and $\mathbf{x}= [x_1, x_2, \ldots x_{nx}]^T$, where **F** represents the feasible solution set, while x_1, x_2, and so on are the variables specifying the desired characteristics of the intended solutions.

- A set of criteria

More than one criterion has to be present in a MCDM problem. A Criterion in general is one aspect of interest, against which the DM wants to learn about the alternatives. Bouyssou (1990) expressed criterion as a particular significance axis or point of view allowing for comparison of alternatives. Henig and Buchanan (1996) stated that criteria are usually "general, abstract and often ambiguous" and could even be "independent of the alternatives." To this end, "criterion," as opposed to "attribute" (which will be introduced next) is a more decision maker-sided concept.

- A corresponding set of attributes

It is critical to be aware of the distinctness and correlation between "attribute" (cited elsewhere as consequence, outcome, result, etc.) and "criterion." An attribute is usually a quantitative (e.g. interval or ratio scale) or qualitative (e.g. verbal, nominal, or ordinal scale) measure on the target alternatives, which is selected or devised in such a way that it reflects the attainment level of a pre-specified criterion. Therefore, attribute is an alternative-sided concept, which should describe the alternative's physical existence. For example, "30 miles per gallon gas" and "moderate gas mileage" are quantitative and qualitative attributes of an automobile, respectively. However, both attribute reflect a car's performance on the criterion -"gas efficiency." Attributes are denoted by a vector $\mathbf{z} = [z_1, z_2, \ldots, z_m]^T$. The performance of alternative i in terms of attribute j is expressed as $z_j(a_i)$. The generation of alternatives as well as the choice of criteria and attributes for a particular problem is by no means a trivia task (Keeney, 1992; Stewart, 1992). In fact, they are an important part of modeling and problem formulation (Sen & Yang, 1998;

Stewart, 1992). This will be further discussed in Chapter 4 in a more specific context of sustainability.

- Preference structure of the decision maker (DM)

A MCDM problem is mathematically “ill-defined”(Vincke et al., 1992), which means that in the presence of multiple conflicting attributes, mathematics by itself could not isolate one single “optimum” (Fu, 2000). Croce and coworkers (2002) depicted this phenomenon as “the vanishing optimum.” Eekels (1995) from a broader perspective argued that the ideal of value-free science held in high esteem is untenable. Under this circumstance, the human decision maker has to intervene and use his/her value judgements to get out of the morass. Based on the inevitable need of human preference, Zeleny (1982) called MCDA “a very human business” and Stewart (1992) vetoed the possibility of the complete automation of MCDA. In practice, tremendous variety exists in eliciting and expressing preference. All these difficulties have made preference handling the most dissentious yet fascinating area for MCDA researchers.

2.2.1.2 The Role of Analyst

Different actors may be involved in a decision-making. In literature, the decision maker, the analyst, the client (Roy, 1996), the stakeholder (Roy, 1999) and the like have been mentioned. Among those, the role of analyst is of particular interest from a MCDA perspective. Past experiences revealed that an unaided decision maker is prone to inconsistencies, irrationality and suboptimal choices, especially with conflicting criteria

(Kahneman et al., 1982). To this end, an analyst is the very individual, sometimes maybe a more or less computerized figure, who interacts with and provides guidance to the DM.

In a theoretical sense, the analyst and the decision maker can not replace each other due to the distinct functions they perform. However, it may be difficult in a real-world case to specify who is the decision maker and who is the analyst. The quest for the role of an analyst originates in part from the suspicion on what make a good decision. It was argued that to base the quality of a decision solely on the DM's satisfaction is not scientific (Henig & Buchanan, 1996). Hence, von Winterfeldt and Edwards (1986) proposed to differentiate a good decision from a good decision outcome. The later refers to the fact that the multi-dimensional performance of the decided alternative satisfies the DM. However, a good decision, on the other hand, essentially is the one produced by a quality decision-making process (Seppala et al., 2002). In pursuit of a scientific and quality decision-making, what an analyst needs the most would be a "normative" theory or process, which, however, should not violate major findings of "descriptive" behavioral research (von Winterfeldt & Edwards, 1986).

2.2.2 Problem Classification

Significant differences exist among the problems under the general title "Multiple Criteria Decision Making." Two most useful classification schemes are introduced here.

2.2.2.1 MADM vs. MODM

A dichotomy that received the most consensus splits MCDM into two distinct camps according to the alternative domain (Hwang & Masud, 1979). One is Multiple Attribute Decision Making (MADM), which deals with picking the most desired solution from an explicit list of finite alternatives. The other class usually has an implicit (either continuous or discrete) alternative domain often containing infinite number of candidate elements. These alternatives all meet certain specified characteristics, for instance, defined by a mathematical programming problem. Such a class in contrast is denominated as Multiple Objective Decision Making (MODM). MODM was also referred to as Multiple Objective Programming/Optimization Problem (MOP/MOOP) or Vector Maximization Problem (VMP).

This classification scheme also appeared in literature under different terminologies, such as "selection" vs. "synthesis" in (Sen & Yang, 1998), and "choice" vs. "design" in (Laumanns et al., 2001), respectively.

2.2.2.2 Six Basic Problematics

By examining how an analyst poses the problem, Roy (1996) categorized four basic decision problematics, namely, selection (or choice), sorting (or assignment), ranking (or ordering), and description (or cognitive). Here the term "problematic," remaining close to its French origin, essentially refers to the category of problem. Two extra problematics: design and portfolio were added by Belton and Stewart (2002). The definitions of these problematics are further discussed in Table 2-2.

Table 2-2 Six basic decision problematics

Problematic	Definition
Selection (or choice)	Choosing one "*best*" alternative
Sorting (or assignment)	Placing alternatives in categories
Ranking (or ordering)	Assigning each alternative a rank, either partial or complete
Description (or cognitive)	Discovering, understanding, or evaluating alternatives and their attributes.
Design	Searching for, identifying or creating new alternatives
Portfolio	Choosing a subset of alternatives by considering their attribute and interactions.

A real-world decision problem may be one of the six basic problematics, a sequence of two, or a hybrid problematic (Roy, 1996). However, the type of problematic to a great extent influences the specific solution techniques to be applied. This can be seen from a simple hypothetic example in Table 2-3.

Table 2-3 Admission of international students with three criteria

The School of Chemical Engineering at Oklahoma State University will be admitting 2 international students this year, which need to be selected from 4 applicants. Three criteria are applied: GRE score, GPA, and TOEFL score.

	GRE	GPA	TOEFL
A	1120	3.94/4.0	612
B	876	2.50/4.0	614
C	1050	3.90/4.0	611
D	998	3.70/4.0	608

In this example, only candidate A and B are non-dominated (this concept will be defined later in Section 3.4). However, simply choosing them may not be appropriate because the dominated applicants C and D, though having slightly lower TOEFL scores, outperform B quite a bit in both GRE and GPA. The bias herein resulted from a mismatch of this sorting problematic (either admitted or non-admitted) to dominance check, a method that is supposed to help screening candidates in a choice problematic.

This dissertation, unless otherwise specified, assumes that all the decision problems are solved in the manner of a choice problematic. In other words, one single "best" alternative needs to be ultimately determined. Optimization is regarded a special case of choice problematic (Roy, 1996).

2.2.3 Relations among Attributes

Decision-making can be understood as a process of exploring the relations among a particular group of candidates. In a multiple criteria setting, the interrelations among different attributes present important characteristics of a MCDM problem. In Figure 2-1, a MCDM problem with a short list of alternatives (i.e. MADM) is expressed in the form of a "decision matrix." Typical relations among alternatives as well as attributes are marked in Figure 2-2 in two perpendicular directions. Relations among attributes are discussed next in this section.

	z_1	z_2	z_3	z_4	
a_1	$z_1(a_1)$	$z_2(a_1)$	$z_3(a_1)$	$z_4(a_1)$	$z(a_1)$
a_2	$z_1(a_2)$	$z_2(a_2)$	$z_3(a_2)$	$z_4(a_2)$	$z(a_2)$
a_3	$z_1(a_3)$	$z_2(a_3)$	$z_3(a_3)$	$z_4(a_1)$	$z(a_1)$
a_4	$z_1(a_4)$	$z_2(a_4)$	$z_3(a_4)$	$z_4(a_4)$	$z(a_4)$
	$z_1(A)$	$z_2(A)$	$z_3(A)$	$z_4(A)$	

Relations
Orders
Preference
Dominance

Conflict
Independence
Incommensurability
Compensability

Figure 2-2 Decision matrix of a typical MCDM problem

2.2.3.1 Conflict

Solving a MCDM problem is often mentioned as "conflict resolution." A decision becomes trivial if there exists an all-around superior candidate. However, the concept of conflict has rarely been defined explicitly, though it does arise in every single case of MCDM. In psychology, conflict refers to a situation in which two or more motives partially block each other. This dissertation differentiates "local," "global," and "universal" conflicts.

- Local conflict

  If $z_1(a_1) \succ z_1(a_2)$ and $z_2(a_2) \succ z_2(a_1)$, then the attribute z_1 is in local conflict with z_2 on $\{a_1, a_2\}$. (Note: as will be seen later in Section 3.5, the sign $\succ$ stands for "strictly preferred to")

- Universal conflict

  If local conflict between attributes z_1 and z_2 holds for any pair of alternatives $\{a_i, a_j\}$ of a given alternative set A, z_1 and z_2 are in universal conflict on A.

- Global conflict

  If the respective best performances on attributes z_1 and z_2 over the entire alternative set A do not coincide at the same alternative a*, z_1 and z_2 are in global conflict on A.

Different conflict relations are illustrated in Figure 2-3, where z_1 and z_2 are two attributes under consideration and assumed "more is better." Figure 2-3b illustrates the case where z_1 and z_2 are in both universal and global conflict within the given range of alternatives. However, if z_1 is modified to a "less is better" type of attribute, universal conflict still holds while global conflict is not satisfied any more. Figure 2-3c further displays that no global conflict arises as long as z_1* and z_2* coincide at the same point, no matter how much conflict exists elsewhere.

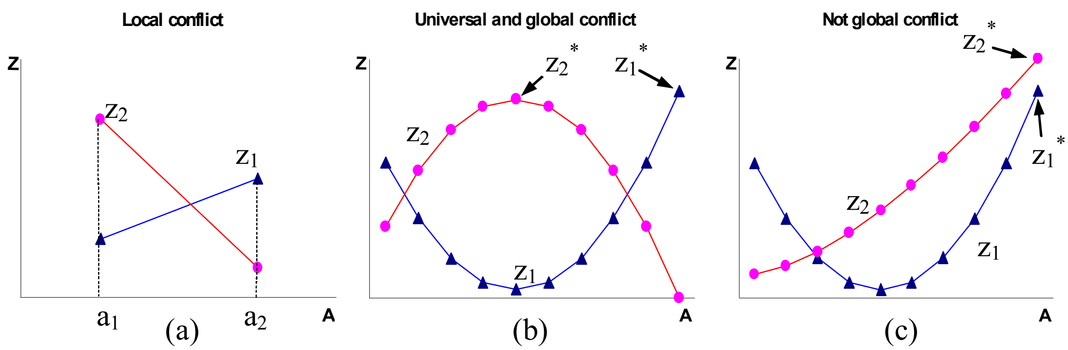


Figure 2-3 Illustration of local, global, and universal conflicts

Globally conflicting attributes that exhibit various levels of local conflict are most common in MCDM. Universal conflict does not occur very often in the real world. In addition, though conflict essentially describes an inter-attribute relation, it has to also depend on the properties of the specific alternative set, on which the attributes are evaluated. From the above definitions, it is possible that a pair of conflicting attributes may become supportive on a different set of alternatives.

2.2.3.2 Independence

Independence among multiple attributes is usually desirable, which requires that an attribute is not predictably related to another by the inherent structure or the formulation of the problem (Calpine & Golding, 1976). The existence of dependency may cause extra difficulties in exploring the DM's value tradeoffs. Hence, in most cases the attributes in a MCDM are independent or assumed to be so. However, as pointed out by Thurston (2001), there is a big misconception which confuses the structural independence in axiomatic design (Suh, 2001) and preference independence in value/utility analysis (Keeney & Raiffa, 1976). The former states that a designer tries to control one attribute (functional requirement) without affecting another. This is exactly the kind of relation defined here, which intends to describe certain properties of the reality (or its model). The latter, on the other hand, reflects the inter-attribute relation in a cognitive and ideological sense, therefore, can only be determined by the DM. Further discussion on independence is given in Chapter 5 where preferential, mutually preferential and difference independence are further defined.

2.2.3.3 Compensability

An entirely satisfactory definition for compensation among attributes does not exist (Vincke et al., 1992). Intuitively, compensation depicts such a situation that the disadvantage of one attribute is counterbalanced by the advantage of another.

In some cases, tradeoffs between attributes are not permitted. This means that an unfavorable value in one attribute (e.g. dirty water) cannot be offset by the advantage in some other attribute (e.g. clean air). Noncompensatory attributes occur predominantly in the case of limited knowledge and ability (Hwang & Yoon, 1981). Sometimes the DM may avoid considering tradeoffs just for simplicity purpose. However, as will be seen in Chapter 5, noncompensatory methods are often not sufficient to determine the desired final alternative.

Compensation among attributes is much more prevalent in practice. In those cases, tradeoffs are made in order to seek a satisfied balance among various performance levels of different attributes. The methods adopting a compensatory strategy are cognitively more demanding but could lead to more optimal or at least more rational decision outcomes, compared with noncompensatory methods (Yoon & Huang, 1995).

2.2.3.4 Incommensurability

Various attributes are usually quantified in different scales and units. For instance, 30 miles/gallon for fuel consumption and $20,000 for retail price of a car. Therefore, these attributes cannot be directly compared or manipulated together. Normalization needs to be conducted in this case, especially for compensatory methods that require inter-attribute comparisons. Through normalization, ratings on different attributes are converted to comparable scales and usually dimensionless units. There exist different normalization techniques, such as linear normalization, vector normalization (Yoon & Hwang, 1995) and the others (Koski & Silennoinen, 1987; Marler & Arora, 2002). However, adoption of different normalization techniques could sometimes have significant impact on which final alternative is decided. More importantly, as will be seen in Chapter 5, a normalization technique may in an implicit manner imply the existence of certain type of partial value function. Hence, caution should be taken in this regard.

Without loss of generality, this author assumes that any pair of attributes in the MCDM problems studied in this work are in global conflict, independent, incommensurate, and compensatory.

2.2.4 Relations among Alternatives

2.2.4.1 Binary Relations on a Set

Binary relations on a set have received extensive interest from the decision community because essentially any decision is made on a set, which initially consists of unordered distinct "objects" (either finite or infinite). Set theory, an underpinning branch of mathematics (Rodgers, 2000; Moschovakis, 1991), is the discipline that is formally dedicated to sets as well as binary relations on a set. In classical set theory, a binary relation R on a set A is obtained by performing the Cartesian product $A \times A$ and essentially results in a collection of ordered pairs of elements of A, which can be equivalently denoted by aRb, $(a, b) \in R$, or R(a, b) with $a, b \in A$.

Different binary relations may exist on a set. For instance, "is more expensive than," "has more powerful engine than," and "is made by the same manufacturer" could be example binary relations on a set of cars. However, different binary relations may exhibit various properties that can label their discrepancy and similarity to one another. A few elementary properties are summarized in Table 2-4. There are more properties to characterize binary relations. Complete description on these properties is given in (Yu, 1985; Fishburn, 1970; Ozturk et al., 2003).

Relations that have certain properties are named as "order" relations. There are large inconsistencies in denoting and defining order relations in literature (Hanne, 2000). The following definitions given in Table 2-5 are in accordance with those described by French (1986):

Table 2-4 Properties of binary relations

Properties	Definitions	Examples
Reflexive	aRa, $\forall$ a$\in$A ($\forall$ means for all)	"Greater than or equal to"
Irreflexive	not aRa, $\forall$ a$\in$A	"Greater than"
Symmetric	aRb $\Rightarrow$ bRa, $\forall$ a, b$\in$A	"Is a brother of"
Asymmetric	aRb $\Rightarrow$ not bRa, $\forall$ a, b$\in$A	"Greater than"
Antisymmetric	(aRb, bRa) $\Rightarrow$ a=b, $\forall$ a, b$\in$A	"Greater than or equal to"
Transitive	(aRb, bRc) $\Rightarrow$ aRc, $\forall$ a, b, c$\in$A	"Is an ancestor of"
Total (complete, connected, comparable)	aRb or bRa or both hold, $\forall$ a, b$\in$A	"Greater than or equal to"

Table 2-5 Names of special relations

Names	Definitions
A preorder (quasiorder)	Transitive and reflexive relation
A partial order (order)	Transitive, reflexive, and antisymmetric relation
A total order (linear, complete)	Transitive, reflexive, and connected relation
A strict order	Irreflexivity, asymmetric and transitive relation
A weak order	Transitive and complete relation
An equivalence	Transitive, reflexive, and symmetric relation

2.2.4.2 Preference as Binary Relations

For a general pair of objects {a, b}, four and only four mutually exclusive cases arise, which are illustrated in the left column of Table 2-6.

Table 2-6 General and preference binary relations between two objects

	General	Preference	
CASE 1	aRb, bRa	a~b (or aIb)	"a is indifferent to b"
CASE 2	aRb, not bRa	a$\succ$b (or aPb)	"a is strictly preferred to b"
CASE 3	not aRb, bRa	b$\succ$a (or bPa)	"b is strictly preferred to a"
CASE 4	not aRb, not bRa	a?b (or a?b)	"a is incomparable to b"

In classical preference modeling (Fishburn, 1970; Keeney & Raiffa, 1976; Bouyssou & Vincke, 1998), preference is regarded as one particular type of binary relations on a target set. However, differing from the others, preference is supposed to reflect human DMs' inner reflection, and may vary on an individual-by-individual basis. Extra syntaxes are introduced to describe the above four different cases in a preference sense, which is shown in the right column of the Table 2-5

Indifference may arise when there is no real difference between objects, while incomparability is useful under such situations as the lack of information, uncertainty, ambiguity, multi-dimensional and conflict preferences. In addition to the three fundamental building block relations: strict preference, indifference, and incomparability, it is sometimes convenient to apply weak preference denoted by $\succeq$, which essentially refers to a combined case in which either $a \succ b$ or a~b holds or perhaps more explicitly "x is at least as good as y."

Difficulties in defining what rationality is and how to attain rationality have attracted psychological behavioral scientists to commit themselves to the so-called "descriptive theories" of decision making. The descriptive study has revealed that a rational DM should exhibit consistency in his/her preference and this consistency is supposed to be embodied by certain characteristics (Simon, 1976). The properties discussed in Table 2-4 present an effective language to axiomatize rationality. The complete axioms and proofs are not presented here, but interested readers may refer to (Fishburn, 1970; Simon, 1976). Two useful theorems regarding preference as binary relations are presented below:

- Theorem 2-1

  Weak preference $\succeq$ is a weak order (complete and transitive)

  Strict preference $\succ$ is a strict order (asymmetric and transitive)

  Indifference $\sim$ is an equivalence relation (reflexive, symmetric, and transitive)

- Theorem 2-2

  $(a \sim b,\ b \succ c) \Rightarrow a \succ c,\ \forall\ a, b, c \in A$

  $(a \succ b,\ b \sim c) \Rightarrow a \succ c,\ \forall\ a, b, c \in A$

  Exactly one of the following holds: $a \succ b$, $a \sim b$, $a \prec b$, $\forall\ a, b \in A$

It should be noted that these axioms constitute important "rational" frontiers, only within which an "appropriate" decision can be made. If a preference model disobeys any of these axioms, the rationality and consistency of the decision-making process using that model is with doubt.

2.2.4.3 Dominance as Binary Relations

Dominance is often utilized to compare two vectors. Essentially, it constitutes another important binary relation on a set. But this concept is often restricted to referring to an intersection of the n coordinate-wise orderings on a set of points in Euclidean n-space. Therefore, a formal definition can be given as:

For two vectors $\mathbf{a} = [a_1, a_2, \ldots, a_m]^T$ and $\mathbf{b} = [b_1, b_2, \ldots, b_m]^T$, **a** dominates **b** iff

1) $\forall$ $i \in \{1,2,\ldots m\}$, a_i is no worse as b_i ($\forall$: for all)

2) $\exists$ $j \in \{1,2,\ldots m\}$, a_j is better than b_j ($\exists$: at least one)

A vector **a** dominates another vector **b** if and only if **a** is no worse than **b** in all dimensions and better in at least one of them (Voorneveld, 2002; Ben Abdelaziz et al., 1999). Such a binary relation is also referred to as weak dominance (denoted by $\succeq_d$) in order to be distinguished with strict dominance (denoted by $\succ_d$), which describes that **a** is better than **b** in all criteria. In recent years, various "relaxed" or "evolutive" dominance relations, such as ε-dominance (Laumanns et al., 2002), constraint-dominance (Deb, 2000; Deb et al., 2000), α-dominance (Burke & Landa Silva, 2002), k-dominance (Farina & Amato, 2003), have been proposed by different authors to fulfill certain specialized purposes.

A dominance check between two vectors may result in three outcomes: 1) one weakly dominates the other; 2) one strictly dominates the other; 3) they don't dominate each other. Recall the binary relation properties depicted in Table 2-4 and consider them against the definitions given above, the following conclusions are drawn:

- Theorem 2-3

  Weak dominance $\succeq_d$ (dominance) is complete and transitive $\Rightarrow$ A weak order

  Strict dominance $\succ_d$ is asymmetric and transitive $\Rightarrow$ A strict order

  Non-dominance $\sim_d$ is reflexive, symmetric, and transitive $\Rightarrow$ An equivalence relation

Theorem 2-3 depicts the important characteristics for dominance as a kind of binary relations on a set. These characteristics turn out to be exactly the same with those introduced in Theorem 2-1, which was deduced with respect to preference with a "rational" assumption. Is this a coincidence?

Some interesting facts can be observed when two kinds of binary relations, dominance and preference, are put in parallel and compared with each other:

- First of all, both concepts essentially reflect certain binary relations on a pre-specified set. However, preference can be applied to a set of anything, while the usage of dominance is restricted to a set of multi-dimensional vectors.
- Second, similar properties in Theorem 2-3 and Theorem 2-1 ensure the rationality of the possible decisions made from dominance relations (though this rationality may not either sufficiently or necessarily lead to the desired single decision). That also provides a compelling theoretical explanation of why so many dominance-based multiple criteria methods prevail today.
- Third, dominance may be treated as a somewhat subset of preference, when both are considered on a set of vectors. Preference, on the other hand, could be seen as a more broad-sensed, however, DM-dependent variant of dominance.
- Fourth, Dominance presents an ordinal, instead of cardinal, description for relative characteristics among vectors. "Vector **a** dominates **b**" does not offer any information with regard to the extent by which **a** dominates **b**. Preference, however, in many cases, has to include not only "ordering" but also "strength" information.

- Fifth, no across-attribute comparison is needed to determine dominance. Each attribute stands on its own during a dominance check, therefore, dominance-based methods are noncompensatory. Greenwood and coworkers, (1997) believed that this fundamentally differentiates dominance from preference, which, on the other hand, has to deal with inter-attribute relations on a completely personal basis.

Unlike dominance occurring between a pair of vectors, a nondominance relation is usually defined over a collection of vectors. A nondominated vector, as illustrated in Figure 2-4, refers to the one that is not dominated by any vector in a pre-specified group. Two points are essential here: 1) a vector, though often not stated explicitly, is non-dominated only within a given or implied set. Non-dominance in general does not make practical sense; 2) There usually exist a lot or an infinite number of non-dominated vectors. Therefore, dominance-based decision-making can only narrow down the focus of the decision to a relatively smaller subset, but could not completely solve the choice problematic without extra preference information being taken into account.

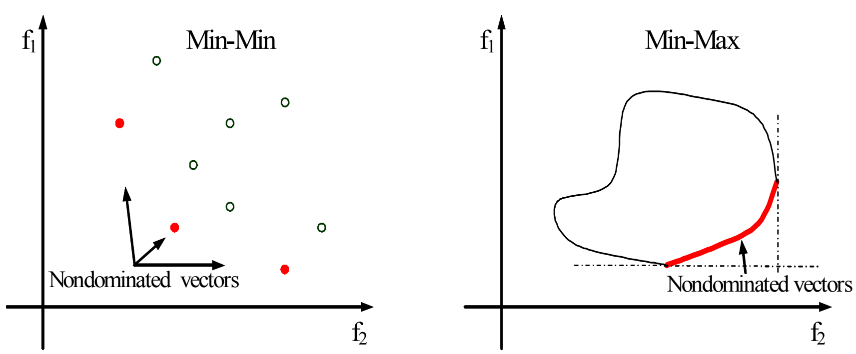


Figure 2-4 Non-dominance relation among two-dimensional vectors

2.2.5 SOLUTIONS TO A MCDM

2.2.5.1 An Optimal Solution

An optimal solution to a MCDM problem (synonymous with ideal, utopian, perfect, or superior in this context), in a strict mathematical sense, is the one that excels over every single competitor in all attributes simultaneously.

2.2.5.2 Pareto Optimal Solutions

The concept of "optimality" for multiple criteria problems emerged in the late 19th century. It was originally proposed by Francis Edgeworth and later generalized by and named after Vilfredo Pareto, an Italian economist. This concept is mentioned differently in different disciplines, for instance, nondominated, noninferior, or efficient solutions in Operations Research, admissible solutions in statistical decision theory, and Pareto optimal solutions in economics (Hwang & Yoon, 1981). Pareto optimality is adopted in this work.

Pareto optimality has a close relationship to the dominance relations defined before. In MCDM settings, human's cognition on alternatives relies solely upon an interested collection of attributes. Therefore, the preference on alternatives, not surprisingly, is equivalent to that on corresponding attribute vectors, denoted by: $\mathbf{z}(a_i) \succ_d \mathbf{z}(a_j) \Leftrightarrow a_i \succ a_j$ (the same equivalence holds for $\succeq_d$ and $\sim_d$). Based on this equivalence, a solution among a given set of alternatives is said to be Pareto optimal or nondominated when its corresponding attribute vector is nondominated. Mathematically, this is expressed as:

For $A = \{a_1, a_2, \ldots, a_n\}$, $a_i \in A$ is Pareto optimal in A, iff $\neg\exists\ a_j \in A$ that $\mathbf{z}(a_j) \succeq_d \mathbf{z}(a_i)$

2.2.5.3 Satisficing Solutions

Satisficing solutions are credited for their simplicity and the capacity of screening out unacceptable solutions. Simon (1976) suggested such a concept based on the fact that he observed- "human beings satisfice because they have not the wits to maximize." Basically, a set of satisficing solutions is composed of the alternatives that exceed all of the aspiration level on each attribute. Goal programming essentially implements the satisficing heuristic (Belton & Stewart, 2002). However, the original satisficing idea didn't not reflect any consideration of tradeoffs (Yu, 1985), though this was rectified in certain later formulations (e.g. weighted goal programming). Satisficing solutions need not to be nondominated (Hwang & Yoon, 1981).

2.2.5.4 A Preferred Solution

Finding a single preferred solution is the ultimate objective of solving a MCDM choice problematic. A solution that is said to be finally "preferred" is anticipated to have three characteristics:

- Decided by the "rational" decision maker.
- Produced from a "quality" decision-making process
- Be Pareto optimal within the target set

For all the MCDM problems in this study, a preferred solution is always pursued.

To conclude this chapter, the vacuum of an operational framework for implementing sustainability in design can be attributed to the difficulty in accommodating problem framing and decision making. Systems thinking further revealed that sustainability is a multiplex status of an integrated system, whose achievement relies upon a satisfied reconciliation among conflicting interests. The problem of this kind is known as Multiple Criteria Decision Making (MCDM), which is discussed thoroughly in this chapter. In the next chapters, it is to be shown that Multiple Criteria Decision Analysis (MCDA) provides not only "rational" and "informed" handling on conflict, but also a scientific platform to incorporate different components that are necessary for practicing the integrated design procedure as illustrated in Figure 2-1.

CHAPTER 3

FORMULATION OF A DESIGN FOR SUSTAINABILITY

A problem well structured is a problem half solved. However, a design task in its pristine form is usually far from being solvable particularly in the presence of multiple goals. As pointed out by many researchers (Haimes, 1985; Keeney, 1992; Bana E Costa, et al., 1997), an adequate and appropriate problem formulation plays a more crucial role than solution. Accordingly, problem formulation is usually harder to deal with in practice. In recent years, the emergence of a large variety of sustainability metrics/indicators partly fulfilled the formulation needs of a design task with sustainability concerns. Nevertheless, it is to be shown in this Chapter that metric usage accounts for only a small part of problem formulation. Converting a sustainability-oriented design into a meaningful MCDM takes a lot more systematic efforts.

3.1 MCDM FORMULATION

Novices or average practitioners are prone to a misunderstanding that Multiple Criteria Decision Analysis (MCDA) is a discipline to only solve ready-made MCDM problems. This is not surprising since a vast majority of literature on MCDA addresses "solution" rather than "formulation." However, where do those MCDMs come from? What if an analyst is given a problem that seems deviated from his/her original intention? As a matter of fact, most frequently cited failures of a typical MCDM result from the problem formulation phase. Guitouni and Martel (1998) figured that "one of the most perplexing aspect of human decision-making is the sensitivity of preference to seemingly minor changes in the way a problem is presented." To this end, MCDM formulation (also seen as structuring, framing, etc) definitely deserves more attention.

The problem formulation of a MCDM is the process of making sense of a "mess" of information (e.g. concerns, objects, people, relations, etc.) and somehow accounting for them in a soluble construct (Belton & Stewart, 2002; French, et al., 1998). This making-sense process may be sometimes informal, but more likely rely upon establishing a representation or approximation of the reality (Nijkamp et al., 1988). This, in scientific terms, is called modeling (i.e. model construction). Roy (1996) defined a model as "a schema (mental or figurative description) that, for a certain family of questions, is considered as a representation of a class of phenomena that an observer has more or less carefully removed from their environment to help in an investigation and to facilitate communications." Models are particularly necessary for probing the systems with complex nature (just like sustainability), as they provide tractable approximation or predictive simulation of the reality (Laumanns et al., 2001).

Von Winterfeldt (1980) considered formulating a MCDM as an art rather than science, which is "left to the intuition and craftsmanship of the individual analyst." This argument has been predominantly based on the absence of a systematic methodology. In the 25 years that follow, some descriptive and empirical guidelines emerged, such as "value-focused thinking" (Keeney, 1992), "habitual domains" (Yu, 1985) along with other notable research on MCDM structuring (Von Winterfeldt & Edwards, 1986; Belton & Stewart, 2002; Brugha, 2004). However, the parlance of "art" still prevails (Belton, 1999), and the "formally acceptable and manageable format" for MCDM problem formulation envisioned in (Von Winterfeldt, 1980) is still lacking. The reason for this has been well recognized today: because there exists no homogeneous foundation of human perception and knowledge, on which diverse MCDM problems can all ground on.

So what exactly is expected from formulating a MCDM? In short, three meaningful sets are intended, namely, a set of alternatives, criteria, and attributes (In Chapter 3, those are defined as three out of four basic elements of a typical MCDM). More importantly, through the formulation process, the analyst and the DM tend to gain a deeper insight into the target problem as well as a clearer understanding of the inter-relationship among different elements (i.e. alternatives, criteria, and attributes). In specific, the following tasks are to be accomplished as summarized in Table 3-1.

Table 3-1 Four tasks to be accomplished in a MCDM formulation

1	Identify criteria and divide criteria into subcriteria
2	Develop or identify an attribute that sufficiently reflects the attainment level on each criterion/subcriterion
3	Develop or identify an appropriate measurement system for each attribute
4	Identify or generate alternatives

With the above tasks clarified, the process of MCDM formulation can be decomposed and performed in a divide-and-conquer manner. In the next section, step-wise discussion is deployed on how to formulate a MCDM in a very specific context – sustainability-oriented design.

3.2 FORMULATING A SUSTAINABILITY-ORIENTED DESIGN

As elaborated in Chapter 1, the innermost kernel of design-for-sustainability, after peeling off various exteriors, always rests on pursuing a satisfied compromise among competing objectives. Recognizing the "grand" and "volatile" nature of the sustainability concept, the author in this work did not attempt any specific "good" formulation. Instead, focus is cast on considering a subset of conflicting environmental concerns raised by the output-type interactions (e.g. pollutant release) of a typical chemical manufacturing process with its encompassing nature. This study, on the one hand, can hopefully contribute to modeling sustainability in the environmental dimension. On the other hand, it is more desired that the succeeding discussion offers a sound "scientific" procedure for aptly formulating a design for sustainability problem into a MCDM, so that the abundant MCDA techniques can be applied. Finally, it should be pointed out that other economic, social, input-type environmental concerns (e.g. fossil fuel consumption) are of the same importance. Taking them into consideration requires profound knowledge from corresponding disciplines. However, the procedure introduced below can be combined with specific domain knowledge and readily extended to formulating various design problems.

3.2.1 Two Strategies

In literature, two distinct strategies are present in dealing with MCDM formulation: top-down and bottom-up (Von Winterfeldt and Edwards, 1986; Buede, 1986; Belton, 1999). The top-down strategy is objective-driven, which starts with ascertaining the global goal of decision-making and followed by identifying criteria, subcriteria, until a final set of attribute measures are obtained and nicely connected to alternatives. This coincides with the "value-focused thinking" proposed by Keeney (1992). The other strategy is just the opposite. Bottom-up, also referred to as "alternative-driven" (Buede, 1986) and "alternative-focused thinking" (Keeney, 1992) advocates an "alternative-attribute-criteria" sequence of structuring.

Belton (1999) viewed the two strategies as complementary ways of helping the decision maker think about the situation and suggested to take on both to yield different insights. As sustainability has been pre-specified as the ultimate goal for design/decision, this study follows the top-down strategy, which, according to Keeney (1992), is a more creative path to decision-making. Therefore, the discussion that follows is laid out in the order they tends to be actually performed.

3.2.2 Criteria/Subcriteria Identification

Criteria identification is a crucial but dynamic step in formulation, which usually demands high creativity, expertise, and the DM's value judgements. Unfortunately, it was often ignored in practice or treated like a tacit trivia. Keeney (1992) offered three explanations of this disregard. In fact, at this stage multiple criteria need to be not only identified, but also structured, analyzed, and understood (Sen & Yang, 1998; Stewart, 1992, Keeney, 1992). Additionally, almost every serious thought about MCDM criteria leads to some sort of hierarchical structure (Keeney & Raiffa, 1976; Stewart, 1992). This resulting hierarchy is known as "value tree," "criteria tree" or "decision tree." However, how does one construct a meaningful value tree? and determine a final set of criteria against which a design can be evaluated in term of sustainability?

3.2.2.1 Idea Stimulation and Capture

A natural starting point with "value-focused thinking" appears to be brainstorming and articulating relevant issues. As a result, lots of concerns more or less pertaining to a given context (i.e. sustainability) emerge. The conceptual discussion on sustainability given in Chapter 1 definitely helps to generate initial ideas, which at this stage may look messy and unorganized. Table 3-2 contains some devices proposed by Keeney (1992) that could assist stimulating and capturing ideas. Also, certain helpful "hi-tech" tools are introduced in (Belton & Stewart, 2002). With these operational tools, the DM and the analyst can think, discuss, reevaluate, and update the initially emerged ideas in a recursive fashion, until a satisfactory collection of unstructured concerns is generated.

Table 3-2 Keeney's ten devices to assist criteria identification

- Making a wish list (checklist)
- Examining existing or hypothetical alternatives
- Recognizing problems and shortcomings
- Identifying consequences and impacts
- Inspecting standards, constraints and guidelines
- Varying perspectives
- Using strategic objectives
- Using generic objectives
- Using structuring objectives
- Using quantifying objectives

As far as an industrial plant is concerned, many different environmental issues (e.g. air pollution, global warming, human toxicity etc.) can be raised. In recent years, particularly after sustainability gained its popularity in 1990s, almost all the environmental concerns have been switching titles to sustainability. It seemed that sustainability is becoming synonymous to a "superset" of essentially all the environmental issues. Is this what people wanted? In answer to the question, the National Academy of Engineering (NAE) and the National Research Council (NRC) (1999) accomplished a research, in which a "paradigm shift" from "greening" to "sustaining" was depicted. It called upon sustainability practitioners to execute a series of profound conceptual transformations, which are revised and charted in Figure 3-1.

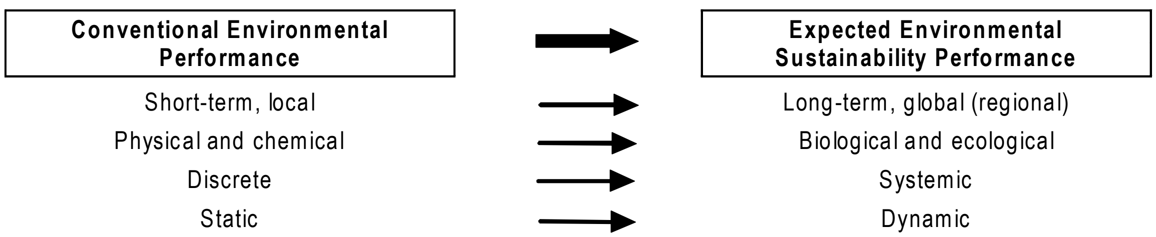


Figure 3-1 Conceptual transformations towards environmental sustainability

Figure 3-1 provides valuable insight to what different environmental concerns should be addressed in a sustainability context, compared with the environmental impacts in the conventional sense. Generally speaking, the interested performance of an industrial plant is going to be more consequential, far-reaching, holistic, obscure and thus harder to observe (Jin & High, 2003b). This can be further expressed as:

- Considering the potential impact over a longer time span and within a larger geographic scope, as opposed to current time and local area.
- Introducing biological and ecological terms to describe environmental outcomes, as opposed to the traditional physical and chemical language.

- Handling the interactions between elements within a holistic ecosystem, as opposed to treating them in isolation.
- Tracing time-dependent environmental characteristics, as opposed to taking a snapshot of the environment.

3.2.2.2 Criteria Structuring and Subdividing

The concerns initially brought up are unstructured. Sometime they could be overlapping, inclusive, contextual, or simply irrelevant to one another. Therefore, a structuring process is needed to probe the interrelations among them. Constructing the value tree usually commences with a list of key areas of general concerns. For instance, if "minimizing negative environmental effects" is the overall decision goal, the general categories of concerns can be defined in several different ways. For example, "impact on air" vs. "impact on water" vs. "impact on organisms," or "long-term effects" vs. "medium-term effects" vs. "short-term effects." One possible form of a value tree of environmental sustainability is illustrated in Figure 3-2.

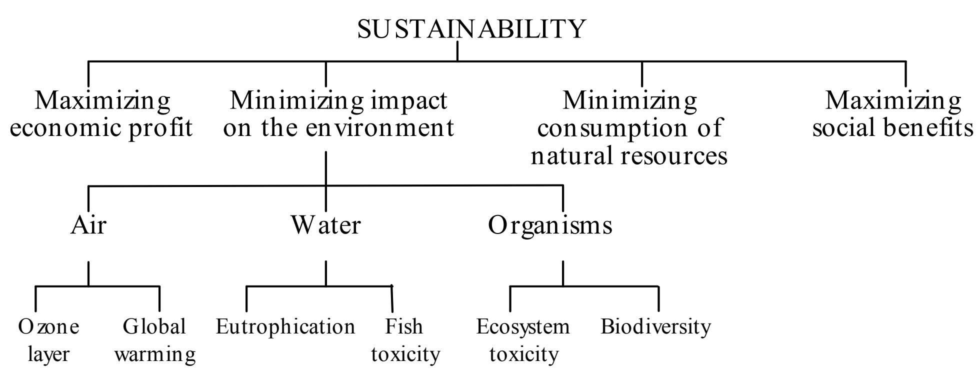


Figure 3-2 A possible value tree for sustainability

Some of the initial criteria are too broad for any specific attribute to indicate the degree to which they are achieved. In this situation, it is often necessary to break them down to more specific and precise lower-level subcriteria, as an attribute can be more easily found for a less fuzzy criterion (this will be further discussed in the next subsection). Therefore, the subdividing of criteria continues until reasonably good attributes are found. Accordingly, a final set of criteria is said to be identified, when each of those criteria characterizes the adjacent higher-level criterion and is well represented by an attribute. Many authors have envisioned desirable properties of the final set of criteria for a MCDM. Keeney and Raiffa (1976) first described them as complete, operational, decomposable, non-redundant, and minimal size, which were agreed in (Miettinen & Hamalainen, 1997). Different elaborations on the desirable criteria properties in literature are put in parallel in Table 3-3 below. It is noted that the structure, elements, and complexity of a value tree may vary a lot in different formulations. No fixed "template" should/could be followed. This is also why criteria identification should be handled with special care.

Table 3-3 Properties of MCDM criteria stated by different researchers

Keeney & Raifa 1976	Keeney 1992	Belton & Stewart 2002	Brugha 2004
Complete	Essential	Value relevance	Accessible
Operational	Controllable	Understandability	Differentiable
Decomposable	Complete	Measurability	Abstractable
Nonredundant	Measurable	Non-redundancy	Understandable
Minimum Size	Operational	Judgemental independence	Verifiable
	Decomposable	Completeness versus conciseness	Measurable
	Nonredundant	Operationality	Refinable
	Concise	Simplicity versus complexity	Usable
	Understandable		

3.2.3 Criterion-Attribute and Alternative-Attribute Mappings

An attribute measures a certain facet of the reality in order to specify the degree to which a target criterion is achieved. Efforts have been made in Chapter 3 to draw a clear distinction between an attribute and a criterion. To give an example, atmospheric temperature is an attribute, while coldness is a criterion. Essentially, attributes constitute a critical bridge filling the gulf between the fuzziness of criteria and the tangibility of alternatives. Henig and Buchanan (1996) stated that in pursuit of an apt set of attributes two crucial mappings need to be established. The first is a criterion-attribute mapping, through which a corresponding attribute is sought to conceivably reflect the attainment level of each criterion. The second mapping is from alternatives to attributes, which tend to come up with a specific measurement system that can express the interested attribute in certain scales.

3.2.3.1 Attribute-Criterion Mapping

At this stage, a typical question to ask is "which attribute is best to measure this given criterion, for instance, minimizing tropospheric ozone impact?" Building a defendable attribute-criteria mapping is challenging, as it always requires value judgements of the DM (Keeney, 1992). Significant inconsistency may take place (Nijkamp et al., 1988), because, first and foremost, the attribute required by a fuzzy criterion is also fuzzy; second, an attribute-criterion mapping may not be a one-to-one relation, for instance, a multitude of possible attributes specify the same criterion and/or a same attribute influence more than one criterion; third, a conceivable attribute may not be attainable in reality (i.e. tough alternative-attribute mapping), or the cost to achieve it exceeds tolerance; last but not least, it is hard to justify the actual "goodness" of an attribute without being aware of how many different options can be alternatively used and what are the differences between them.

Keeney (1992) defined three types of attributes according to different relations to the target criteria as well as how they are obtained:

- Natural attributes: the attributes that have obvious utilization and a common interpretation to everyone, e.g. atmospheric temperature to specify coldness.
- Constructed attributes: the attributes developed in a specific decision context, which often tend to measure more than one aspect of a complex problem, e.g. wind chill factor (a devised variable calculated from temperature and wind speed) to specify human sensed coldness.
- Proxy attributes: the attributes that are resorted to when neither natural nor constructed attributes are available. Proxy attributes measure the target criteria in a somewhat indirect manner, e.g. the amount and type of clothes that people wear to specify coldness.

The selection of a natural attribute seems the most obvious. Some of the constructed attributes, after a long time use with undisputed implication, could become "natural," such as Gross National Product (GNP). Gaining a natural or "pseudo-natural" attribute would be the most ideal way to proceed. However, for sustainability, explorations in many ideological and implemental areas are still underway. No widely accepted common ground appears to exist. To this end, people may have to search for a constructed or proxy attribute when a criterion is raised in a sustainability context.

Now let us consider the task with a little bit more detail. Suppose benzene is emitted from a manufacturing plant. Gaseous benzene may cause a variety of adverse effects to human and the ecosystem. The primary concern here is to minimize the impacts originating from forming ground-level ozone, a major air pollution affecting most people today. In reality, the possible attributes for the criterion "minimizing the impacts from tropospheric ozone" are diverse. Hence somehow classifying them becomes an obvious choice. Figure 3-3 presents a simplified illustration of the causal relations of formatting tropospheric ozone as well as its associated impacts. Five different possible attributes are labeled accordingly. The different locations of these attributes essentially offer a fundamental mechanism to differentiate them.

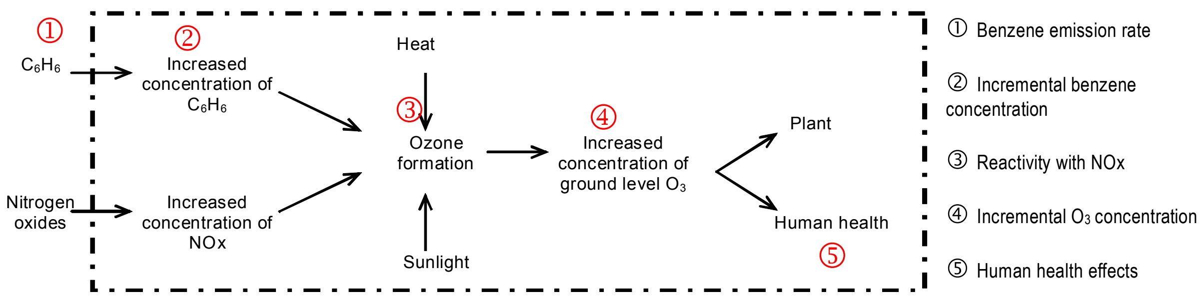


Figure 3-3 Five candidate attributes measuring photochemical ozone generation

The author envisages that a multi-level hierarchy could not only visualize the diversity, but also further partition different attributes (Jin & High, 2003a; Jin & High, 2003b). Some hierarchical frameworks have been previously developed. In the early 1990s, the Organization for Economic Cooperation and Development (OECD) started to adopt a "Pressure-State-Response" (PSR) framework for environmental reporting at national level (OECD, 1991). This framework set a foundation of environmental indicator typology. With PSR, its three layers allow for measuring disparate environmental attributes for a same performance reporting. These three layers of attributes are:

- Pressure – The original causes that may potentially induce the environmental problem of interest, usually emissions from certain human activities such as operating a chemical plant,
- State - The changes in the physical conditions of the environment affected by the pressure.
- Response - The technical or policy reactions made by the society to prevent, mitigate or recover the exerted pressure and corresponding state changes.

Many adapted derivatives of PSR framework have been developed and applied by different organizations (Jin & High, 2004a). These derivatives include the "Driving force-State-Response" (DSR) by the United Nation Commission on Sustainable Development (UNCSD), the "Pressure-State-Impact-Response" (PSIR) by the United National Environmental Programme (UNEP) and the Netherlands National Institute of Public Health and the Environment (RIVM) as well as the "Driving force-Pressure-State-Impact-Response" (DPSIR) by European Union (EU).

Some shortfalls of these existing hierarchies are recognized, such as fuzzy dividing lines between certain adjacent levels and lack of sustainability-oriented characteristics. This study proposes a new conceptual hierarchy in order to more explicitly categorize attributes with respect to evolutionary causality and better embrace the sustainability concept. This hierarchy consists of five levels, which are elaborated below, respectively.

- Stressor – The attributes that specify the magnitude of the direct physical pressure imposed by a given human activity on the environment (e.g. air pollutant emission, petroleum spill). Stressor attributes are simplest and most widely used in industry. Examples include VOC emission and SO_2 discharge, etc.
- Status - The attributes that specify the degree to which the physical or chemical state/property change is induced by the given stressor to the directly exerted environmental compartment (such as air, water or soil). Examples include incremental concentration of tropospheric ozone and incremental VOC reactivity.
- Effect – The attributes that specify the resulting impacts caused physically, chemically, biologically or ecologically by the stressor and its consequent status change. It is essential that an effect attribute should closely match one aspect of interested societal concern. Examples include global temperature increase, Disability-Adjusted Life Years (DALYs) and loss of crop production.
- Integrality – The attributes that specify the potential influence on the greatest property of the overall environment (that is, the ecosystem). Basically, an integrality attribute presents a descriptor of the environment as a whole, regarding its component completeness, structural rationality and functionality. Examples include ecosystem health and ecosystem resilience.
- Well-being - The attributes that specify the extent to which certain damages are caused to human welfare by all the prior factors. Well-being attributes are most

straightforward for interpretation of sustainability, but toughest to implement. Possible examples of well-being attribute include quality of life, for instance.

Altogether, they compose a hierarchy in the form of "Stressor-Status-Effect-Integrality-Well-being" (SSEIW), as illustrated in Figure 3-4. This hierarchy shows the extended causality and extra usable attributes compared with its counterparts. The following points should be noted to gain a thorough understanding on the SSEIW hierarchy:

First, the hierarchical structure presents a panoramic yet stratified view of the full spectrum of measuring environmental sustainability. Five distinct layers provide different types of candidate attributes. The sequence in which the five levels are arranged does not necessarily reflect the absolute priority for their application, nor should it be seen as an exact linear causality. This layout simply indicates that the range of attributes for environmental sustainability can be effectively sorted into five different categories.

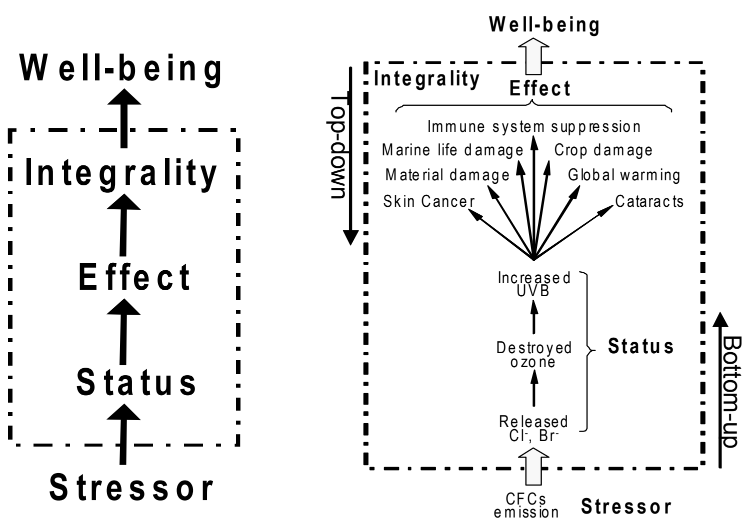


Figure 3-4 SSEIW hierarchy and ozone layer depletion example

Second, though efforts have been made to distinguish effect from status attributes through delicately tuned descriptions, intersections may occur between the two. The reason is mainly due to the variously defined societal concerns that an effect attribute is supposed to embody. For example, temperature or sea level increase could be an indicator at the effect level with respect to global warming. However, if one's concern doesn't go that far, "relative heat trapping capacity," a status attribute by definition, could be an effect attribute as well.

Third, sustainability is such a grand concept that it incorporates almost every aspect of the environment. However, even a complete set of attributes from the first three levels is not sufficient to measure a holistic environment, because significant cross linkages exist between different causal relationships, which were particularly realized after the discipline of ecology was formed in 1970s. However, this interconnectedness was ignored in traditional environmental attributes. Moreover, some characteristics of the environment can be discovered only when the wholeness is stressed, such as resilience, self-sustaining, and so on. Many researchers have figured out that sustainability calls for the integrated assessment of all the variables and processes that are involved (Pykh et al., 2000; Kruijf & Vuuren, 1998). A holistic, integrated approach will outperform in many aspects where the reductionistic approaches have failed. Therefore, even though integrality may be regarded as a subset of the environmental effects, it's actually beneficial to have it considered separately. Integrality attributes were historically excluded from industrial environmental assessments because of their obscure cause-effect relationships. However, with scientific progress, sustainability analysts have started to explore how a given industrial behavior affects the capacity of natural systems to maintain their vigor, organization and resilience.

Fourth, the square with the dashed border in Figure 3-4 represents the environment. Therefore, the status, effect and integrality attributes are essentially different means to measure the same environmental degradation. Each of them holds one part of a bigger truth. However, it is not necessary to use all of them in a single case. The number and type of attributes applied have to depend on the one's judgement and preference.

3.2.3.2 Alternative-Attribute Mapping

In the eyes of a decision maker, an alternative is virtually equivalent to the measures on the interested collection of attributes, as those are the only sources from which all of his/her perception of the alternative comes from. Therefore, the alternative-attribute mapping tends to establish a specific measurement system on the given set of alternatives. From the analyst's perspective, this measurement system is expected to be scientific and precise. At the same time, it should be convincing and well-understood for the DM. Henig and Buchanan (1996) believed such a mapping is "objective," since it shows "independence of the DM's preference." However, Phillips (1996) argued that there's no way to establish an entirely objective mapping from an alternative to an attribute. Actually, both contentions are partly true, because, on the one hand, an alternative-attribute mapping supposedly reflects certain aspect of the reality and there is only one truth! However, on the other hand, some attributes per se are personal, for instance, the aesthetics of a car. Furthermore, subjectivity arises where choices have to be made from a multitude of options that can accomplish a same mapping.

Measurement may aim to systematically specifying not only something in physical existence (e.g. length of a box), but also likely anything imaginable (e.g. confidence, intelligence). In practice, many questions have to be answered before a specific measure can be identified or established. These questions include: in what scale the attribute is expressed? what variable is formulated or defined to describe the attribute? How is the required data obtained?

1. Measurement scales – Table 3-4 contains four types of measurement scales (also seen as measurement levels) that are commonly distinguished. An attribute could be expressed in any of those scales, which essentially offer different means to express measurement results. However, which scale to use has to rely on their availability and the requirements of a specific problem. As pointed out in (Nijkamp et al., 1988), a perhaps too stringent assumption traditionally taken for granted by many decision problems is that a metric measurement system exists for all the involved variables. However, measurement in reality is often implemented in non-metric sense. Here, a metric refers to a devised means that provides *quantitative* measurement on the attributes of interest that can not always be directly observed (Ott, 1978; Merkle & Kaupenjohann, 2000). The term "metric" in this work is applied interchangeably with "indicator," though "indicator" is used by some for qualitative measures. In physical science and engineering fields, quantitative scales are preferred over qualitative ones. Hence, in the

discussion that follows, the performance measure expressed in a quantitative scale is always pursued where-ever available.

Table 3-4 Different measurement scales

Scale	Category	Explanation	Example
Nominal	Qualitative	The scale whose elements stand for different categories	Colors
Ordinal	Qualitative	The scale whose elements constitute a ranking	Age
Interval	Quantitative	The scale whose elements are equidistant cardinal points	Temperature (°F)
Ratio	Quantitative	Same as interval scale but with a rationale zero point	Temperature (K)

2. Metric identification – As a matter of fact, applying metrics has been a dominant practice of measuring sustainability attributes. In recent years, a great deal of metric sets (over 500 sets) (IISD, 2000) have been developed and utilized at various levels, ranging from global, national, regional, city, community, site to facility and so forth. Table 3-5 presents a list of the alternative metrics to measure different attributes for ground level ozone impacts that are labeled in Figure 3-3.

Table 3-5 Different ozone depletion metrics measuring different attributes

Attribute #	Metric	Data Source
1	Discharged C_6H_6 per hour	Operation or design data
1	Discharged C_6H_6 per unit production	Operation or design data
2	Incremental C_6H_6 concentration in atmosphere	Environment monitoring data
3	Photochemical Ozone Creation Potential (POCP)	(Derwent & Jenkin, 1991)
3	Maximum Incremental Reactivity (MIR)	(Carter, 1994)
3	Updated MIR	(Carter, 1998)
3	VOC reactivity	(Bergin et al., 1995)
4	Incremental O_3 concentration in atmosphere	Environment monitoring data
5	Disability-Adjusted Life Years (DALYs)	(Murray & Lopez, 1996)

In the past, metric identification was not much of a problem because, in many cases, only one or a very limited number of metrics are known and adopted anyway. But that may not be the case any more, as increasing alternative metrics come to play. It is necessary to explore some common themes in various approaches of quantifying different environmental attributes so as to establish links between different approaches and allow users to switch between them according to their specific situation and preference.

In general, environmental metrics can be partitioned into two camps. One suite of metrics aim to assess the environmental performance of a particular human activity (e.g. an industrial plant), while the other gauges the condition of the ecosystem. These two classes of metrics were developed by two different cadres of professionals from their own perspectives. Unfortunately, little interaction took place between the two camps in the past. The scarcity of communications has severely impeded the progress of either side (Schulze & Frosch, 1999). In this study, only the former is interested.

The ultimate goal is to predict or estimate the extent to which negative outcomes will be or have been caused to the environment. For a rather long time, simple and crude measures (e.g. mass flow) were used, which do not reflect actual environmental effects. Today, progress has been made to persistently move closer to revealing the real damage caused to the environmental. In addition, growing inspiration for sustainability further stimulated people's curiosity of exploring what exactly is going to happen in the environment. However, the pursuit of realism is costly, because too many factors contribute to it.

First of all, the magnitude of an undesired chemical release to the environment has to be primarily considered. A general experience tells that "more release, more harm." A premise for this to hold valid is that the comparison is carried out with respect to two different quantities of a same chemical species in identical environmental conditions. Obviously, a comparison like this is of little meaning in practice. Therefore, more factors have to be taken into consideration.

Second, the properties of the released chemical essentially affect its environmental behaviors. For example, both carbon dioxide and methane are identified as greenhouse gases. However, their ability to cause greenhouse effects differs. In other words, the same amount of methane and carbon dioxide will result in disparate effects of the so-called "global warming." Chemicals may exhibit a wide range of environment relevant properties, such as toxicity, transport, persistency, reactivity, bioaccumulation, heat-trapping capacity and so on, varying with the environmental problem that is concerned. More importantly, investigation of these properties replies closely on specific environmental contexts in which they are addressed.

Third, environmental conditions also have significant influence on the potential environmental consequence. Before a chemical causes a concerned damage, it may transport, degrade, accumulate, transform or even react with others in the environment. All those behaviors rely on environmental conditions, which is often site-specific.

In practice, a contradiction is always present between what should be measured and what can be measured. People are interested in gaining awareness as much as possible to the actual environmental effects resulting from a target activity. Sustainability, over the recent years, has fostered a remarkable raise in the attention given to more consequential and less discovered environmental impacts. However, on the other hand, sustainability calls for proactive measurement of obscure environmental effects over an expanded time scale. In this case, chemicals are going to spend more time in the environment. As a consequence, specific environmental conditions will likely contribute more to the final damage. As just mentioned, a metric measuring real effects has to involve comprehensive considerations of three aspects of information, namely, release quantity, chemical properties, and environmental conditions. This comprehensiveness usually leads to a significant increase in complexity, sophistication, and uncertainty, which sometimes may exceed people's tolerance.

3. A proposed metric classification scheme – To specifically help identify different metrics, this author presents a classification scheme based on different involvements of the factors that influence actual environmental outcomes (Jin & High, 2004b). The scheme consists of four classes, each of which is described below. Table 3-6 summarizes their different characteristics.

- Class 1: The metrics that only use quantity of releases.
- Class 2: The metrics that reflect the relative differences among chemicals, but without involving any effort to account for environmental conditions.
- Class 3: The metrics that measure the chemical-specific environmental properties using a "generic" or "standard" environmental scenario.
- Class 4: The metrics that measure the actual environmental effects by taking into account "real" environmental conditions.

Table 3-6 The proposed 4-class metric classification scheme

Class	Characteristics	Suited to	Metric Examples
Class 1	Not chemical-specific Not site-specific	Comparative assessments	Toxic Release Inventory (TRI)
Class 2	Chemical-specific No environmental information	Comparative assessments	Human Toxicity Potential (HTP)
Class 3	Chemical-specific Generic environmental condition	Comparative assessments	Photochemical Ozone Creation Potential (POCP)
Class 4	Chemical-specific Site-specific	Absolution assessments	Human health and ecological risks

The metrics in classes 1-4 basically cover various efforts that people have typically made to measure environmental attributes associated with chemicals. Since the 1970s, the environmental performance metrics have evolved quite a bit from simplicity to sophistication, from universality to specificity, and from irreality to realism. The involvement of environmental conditions also received ever-growing attentions. As a consequence, the metrics are getting more sophisticated and complex. It becomes more difficult for an average metric user to establish sufficient insight so as to identify the metrics suited to his/her applications.

In the following subsections, detailed discussion is given to the four classes of metrics, respectively, with respect to different characteristics and utilization of each class. Example metrics for each class are described to help understand their underlying distinctions.

Class 1- The metrics of Class 1 use direct inventory data or in variant forms (e.g. relative, indexed, aggregated, etc.). For instance, a waste emission can be expressed as annual emission, emission flowrate, emission vs. baseline value, emission per unit raw material, emission per unit product, emission per unit profit, etc. Historically, this kind of metrics dominated most applications in regulatory, business and industrial areas. However, due to their inherent deficiencies, they are confined to the scenarios without ambitions to measure actual environmental outcomes.

Toxic Release Inventory (TRI) is one very successful Class 1 metric in the United States, which was mandated by Emergency Planning and Community Right-to-Know Act (EPCRA) of 1986. Companies are required to annually report the quantity of each of their releases of over 600 listed chemicals. The information of TRI is maintained by Environmental Protection Agency (EPA) and publicly accessible. A typical TRI record contains information like "3,957 lb/year ethylene glycol emission from the point sources at Mercury Mercruiser facility, Stillwater, Oklahoma."

Class 2- Modifying inventory data by a factor in whatever titles (e.g. potentials, equivalency, characterization factors, potency, etc.) has become a mainstream practice in the area of environmental performance measurement. This factor is used to account for chemical specificity via comparing relative significance of potential environmental effects caused by different chemicals. Metrics in both Classes 2 and 3 fall in this group.

In general, chemical-specific properties need to be derived in certain environmental conditions. Characterization of specific environmental conditions is often conducted by performing a series of analysis. Metrics differ in their specific techniques to carry out those analysis, which may include:

- Fate analysis (e.g. degradation, accumulation, persistency, transformation etc.);
- Transport analysis (within a media or across medias);
- Exposure analysis (e.g. magnitude, frequency, duration, route of exposure)
- Effect analysis

In many cases, metric developers did not intentionally devise environmental conditions to be applied in their metric derivation, or the "default" environmental conditions underlying a metric are unspecified. This ignorance leads to the difficulties in analyzing the extent to which the assessment results will deviate from actual environmental outcomes, which supposedly originates from the underlying deviation between "actual" and "applied" environmental condition. Therefore, Class 2 & 3 metrics are separated in the proposed scheme, just in order to distinguish whether environmental conditions are specified or not.

For Class 2 metrics, chemical-specificity is addressed usually via assigning scores for different chemicals. These scores are derived from experiments and/or model-based simulation in such a manner that the chemical's possible behaviors in the environment are not accounted for or specified.

Examples of Class 2 metrics can be found in many human toxicity metrics, such as Threshold Limit Value (TLV) by American Conference of Governmental Industrial

Hygienists (ACGIH) and Permissible Exposure Limit (PEL) by Occupational Safety and Health Administration (OSHA). These metrics focusing on toxicity effects assume that chemicals are exposed to human receptors through direct oral, inhalation, or dermal contact. Therefore, they do not incorporate any indication of the effects associated with chemical's environmental behaviors. These metrics, in their original form, though have been useful in safety and health assessments, they are not suited for environmental performance assessments, especially when sustainability is concerned.

Class 3- Similar to the metrics in Class 2, Class 3 metrics reflect chemical-specific properties, ordinarily in the form of certain scoring systems. Nevertheless, Class 3 metrics contain readily identified environmental conditions that were devised or specified in the metrics' original derivation. This gives a big advantage to the metrics of Class 3 in comparison with those in Class 2, because the transparency of this background information, to some extent, allows users to be more convinced about metrics' utilization and the degree to which the obtained results should represent actual environmental impacts.

The embedded set of environmental conditions in a Class 3 metric is "generic" or "standard." Unfortunately, "actual" environmental conditions seem always differentiate from the "generic" conditions. Therefore, Class 3 metrics still cannot reflect actual effects. However, as the disparity between actual and generic environmental conditions are known, the eventual discrepancy from realism is almost predictable, though sometimes implicitly and qualitatively. It is a daunting task to explicitly state how a metric would perform in terms of its closeness to realism, because in most cases people's perception of actual environmental effects solely relies upon the measurements that they conduct.

The examples selected for Class 3 are Human Toxicity Potential (HTP) and Photochemical Ozone Creation Potential (POCP). HTP was developed in the University of California, Berkeley and the Lawrence Berkeley National Laboratory (Hertwich et al., 2001). The generic environmental conditions are simulated by a multimedia, multiple pathway fate and exposure model, CalTOX. CalTOX determines pollutant concentrations in uniformly mixed environmental compartments from intercompartmental mass transfer equations. It models exposure pathways using partitioning and biotransfer relationships, and both cancer and noncancer health impacts are considered. POCP was developed in 1990s by European researchers in order to identify hydrocarbons that most significantly contribute to forming tropospheric ozone. A trajectory model is applied to describe multi-day photochemical behaviors of hydrocarbons during long range transport in air parcels across north west Europe towards the British Isles (Derwent et al., 1996). Users should be noted that POCP was made as realistic as possible to mimic the conditions in northwest Europe. If it is applied elsewhere, deviations in geophysical conditions will reduce its credibility.

Class 4- Table look-up may constitute the only job for an average metric user to apply a chosen metric in Class 2 or 3, since those metrics simply modify inventory data by a score accounting for the interested chemical-specific properties. However, implementing the metrics of Class 4 turns out to be much more complicated, because site-specific environmental conditions need to be involved.

Class 4 metrics may differ widely from each other in answering a series of questions; what site-specific information is available? how this information is used, and how is the final measure devised? Usually it is difficult to account for widely variant environmental behaviors (e.g. fate, transport) with a same environmental model just via switching parameters. Therefore, models in a Class 4 metric sometimes need to be identified or even developed by assessors. This imposes a considerable burden on the assessors without expertise. A metric, in this case, could possess similar degree of sophistication and complexity as a full assessment.

Certain methods of risk assessment involving site-specific data can be regarded as typical Class 4 metrics. Class 4 metrics inherently need to be handled in a case-by-case fashion, due to its site-specificity. Also, risk assessments usually come to play as a methodological framework, instead of metrics.

3.2.4 Alternative Generation

Alternatives in a MCDM may be discrete and explicitly listed, such as selection among the bidders for a contract, or comparison of several pump models, or they may be continuous and implicitly characterized, such as seeking the optimal operating conditions subject to within an allowable range of product quality. Though the rationale for MCDA appears to be the evaluation of given alternatives (Belton & Stewart, 2002), several authors have mentioned the danger of settling upon a given set of alternatives too fast (Zeleny, 1982). Consequently, growing consciousness has been raised that a good MCDA should also be able to invent new and better alternatives (Henig & Buchanan, 1996, Keeney, 199).

Admittedly, the issues of alternative generation were very seldom addressed in MCDA literature. Hobbs & Meiser (2000) stressed the motive to have some reasonable number of alternatives, which tend to display the meaningful differences in alternative types and impacts. The ingredients of a successful generation of alternatives were introduced in (Zeleny, 1982), which are searching for an ideal, breaking self-imposed constraints; learning to invent; evolving and unfolding current options. Yu (1985) argued that exploring good decisions is accomplished only through purposefully challenging and extending one's habitual domain. The perhaps most important contribution came from (Keeney, 1992), in which a series of helpful guidelines to aid the search for alternatives were discussed in details. These guidelines are summarized in Table 3-7.

Table 3-7 Guidelines for generating good alternatives (Keeney, 1992)

Counteracting cognitive biases
Using fundamental, means and strategic objectives
Working on the current alternatives
– Focusing on high-value alternatives
– Improving good alternatives
– Defining generic alternatives
– Analyzing coordinated alternatives
Removing constraints
Better utilizing resources
Screening to identify good alternatives

As will be seen in Chapter 6, solving a MCDM with an implicit set of alternatives (i.e. MODM) relies on properly tackling two tasks: decision and search. The search sub-process therein essentially generates alternatives in a recursive manner and within a pre-defined space. It is interesting to observe that some ideological similarity may exist between various numerical search techniques and those descriptive alternative generation guidelines proposed in (Keeney, 1992).

3.3 THREE LAYERS OF MODELS

Differing from early time designs based on crafts and experience, a modern design features intensive models that implement various axioms, theory, algorithms, and even heuristics. Most of those models were derived from years of study and have been justified by real-world proof. For a sustainability-oriented design in particular, three different types of models are generally required. The different models can be arranged in a three layer construct as illustrated in Figure 3-5. It is worth pointing out that inner layer models have more straightforward and significant impact on the quality of a target design. Furthermore, the attainment of outer layer models will have to rely on those inner layer models.

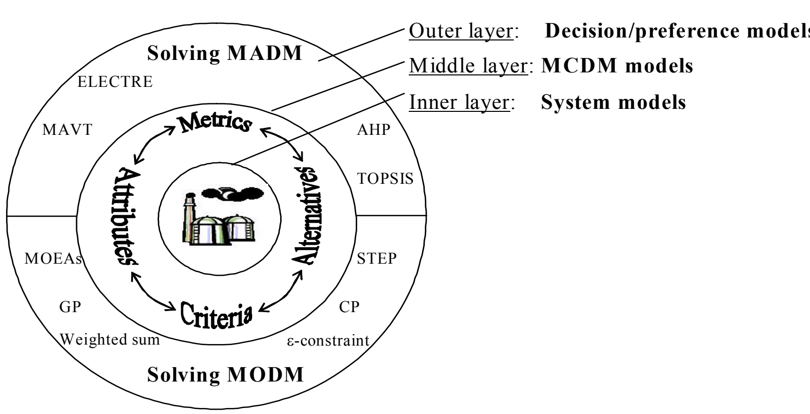


Figure 3-5 Three layers of models in design for sustainability

First of all, “system models” depict the condition of the target system, which are fundamental for designers to understand and execute a design. In a chemical process design, system models have been pretty mature and essentially consist of different unit operation models, discipline-wise, including kinetic models, thermodynamic models, transport models, hydraulic models, and the like.

Second, building “MCDM models” has just been discussed in this Chapter. The ultimate goal is to achieve a collection of alternatives whose performance is well evaluated against multiple identified criteria. The required models would include the metrics to quantify the performance of a candidate design and possibly the cognitive models to assist performing value judgements.

Third, the accomplishment of first two layer modeling lays a solid foundation for the designer/decision maker to move on to the outmost layer: “decision or preference models.” These models are needed in the solution process of the formulated MCDM that leads to the final solution. The models in this layer will be elaborated in Chapter 5 and Chapter 6.

3.4 UNCERTAINTIES IN A SUSTAINABILITY MCDM FORMULATION

So far in this chapter the formulation issues have been elaborated in a deterministic and crisp sense. However, “nothing is certain except the past.” Most, if not all, decisions are made under uncertainty (Wallace, 2000). The affliction associated with uncertainties in handling sustainability is expected to be more deeply embedded, given the aforementioned nature of the concept (e.g. distant future, debatable meanings, less insight). Therefore, serious considerations are necessitated in this respect. In practice, uncertainty may come from various sources, such as four main uncertainty sources defined in (Roy, 1988), and take on a diverse range of different forms, such as statistical variation, unsure judgement, physical randomness, discrimination and disagreement, simplified approximation, and so forth. Two types of uncertainties can be roughly differentiated: internal uncertainty and external uncertainty (Stewart, 2005) or exogenous and endogenous uncertainty (Ozturk et al., 2005). It should be noted that those terms were sometimes cited by different authors in an exactly antithetic manner. The terminology in this study follows Stewart (2005).

According to (Belton & Stewart, 2002; Stewart, 2005), internal uncertainty originates from the chaos inherent in human judgement or the imprecision in eliciting and modeling judgement. As far as a sustainability-related MCDM is concerned, internal uncertainty may arise from the following areas: First of all, the conceptual ambiguity and broad appeal of the sustainability concept give rise to significant difficulty and disagreement in what an appropriate value tree is supposed to be. To this end, criteria and attributes could be "ill-defined." Second, societal valuation of sustainability criteria/attribute is somewhat young, which leads to a very dynamic judgment of relative significance among multiple sustainability attributes that appear to be "orange and apple." Therefore, arbitrariness associated with eliciting preference is usually significant. Third, restricted by the knowledge horizon of a human decision maker, the course of decision-making often exhibits progressive establishment of the required insight and persistent updates of previous recognition. Fourth, sustainability calls for equity not only within but also between generations. Accordingly, various stakeholders with controversial interests are often present as multiple decision makers. How all these different interests can be taken care of in the course of formulation, and how the stakeholders with similar or diametrically opposed interests can be treated differently constitute another challenge (Jin & High, 2004c).

On the other hand, external uncertainty usually refers to the situation where knowledge is insufficient or imprecise to measure the intended attributes. French (1995) and Stewart (2004) both mentioned the distinction between external uncertainties arising either from related decision-areas or the environment. For a sustainability-related MCDM, up until today, numerous questions still remain open and their underlying issues are not completely understood (e.g. global warming). Therefore, there are cases where the knowledge applied during the formulation is incomplete or flawed, which certainly leads to improperly identified/developed attribute measures. In addition, a major hindrance for establishing the aforementioned two mappings lies in the scarcity information and data. As a consequence, attribute measures may end up to be "a mixture of quantitative and qualitative, precise and imprecise, subjective and objective data" (Hersh, 1999).

CHAPTER 4

SOLVING MULTIPLE ATTRIBUTE DECISION MAKING

Once a sustainability-oriented design has been formulated as a MCDM, the next step is to solve this MCDM and make a final decision. However, an indeliberate or ill-managed process of decision-making may jeopardize all the previous design efforts and end up with an "unsustainable" design. Therefore, the chapter as well as Chapter 6 cast focus on solving different MCDMs with intention to explore the scientific basis of achieving the reconciliation of conflict, which, once again, is the underpinning kernel of sustainability.

4.1 PREFERENCE MODELING

Multiple Attribute Decision Making (MADM), as introduced in Chapter 3, constitutes a subset of MCDM. Solving a MADM problem aims to single out the most desirable solution from an explicit list of candidates against conflicting criteria. A typical MADM can be expressed by a decision matrix, as illustrated in Figure 3-1.

The issues of objectivity and subjectivity have been a persistent philosophical debate in MCDA (Buchanan et al, 1998; Stewart, 1992). Part of the scientific community has been questioning its "rigorousness" from time to time. This is attributed to the fact that a MCDM problem is mathematically "ill-defined" (i.e. it has no single objective solution)

(Vincke et al., 1992). As a result, "subjective" inputs known as preference from a human decision maker is inevitably required for the sake of successfully resolving the problem.

Since preference is not directly observable by an outsider, it is often desired to express or record the DM's preference in the form of certain "models." However, modeling preference differs substantially from that of essentially external realities. The actual system models, though impossible to capture all aspects of reality, can be tested and validated against the conditions of the real world. In contrast, people can hardly understand what exactly their preferences are, especially at earlier decision stages (Belton & Stewart, 2002). Besides, how "real" different models describe the actual preference can barely be evaluated relatively with one another, due to the different type and strength of the assumptions made. To this end, Belton and Stewart (2002) alleged the "constructive intention" in a practical effort of modeling preference, which emphasizes guiding the DM to establish the required insight to his/her aspiration and preference for the contexts of a given problem.

In Chapter 3, binary relations as a classic language to express preference were introduced. Also, certain characteristics have been revealed in order to ensure rationality and consistency in eliciting preferences. However, this language turns out to be rather cumbersome when manipulated in a practical decision case, particularly in the presence of multiple criteria, because, first of all, even under one single criterion, a few problems may be raised from merely using binary relations (Bouyssou & Vincke, 1998), such as being purely declarative without observable basis, trouble in handling non-numeric relations, and lack of ability to account for preference strength, credibility, and instability. On the other hand, when multiple points of view emerge (i.e. MCDM), further mechanisms are mandated to attain a "collective" or "comprehensive" preference from multiple concurrent preferences expressed in binary relations. To this end, a MCDM preference model usually contains two primary components (Belton & Stewart, 2002):

- Single criterion preference model;
- An aggregation (also, synthesis, amalgamation) model

The first component may appear straightforward, if the attainment level of the corresponding criterion is nicely evaluated by a quantitative measure on the identified attribute. However, such a surmise is dangerous, as the DM's satisfaction/preference is not necessarily either linear or proportional to the magnitude of attribute measures (Roger et al., 2000; Belton & Stewart, 2002). Hence, modeling the single criterion preference should not completely rely on seemingly "objective" attribute measures, instead, it takes serious efforts in exploring the DM's value judgement.

A wide variety of aggregation models exist, which probably constitute the most important demarcating property for different MCDA methods. According to Roy (2005), two types of operational approaches can be distinguished, namely, approaches based on a synthesizing criterion and approaches based on a synthesizing preference relational system. Though distinct expressions for this same dichotomy exist in literature (Guitouni & Martel, 1998), it is exoterical to refer them as "American school" and "French school" (sometimes "European school") (Geldermann & Rentz, 2000; Dyer, et al., 1992; Siskos and Spyridakos, 1999; Coello Coello et al., 2002). The two schools of approaches are introduced below respectively.

4.2 AMERICAN SCHOOL APPROACHES

The so-called American school primarily refers to the approaches theoretically backed up by value/utility measurement theory. Those approaches enjoy the most widespread applications and the best-shaped axiomatic foundation among all methods. Other approaches applying otherwise mechanisms (such as TOPSIS using reference point, Yoon & Hwang, 1995) to perform inter-criteria synthesis are not covered in this work.

It is intuitively very appealing to associate human preferences with certain numerical systems. Once available, the numerical values of the so-called value function V() on a target set A make alternative comparison obvious (Stewart, 1992). However, a value function is entirely decision maker-dependent, which means different decision makers may have totally different value functions for a same problem (Miettinen, 1999). Though the term "utility" seems own more orthodox historical tradition, this work, following (Keeney & Raiffa, 1976; Dyer & Sarin, 1979), reserves "utility" for the cases with uncertain or stochastic attributes, while "value" is used for deterministic applications.

Value measurement theory essentially comprises a set of axiomatic prerequisites and rules for constructing a desired value function so that numbers can be assigned to valuable objects (Keeney & Raiffa, 1976; von Winterfeldt & Edwards, 1986). When multiple attributes are present, it becomes difficult to obtain a holistic value measurement (i.e. function) that takes implicit account of all factors relevant to the DM's overall preference. In this case, multi-attribute value theory (MAVT) extends single-dimensional value measurement and tends to tackle this problem in a "divide and conquer" manner. MAVT assumes an unknown overall preference function that constitutes an implicit function of a set of "marginal" or "partial" value functions $v_j()$, each of which corresponds to an individual criterion, as shown in (4.1):

$$V(A) = f(v_1(A), v_2(A), \ldots v_m(A)) \tag{4.1}$$

By doing this, the difficulty task of battling contradictory viewpoints is first decomposed into a sequence of relatively easier explorations of value measurement against a single criterion. After each partial value function is established, efforts are made to synthesize them back into a unique function on A, but this time in a explicit and justified fashion. This synthesis step is sometimes referred to as "weighting," as opposed to "scoring" referring to the aforementioned step of building partial value functions.

4.2.1 Construction of Partial Value Functions (Scoring)

A partial value function $v_j()$ essentially is a score measuring the worth or desirability to the DM (Hobbs & Meier, 2000), which can be established either directly from an alternative or indirectly via the attribute measures on that alternative. This study casts interest particularly on attaining the partial value function from a quantifiable attribute value, as sustainability metrics essentially constitute the required attribute measures. As mentioned before, it may be problematic to directly adopt the value of a quantifiable attribute as the score (i.e. $v_j(a_i) = z_j(a_i)$) to reflect the extent of the DM's aspiration of that attribute. In other words, nonlinear value function may exist. For instance, people seem to always attach more value to the first millions dollars earned than the second. In this situation, a concave rather than linear partial value function should be more appropriate.

Ordinal and measurable value functions can be distinguished according to the different scales in which the expected functional values are interpreted. The former refers to such a value function $v_j()$ on a set A that a $\succ$ b if and only if $v_j(a) > v_j(b)$ for all a and b in A. Such a function preserves the preference ordering and only exists when the DM's preference is a weak order (transitive and comparable) (Belton & Stewart, 2002). Therefore, $v_j(a) = z_j(b)$ offers a viable ordinal value function if the DM's preferences increase monotonically with the value of the attribute measure $z_j()$. However, the resulting order-preserving value function $v_j()$ is ordinal and does not by any chance indicate the strength of preference.

In order to overcome this shortage as well as mitigate ambiguity, a measurable value function is more widely used to capture preference intensity, in which the preference difference between a and b is greater than that between a and c if and only if $v_j(a) - v_j(b) > v_j(a) - v_j(c)$. A value function meeting this requirement preserves the order of the difference in preference strength and is therefore in an interval scale. In practice, a measurable value functions could be constructed from direct alternative rating, direct comparison or even ratio comparison of preference difference (von Winterfeldt & Edwards, 1986; Kirkwood, 1997).

4.2.2 Aggregation (Weighting)

Attributed to its simplicity and robust performance with mild non-linearities (Hobbs & Meier, 2000), additive aggregation is most common for constructing an overall value function, which can be expressed as:

$$V(a_i) = \sum_{j=1}^{m} w_j \cdot v_j(z_j(a_i)) \tag{4.2}$$

m: The number of attributes

v_j: Partial value function of attribute z_j

w_j: Weight of attribute z_j, $\sum_{j=1}^{m} w_j = 1$

Here, all m partial value functions $v_j()$ are standardized to the same scale. It is vital to note that the required properties of partial value functions and the form of aggregation are critically interrelated (Belton & Stewart, 2002). For an additive value function as shown in (4.2) to exist, the target set of attributes need to be "mutual preferential independent" in the case of ordinal partial value functions. On the other hand, measurable partial value functions demand a condition called "mutually difference independence" to validate an additive aggregation. The relevant definitions are given below in Table 4-1.

The algebra of an additive value function appears to be very simple, but the underlying issues regarding its validity and weight derivation are esoteric, especially for an unsophisticated user. If an additive value function is intended, at least two tasks have to be properly accomplished: to verify the independence conditions among concerned attributes and to justify and assess the weights with the DM. The former sometimes appears inexplicable for the DM to elicit. Some useful techniques to assist the DM in this regard are introduced in (Keeney & Raiffa, 1976). The later can be performed in different ways varying with properties of partial value functions. Representative weighting techniques include direct weighting (Hobbs & Meier, 2000), swing weights (von Winterfeldt & Edwards, 1986), indifference tradeoff weights (Keeney & Raiffa, 1976), and ratio assessment in AHP (Saaty, 1980).

Table 4-1 Definitions of independence relations among attributes

Definition 4-1
An attribute z_i is preferential independent of another attribute z_j if the preferences of z_i do not depend on z_j.
Definition 4-2
A set of attribute $\{z_1,z_2,\ldots,z_m\}$ is mutually preferential independent of another attribute set $\{z_{m+1},z_{m+2},\ldots,z_{m'}\}$ if attributes values in second set do not affect the preferences of attributes in the first set and vice versa.
Definition 4-3
Mutually preferential independence holds on the set $\{z_1,z_2,\ldots,z_m\}$ if and only if all its possible subsets are mutually preferentially independent of their corresponding complementary sets.
Definition 4-4
An attribute z_i is difference independent of another attribute z_j if ordering of the preferences difference on z_i does not depend on the value of z_j.
Definition 4-5
Mutually difference independence holds on the set $\{z_1,z_2,\ldots,z_m\}$ if and only if all its possible subsets are mutually deference independent of their corresponding complementary sets.

Finally, other forms of aggregation do exist in theory, such as the multiplicative form shown in (4.3):

$$1+\lambda V(a_i)=\prod_{j=1}^{m}[1+\lambda\cdot w_j\cdot v_j(a_i)] \tag{4.3}$$

$$\sum_{j=1}^{m} w_j \neq 1 \tag{4.4}$$

$$1+\lambda=\prod_{j=1}^{m}[1+\lambda\cdot w_j] \tag{4.5}$$

where w_j is the weight of a criterion, and λ is a parameter defined such that (4.5) holds. Discussion on more non-additive aggregations as well as their theoretical requirements and applicative limitations can be found in (Keeney & Raiffa, 1976). These non-additive aggregations can usually be validated by less restrictive assumptions than those for additive synthesis. However, these models involve extra parameters and are very difficult, if not impossible, to be manipulated in reality.

4.2.3 Analytic Hierarchy Process

The Analytic Hierarchy Process (APH) developed by Saaty (1980) gained perhaps the most widespread commercial usage and at the same time extensive harsh criticism for the same reason: AHP was devised to offer an easily understood means of making multi-criteria decisions, however, at the cost of diminution of axiomatic justifiability and preciseness. Though AHP was developed independently in history with different thinking compared to MAVT, as Belton (1986) pointed out, it can be viewed as a variation of additive value function preference. Nevertheless, these two methods exhibit significant distinctions on many fundamental aspects, which are summarized in Table 4-2. More complete introductions and proponent views regarding AHP are presented in (Saaty, 1980; Saaty & Vargas, 2001; Saaty, 2005), while the incisive remarks and critiques are expressed in (Belton, 1986; Dyer, 1990; Salo & Hamalainen, 1997).

Table 4-2 Comparison between MAVT and AHP

	MAVT	AHP
Partial value measure	Interval cardinal scale with two anchor points specified	Verbal scale mapped into a nominal scale (1-9) which is interpreted as a "ratio"
Weight interpretation	Relative worth of swinging two partial value difference	Relative worth of total attribute score
Weight derivation	Direct, swing, or indifference tradeoff weighting	Eigenvector and logarithmic or geometric least square

4.3 FRENCH SCHOOL APPROACHES

A binary relation referred to as "outranking" stands central to the approaches in French school. An outranking relation can be schematized as follows: "a outranks b" if there exist sufficient arguments to affirm that *a* is at least as good as *b* and no compelling reason to be the contrary. Brans and Vincke (1985) described outranking as a non-excessive and realistic enrichment of the dominance relation. Various outranking approaches essentially coincide in the appeal to pairwise comparison, however, differ in the specifics in taking into account problem information as well as the DM's preference. In comparison to MAVT, outranking approaches may, to some extent, constitute an advantageous alternative for the following scenarios: allowing for incomparabilities, no requirement for preference transitivity, existence of non-quantifiable attribute, difficulties in unifying heterogeneous attribute scales, no compensation among attributes (Vincke, 1999). On the other hand, serious criticism has been articulated for the outranking approaches, particularly on vacant axiomatic basis, non-intuitive inputs, arbitrariness in eliciting threshold levels, high operational complexity and cognitive burden on the DM (Belton & Stewart, 2002).

An outranking method is employed usually in two phases: the building of the outranking relation(s) and the exploitation of the obtained ranking to have the target problem solved. Different methods differ in the way implementing these two steps.

4.3.1 ELECTRE

ELECTRE abbreviates the French phrase “elimination and (et) choice translating algorithm.” This technique was first developed by Bernard Roy and has evolved into a whole family consisting of distinct versions (ELECTRE I, II, III, IV, TRI, IS, etc.). The pioneering and pedagogical ELECTRE I is introduced below, in order to showcase the basic idea regarding how this class of methods function.

4.3.1.1 Building an Outranking Relation

The outranking relation is based on evaluating two indices, namely concordance and discordance index, on all possible pairs of alternatives. In ELECTRE I, the concordance and discordance index is defined as (4.6) and (4.7), respectively.

$$C(a,b) = \frac{\sum_{i \in Q(a,b)} w_i}{\sum_{i=1}^{m} w_i} \tag{4.6}$$

$$D(a,b) = \frac{\max_{i \in R(a,b)} [w_i (z_i(b) - z_i(a))]}{\max_{i=1}^{m} \max_{c,d \in A} [w_i |z_i(c) - z_i(d)|]} \tag{4.7}$$

Where Q(a, b) is the set of attributes for which a is at least as good as b, and R(a, b) is the set of attributes for which b is strictly preferred to a. Such a concordance index is interpreted as the proportion of criteria weights allocated to those criteria for which a is preferred or equal to b, while the discordance index represents the proportion of the maximum weighted value by which b is better than a to the maximum weighted difference between any two alternatives on any attribute.

With concordance and discordance indices, a is defined as outranking b if C(a, b) ≥C* and D(a, b) < D*, where C* and D* are concordance and discordance (i.e. veto) threshold respectively to be specified for a particular outranking relation. They may vary to give different extents of severity of outranking relations. An outranking relation becomes more severe as C* increases and D* decreases.

Two points should be noted in constructing an outranking relation with ELECTRE I. First, an informative and useful outranking relation ultimately depends on the appropriate threshold levels (i.e. C* and D*), which, however, are prone to arbitrariness in practice. To this end, some kinds of ad hoc sensitivity and robustness investigation are necessary (Belton & Stewart, 2002; Vincke, 1999). Second, given the way it is manipulated, the weight of a criterion can be likened as the number of votes for the given criterion in a voting procedure. Rogers and coworkers (2000) provided four different methods of assigning weights to criteria.

4.3.1.2 Exploiting the Outranking Relation

The second step utilizes the obtained outranking relation to identify a best alternative. ELECTRE I achieves this goal by determining a subset of alternatives referred to as kernel, which is defined by two characteristics: 1) any alternative not in the kernel is outranked by at least one element in the kernel; 2) all alternatives in the kernel are incomparable. The identification of the kernel can be conducted with the help of a graph, which is discussed in details in (Roger et al., 2000).

4.3.2 Other Outranking Methods

Many different methods based on the outranking concept exist, which have been particularly popular in French speaking countries. Except for the ELECTRE family, PROMETHEE (Brans & Vincke, 1985), REGIME (Hinloopen et al., 1983), QUALIFLEX (Paelinck, 1977), and many other methods provide somewhat alternative ways of defining outranking binary relations and building up final recommendations. Some peculiar methods have also been developed to handle ordinal or stochastic data. For more complete discussions on different methods, (Martel & Matarazzo, 2005; Brans & Mareschal, 2005; Vincke, 1999) are good references.

4.4 METHOD SELECTION

For a discrete MCDM problem, the solution techniques mentioned in this Chapter mainly under the banner of American and French school only account for part of the plethora of existing methods (Yoon & Huang, 1995; Stewart, 1992; Guitouni and Martel, 1998). In practice, though admittedly MCDA method selection relies frequently on the affinity and familiarity of a specific method, a dilemma seems always present: procedural simplicity and robustness can hardly live in harmony with theoretical soundness and elegance (von Winterfeldt and Edwards, 1986). Hence, method selection itself usually constitutes a MADM problem, which was named “the meta decision problem” by Hanne (2001). In literature, this topic has been extensively elaborated and various suggestions have been provided, such as Guitouni and Martel’s seven tentative guidelines (1998), Hwang and Yoon’s tree diagram (1981), and Hanne’s qualitative criteria (2001). This author taking an engineer’s standpoint highlights two thoughts:

- It is not always necessary to pursue theoretically justified methods. Ad hoc or empirical methods (e.g. lexicographic order) in some cases provide effective solutions at reduced cost. However, the fundamental hypothesis for any interested method (e.g.

preferential independence for additive value function) should be verified or at least acknowledged.

- The ability and habits of both the analyst and the DM play an important role in method selection. Cooperation and interaction are keys. It should be avoided for one party to make unilateral presumption on the other without communications.

4.5 COPING WITH UNCERTAINTIES

It is evident that the primary motive with uncertainties is to eliminate, if possible, or somehow mitigate them, so that the decision maker can make least questionable decisions. If this is not attainable, the second priority is to find a way to work things out in the presence of incomprehension or misjudgement. As introduced in Chapter 4, the uncertainties for a particular MCDM problem may arise from diverse origins and exhibit widely variant characteristics. In practice, uncertainty is often undertreated or mistreated (Dror, 1988), as most MADM solution methodologies were developed deterministically. Uncertainty handling approaches, particularly those capable to systematically tackle different kinds of uncertainties, remain an open problem (Stewart, 1992).

In Chapter 3, a dichotomy proposed in (Stewart, 2005; Belton & Stewart, 2002) was adopted to distinguish two disparate types of uncertainties in a typical MCDM. In order to tackle internal uncertainties associated with human judgements, fuzzy set (Fuller & Carlsson, 1996) and rough set (Greco et al., 1999) theories have been attempted. However, these methods using "obscure" languages lead to even greater misunderstanding and augmented complexity (Stewart, 1992). A somewhat obvious mechanism to fundamentally deal with internal uncertainties appears to be iteratively formulating and solving an updated deterministic decision problem with hopefully more convinced and rational value judgements.

Stewart (2005) reviewed four broad approaches to dealing with external uncertainties related to imperfect knowledge concerning attribute measures. Those approaches are 1) multiple attribute utility theory and its extensions; 2) pairwise comparison applying stochastic dominance concepts; 3) the use of surrogate risk measures as additional decision criteria; 4) scenario planning. It is observed that all those approaches have been, more or less, devised to solve a lottery-like decision problem with risky attributes, which occur or are perceived to occur according to a (estimated) probability distribution. However, probabilities, essentially representing one's subjective judgements on degree of belief (Kirkwood, 1997), may not necessarily arise in every scenario or are sometimes not available.

From the above discussions, specific techniques to overcome uncertainty in practice vary with the type and degree of the uncertainties in a given problem. In this study, sensitivity analysis is applied to explore how the internal uncertainties in weight assignment affect the ultimate decision. The details with respect to sensitivity analysis is discussed and illustrated with the VOC recovery case study in the next section.

4.6 VOC RECOVERY SOLVENT SELECTION CASE STUDY

4.6.1 Case Description

This case study investigates a typical decision problem in engineering design. Specifically, a solvent for a VOC recovery plant is to be determined against a multiplicity of conflicting criteria. More detailed background information regarding this process is provided in Appendix A.

The original work on this process can be found in a series of publications by the researchers at Michigan Technological University. However, their work, from a MCDA perspective, laid particular stress on alternative generations (e.g. different absorption or adsorption technologies in (Shonnard and Hiew, 2000), solvent comparison in (Chen et al., 2001) and operating conditions in (Chen et al., 2002)) and attribute measurements (e.g. environmental attributes in (Shonnard and Hiew, 2000), environmental and economic attributes in (Chen et al., 2003)). No serious effort was put into the areas of making a meaningful decision.

In this study, the author aims to decide one "best" candidate out of 23 organic solvents, which are to be applied in an absorption-based recovery process operated with fixed process configurations and operating conditions. Disparate solvents will potentially lead to the designs with different performances. Four environmental concerns are of particular interest in this case study. They are Fish Toxicity (FT), Global Warming (GW), Smog Formation (SF), and Acid Rain (AR). The attribute measures in the form of environmental indices are directly drawn from (Chen et al., 2001), as listed below in Table 4–3.

Table 4-3 Environmental indices with different solvents

#	Solvents	I_{FT} (kg/year)	I_{GW} (kg/year)	I_{SF} (kg/year)	I_{AR} (kg/year)
1	1,2,4-Trichlorobenzene	1.13E+04	5.42E+06	2.45E+01	8.25E+03
2	1-Bromo-4-ethoxy benzene	5.62E+04	2.21E+06	9.27E+00	3.12E+03
3	1-Decanol	3.72E+02	2.30E+06	1.47E+01	4.95E+03
4	1-Methy-naphthalene	1.83E+03	2.14E+06	1.06E+01	3.55E+03
5	2-Decanol	2.66E+04	3.35E+06	1.58E+01	5.33E+03
6	4-Chlorobenzotrichloride	9.52E+05	2.42E+06	1.09E+01	3.66E+03
7	Anethole (trans)	5.78E+04	3.04E+06	1.00E+01	3.38E+03
8	Butyl benzoate	3.68E+03	1.56E+06	8.62E+00	2.90E+03
9	Dibenzyl ether	1.29E+03	1.07E+06	7.40E+00	2.49E+03
10	Diethylene glycol butyl ether acetate	3.30E+03	1.69E+06	9.07E+00	3.05E+03
11	Diethylene glycol dibutyl ether	3.08E+03	1.60E+06	8.53E+00	2.87E+03
12	Diethylene glycol monobutyl ether	2.78E+01	1.63E+06	1.04E+01	3.50E+03
13	Diethylene glycol monoethyl ether acetate	3.62E+03	2.78E+06	1.14E+01	3.82E+03
14	Dodecane	1.39E+04	6.39E+06	3.32E+01	1.12E+04
15	Ethyl cinnamate	3.69E+04	1.40E+06	7.84E+00	2.64E+03
16	Hexadecane	4.58E+04	2.68E+06	1.86E+01	6.25E+03
17	Nitrobenzene	5.65E+03	2.76E+06	8.77E+00	2.95E+03
18	o-Bronoanisole	5.13E+04	2.53E+06	8.81E+00	2.96E+03
19	Octanoic acid	3.99E+02	1.62E+06	9.13E+00	3.07E+03
20	o-Dibromobenzene	2.06E+04	2.03E+06	8.49E+00	2.86E+03
21	p-Chlorobenzoyl chloride	1.88E+03	2.55E+06	1.09E+01	3.66E+03
22	Quinoline	4.20E+03	2.49E+06	1.43E+01	4.80E+03
23	Tetradecane	2.78E+03	3.36E+06	2.24E+01	7.54E+03

Obviously, this is a typical MADM problem to be solved as a choice problematic. Therefore, the pairwise analysis of dominance binary relations on the alternative set can help screen out a rational smaller subset of options. In this case, only three solvents as collected in Table 4-4 remain nondominated, which need to be further decided.

Table 4-4 Nondominated solvents and their environmental indices

	z_1	z_2	z_3	z_4
a_9	1.29E+03	1.07E+06	7.40E+00	2.49E+03
a_{12}	2.78E+01	1.63E+06	1.04E+01	3.50E+03
a_{19}	3.99E+02	1.62E+06	9.13E+00	3.07E+03

Decision matrix in Table 4-4 essentially contains quantitative attribute measures $z_j(a_i)$. Starting with these data, a MAVT method is developed to help construct an overall value function through both intra- and inter-attribute operations.

4.6.2 Measurable Partial Value Function Construction

The objectives of this step are twofold. The superficial intent appears to be converting four heterogeneous attribute measures to a homogeneous interval scale (0-10 in this case). However, more importantly, the obtained scores on a particular attribute are supposed to reflect the extent to which the DM values the attainment levels on that attribute. Hence, many numerical normalization techniques, though satisfying the first objective (i.e. unifying scales), fail to meet the second (i.e. capture the DM's preference).

The definition of an interval scale usually necessitates two reference points to be specified for each individual attribute (often the best and worst attribute values corresponding to the two scale extremes respectively). The intended scale can be defined in a either local or global sense (Belton & Stewart, 2002). The former considers only the alternatives at hand. In the VOC recovery case, only the three nondominated alternatives in Table 4-4 are of further interest. On the other hand, a globally defined scale tends to take into consideration a wider set of possible performances on an attribute, which are either conceivable by the analyst or likely to occur in reality. Accordingly, all 23 candidate solvents should be involved to build a more general "global" scale. Table 4-5 contains the two reference points defined for each attribute in local and global sense, respectively.

Table 4-5 Reference points for different attributes to define an interval scale

		z_1	z_2	z_3	z_4
v_j=0	Local	1.29E+03 (a_9)	1.63E+06 (a_{12})	1.04E+01 (a_{12})	3.50E+03 (a_{12})
	Global	9.52E+05 (a_6)	6.39E+06 (a_{14})	3.32E+01 (a_{14})	1.12E+04 (a_{14})
v_j=10	Local	2.78E+01 (a_{12})	1.07E+06 (a_9)	7.40E+00 (a_9)	2.49E+03 (a_9)
	Global	2.78E+01 (a_{12})	1.07E+06 (a_9)	7.40E+00 (a_9)	2.49E+03 (a_9)

Let's use z_2 (global warming index) as an example to illustrate how to derive an apt partial value function. Obviously, the preference here is consistently for lower index values that indicate less environmental impact, hence, the intended $v_2()$ should decrease monotonically with z_2 increasing. However, as mentioned before, $v_2()$ is not necessarily linear to z_2. Many behavioral experiments have indicated that a seemingly intuitive linear value function may deviate, sometimes severely, from the DM's real preference (Stewart, 1993). Whether a value function is linear or nonlinear (concave, convex, or with peaks), on one hand, depends on an individual DM's attitude and valuation. On the other hand, it intimately relates to how well an attribute measure reflects the DM's value concerns.

In general, a partial value function can be assessed through two distinct routes. First, multiple discrete value points are joined together to construct a piecewise linear function. Second, a likely mathematical form is first determined or estimated, such as an exponential value function, the DM is then involved to further decide the specifics of the function (Kirkwood, 1997). In literature, bisection (von Winterfeldt & Edwards, 1986) and difference (Watson & Buede, 1987) methods provide different means to assess a piecewise linear value function. This study adopts bisection method, in which the DM is asked to identify a midpoint that is halfway in value terms between two specified attribute measures. With two extreme points identified in Table 4-5 for global warming index, the question can be asked to the DM like "what attribute measure is of the halfway value (i.e. scoring 5) between 1.63×10^6 kg/year and 1.07×10^6 kg/year?" or applying the mathematical mean (1.35×10^6) that may be more intelligible to the DM: "is the decrease of global warming index from 1.63×10^6 to 1.35×10^6 a bigger or smaller increase in value than the decrease from 1.35×10^6 to 1.07×10^6?" The second question may need to be asked multiple times with the different attribute measures adjusted against the DM's answers. Once the midpoint of the two extreme points are located, next step is to find more value midpoints so that a piecewise linear value function can be sketched more accurately. In general, 5 points (2 extreme and 3 midpoints) are sufficient to enable smoothing a value curve (von Winterfeldt & Edwards, 1986; Stewart, 1996).

For the global warming attribute, Table 4-6 (a) and (b) present 5 points identified in the case of local and global scale, respectively. Joining those 5 points leads to a value function consisting of four linear line segments, as illustrated in Figure 4-1. The global warming indices listed in Table 4-4 are converted to the value function scale through interpolation between two adjacent end points of the corresponding line segment that they fall in. The corresponding Global Warming partial value function values of the three nondominated alternatives are summarized in Table 4-7.

Table 4-6 (a) Five value points for global warming in local scale

z_2	1.07E+06	1.12E+06	1.23E+06	1.41E+06	1.63E+06
v_2	10.00	7.50	5.00	2.50	0.00

Table 4-6 (b) Five value points for global warming in global scale

z_2	1.07E+06	1.99E+06	2.97E+06	4.30E+06	6.39E+06
v_2	10.00	7.50	5.00	2.50	0.00

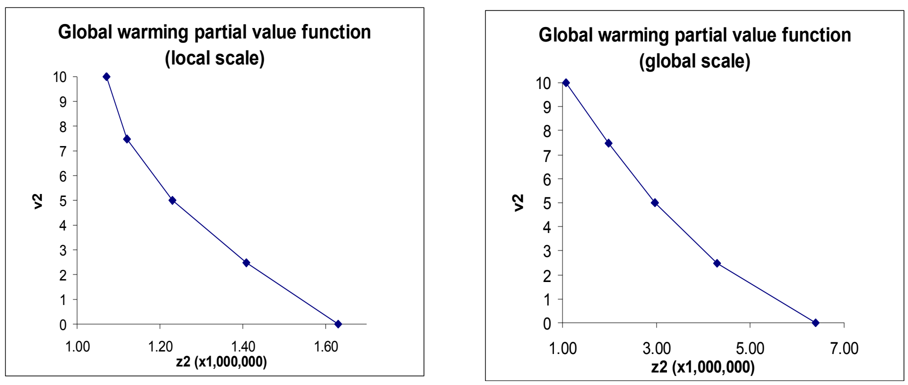


Figure 4-1 Piecewise linear partial value function for global warming

Table 4-7 GW partial value function values of nondiminated alternatives

	z_2	v_2 (local)	v_2 (global)
a_9	1.07E+06	10.00	10.00
a_{12}	1.63E+06	0.00	8.48
a_{19}	1.62E+06	0.11	8.51

From the above constructed partial value function, it can be concluded that an identical unit decrease in global warming index actually worth more for the DM when evaluating a better performed alternative than the alternatives with worse performance. The partial value function for other attributes, namely, fish toxicity, smog formation, and acid rain, can be assessed in a similar manner. The obtained piecewise linear partial value functions are illustrated in Figure 4-2, while the functional values for three nondominated alternatives are summarized in Table 4-8.

Table 4-8 Partial value function values of three nondominated alternatives

	Local scale				Global scale			
	v_1	v_2	v_3	v_4	v_1	v_2	v_3	v_4
a_9	0.00	10.00	10.00	10.00	9.68	10.00	10.00	10.00
a_{12}	10.00	0.00	0.00	0.00	10.00	8.48	7.30	8.80
a_{19}	4.40	0.11	0.355	3.8	9.91	8.51	7.935	9.31

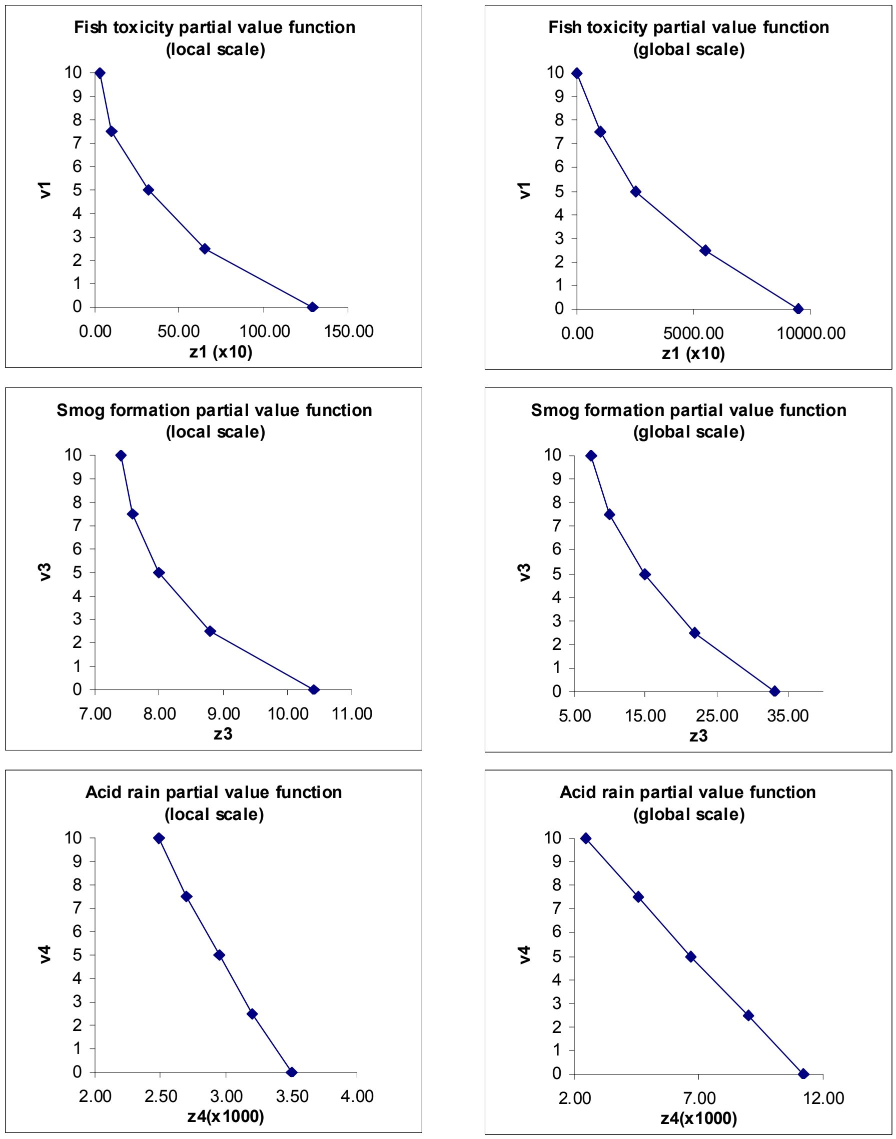


Figure 4-2 Partial value function plots for FT, SF, and AR

4.6.3 Aggregation and Weight Elicitation

With partial value functions obtained, the simplest additive aggregation should be applied wherever possible. However, the corresponding necessary conditions described in 4.2.2 should be satisfied beforehand. Since measurable partial value functions (i.e. interval scale) are used in this case, the condition of "mutually difference independence" needs to be verified for the given attribute set. However, differing from the structural independence mentioned in 3.4.2, preference independence relies solely on the DM's insight to the interrelations among the target attributes, which, therefore, can only be verified with the DM. A successful fulfillment of verification in practice takes a lengthy and tedious questioning procedure between the analyst and the DM. In a general sense, the four attributes in this case study, namely, z_1 (fish toxicity), z_2 (global warming), z_3 (smog formation), and z_4 (acid rain) appear not conceivably relevant whatsoever. Therefore, mutually difference independence is assumed here without digging into an individual DM's specific perception on these attributes. As a consequence, the additive synthesis as shown in (4.7) can be applied:

$$V(a_i) = w_1 \cdot v_1(z_1(a_i)) + w_2 \cdot v_2(z_2(a_i)) + w_3 \cdot v_3(z_3(a_i)) + w_4 \cdot v_4(z_4(a_i)) \tag{4.7}$$

Determining weights (w1, w2, w3, and w4) appears to be nothing more than the DM's brainwork. However, there are considerable practical difficulties in achieving meaningful weights particularly for a given preference model. The oft-heard assertion "weights reflect the relative importance of criteria" seems natural, but makes little practical sense, as people can hardly perceive "what relative importance really means" in a consistent way and their responses may not match the succeeding aggregation (Belton

& Gear, 1997; Belton & Stewart, 2002). As a matter a fact, the debate on the intended meaning of "relative importance of criteria" has been scorching and continues to rage (Roy & Mousseau, 1996). Choo and coworkers (1999) concluded an array of 13 plausible interpretations of "weight" and further pointed out the way of interpreting and eliciting weights should not be independent of the specific preference models in which weights are manipulated. The procedures for deriving weights can be characterized by whether it is statistical or algebraic, holistic or decomposed, direct or indirect (Weber & Borcherding, 1993).

In the case of additive MAVT, weights are more clearly defined compared with other preference models such as AHP and ELECTRE. For instance, in (4.7) fish toxicity carries the weight w_1 and the weight for global warming is w_2. This should be interpreted as that one unit of value (for the DM) gained in fish toxicity compensates (w_1/w_2) units of value loss in global warming. Or, it can be expressed in (4.8) as:

$$w_1/w_2 = [v_2(z_2(a)) - v_2(z_2(b))]/[v_1(z_1(a)) - v_1(z_1(b))] \quad (4.8)$$

In this case study, swing weighting (von Winterfeldt & Edwards, 1986) is applied, which, according to (Belton & Stewart, 2002), captures both the psychological concept of "importance" and the extent to which the measurement scale adopted in practice discriminates between alternatives. Specifically, a swing (or increment) from the worst value (i.e. $v_j = 0$) to the better value (i.e. $v_j = 10$) in each attribute is visualized. The DM is then involved to give considerations to comparing one swing to another in terms of the extent to which the overall value is consequently increased, both qualitatively and quantitatively. As far as the four attributes in this case study is concerned, the consequent overall value change caused by different swings is evaluated as:

$$\Delta V\,(v_{3,\,max} - v_{3,\,min}) > \Delta V\,(v_{2,\,max} - v_{2,\,min}) > \Delta V\,(v_{4,\,max} - v_{4,\,min}) > \Delta V\,(v_{1,\,max} - v_{1,\,min})$$

$$\Rightarrow\; w_3 > w_2 > w_4 > w_1$$

And quantitatively, ratio scale is obtained as follows:

$$(w_3 \,/\, w_1) = 2.0$$

$$(w_2 \,/\, w_1) = 1.5$$

$$(w_4 \,/\, w_1) = 1.2$$

The DM tends to intuitively interpret weights as percentage of a total weight. Hence, it is often useful to normalize the weights to sum to 1. Therefore:

$$w_1 + 1.2w_1 + 1.5w_1 + 2.0w_1 = 1$$

$$w_1 = 0.18$$

$$w_2 = 0.25$$

$$w_3 = 0.36$$

$$w_4 = 0.21$$

With these weights as well as the data in Table 4-8, the overall value (preference) can be computed from (4.7), which are summarized in Table 4-9.

Table 4-9 Overall value of the nondominated alternatives

	Local scale					Global scale				
	v_1 (0.18)	v_2 (0.25)	v_3 (0.36)	v_4 (0.21)	V	v_1 (0.18)	v_2 (0.25)	v_3 (0.36)	v_4 (0.21)	V
a_9	0.00	10.00	10.00	10.00	**8.20**	9.68	10.00	10.00	10.00	**9.94**
a_{12}	10.00	0.00	0.00	0.00	1.80	10.00	8.48	7.30	8.80	8.40
a_{19}	4.40	0.11	0.355	3.8	1.75	9.91	8.51	7.935	9.31	8.72

Therefore, it is clear from Table 4-9 that the ninth alternative: dibenzyl ether offers a most preferred solvent to be applied in the VOC recovery process. However, what matters here is not which alternative is ultimately selected or which criterion happens to be more important to the DM. Instead, the case study tends to draw attention to a justifiable manner of decision making against multiple criteria, which is supposedly embodied in every single step (e.g. mutually difference independence, interval marginal values and ratio judgement on weights) when moving closer to the final decision.

4.6.4 Sensitivity Analysis

Sensitivity analysis, in its mathematical and statistical essence, aims to ascertaining how the output of a quantitative analysis depends on the inputs (Insua, 1999). It has been long applied to multiple criteria decision problems mainly for investigating the significance of uncertainties, establishing the insight to different aspects of the model, discovering implications and possible inconsistency in the DM's judgements, or simply testing the robustness of the result. Many researchers have expostulated to view sensitivity analysis as a standard ingredient for any MCDA methods (French, 2003; von Winterfeldt & Edwards, 1986).

In this case study, sensitivity analysis is used to explore how the uncertainties raised by indeterminate value judgements on weights, a particular type of aforementioned internal uncertainties, would impact the final decision. Certainly, an intuitive way to conduct sensitivity analysis is to manually make adjustments to the weights that are interested, then examine how the results change. However, altering weights on different criteria simultaneously is error prone and time consuming (Kirkwood, 1997). More importantly, it is hard to identify the contribution of each weight alteration to the observed results. However, on the other hand, manipulating one-dimensional weight adjustment has also been criticized as misleading (Butler et al., 1997), due to its ignorance of possible interactions among multiple weight changes. In this case study, systematic investigation is performed on manipulating one weight at a time while keeping other weights "steady" in such a fashion that makes sense.

A difficulty that may arise is that at least one other weight has to be changed when adjusting the interested weight, as all weights must sum to 1. A solution to this is to keep the ratios among the other weights constant while performing the one-dimensional weight adjustment (Kirkwood, 1997). As an example, let's use the weights assessed in 4.6.2 as a base case, in which $[w_1, w_2, w_3, w_4] = [0.18, 0.25, 0.36, 0.21]$ respectively. What other weights are supposed to change, if w_2 takes on a new value 0.1? With additive value function in (4.7) and the premise that ratios among the other weights hold constant, the following equations can be used to compute the corresponding the altered values of w_1, w_3, and w_4:

$$w_1' = (1 - w_2') / (1 + w_3/w_1 + w_4/w_1)$$

$$w_3' = (1 - w_2') / (1 + w_1/w_3 + w_4/w_3)$$

$$w_4' = (1 - w_2') / (1 + w_1/w_4 + w_3/w_4)$$

The experimental results of repeatedly varying each weight with both local and global scale data for partial value functions are contained in Table 4-10(a) and (b). These results are plotted in the Figure 4-3 and 4-4 to allow for intuitionistic and convenient observations.

From the figures, it is easy to conclude that 1) dibenzyl ether (a_9) is the most preferred solvent regardless of the specific weights on w_2 (global warming), w_3 (smog formation), and w_4 (acid rain), therefore, uncertainties on these weights, even though high, are not likely to change the final decision. 2) The only chance for not choosing dibenzyl ether (a_9) is that fish toxicity takes a major portion of the DM's overall weight. Therefore, the weight on fish toxicity needs to be elicited with care. 3) Different scales (i.e. local or global) for partial value functions could potentially lead to disparate results, but the difference in this case is not obvious, due to the existence of a significantly better solution (i.e. a_9) for this choice problematic.

In this chapter, an overview of some major techniques of solving MADM is presented. In addition, a MAVT-based method is proposed and demonstrated with a chemical engineering case study. This method, though has some desired advantages, such as justified theoretical foundation, friendly elicitation from decision-maker, and uncertainty handling, is not possible to be superior to its peers in all cases. The point here is that, in making a multiple attribute decision, the method to be applied has to be adapted and justifiable against the specific occasion, including the problem details, the habits and ability of the analyst as well as the decision-maker.

Table 4-10 (a) Local scale overall values with varying weights

w_1	w_2	w_3	w_4	$V(a_9)$	$V(a_{12})$	$V(a_{19})$
0.00	0.32	0.43	0.26	10.00	0.00	1.16
0.10	0.29	0.38	0.23	9.00	1.00	1.48
0.20	0.26	0.34	0.20	8.00	2.00	1.81
0.30	0.22	0.30	0.18	7.00	3.00	2.13
0.40	0.19	0.26	0.15	6.00	4.00	2.45
0.50	0.16	0.21	0.13	5.00	5.00	2.78
0.60	0.13	0.17	0.10	4.00	6.00	3.10
0.70	0.10	0.13	0.08	3.00	7.00	3.43
0.80	0.06	0.09	0.05	2.00	8.00	3.75
0.90	0.03	0.04	0.03	1.00	9.00	4.08
1.00	0.00	0.00	0.00	0.00	10.00	4.40
0.24	0.00	0.48	0.29	7.62	2.38	2.30
0.21	0.10	0.43	0.26	7.86	2.14	2.08
0.19	0.20	0.38	0.23	8.10	1.90	1.86
0.17	0.30	0.33	0.20	8.33	1.67	1.64
0.14	0.40	0.29	0.17	8.57	1.43	1.43
0.12	0.50	0.24	0.14	8.81	1.19	1.21
0.10	0.60	0.19	0.11	9.05	0.95	0.99
0.07	0.70	0.14	0.09	9.29	0.71	0.77
0.05	0.80	0.10	0.06	9.52	0.48	0.55
0.02	0.90	0.05	0.03	9.76	0.24	0.33
0.00	1.00	0.00	0.00	10.00	0.00	0.11
0.27	0.41	0.00	0.32	7.30	2.70	2.47
0.24	0.36	0.10	0.29	7.57	2.43	2.26
0.22	0.32	0.20	0.26	7.84	2.16	2.04
0.19	0.28	0.30	0.23	8.11	1.89	1.83
0.16	0.24	0.40	0.19	8.38	1.62	1.62
0.14	0.20	0.50	0.16	8.65	1.35	1.41
0.11	0.16	0.60	0.13	8.92	1.08	1.20
0.08	0.12	0.70	0.10	9.19	0.81	0.99
0.05	0.08	0.80	0.06	9.46	0.54	0.78
0.03	0.04	0.90	0.03	9.73	0.27	0.57
0.00	0.00	1.00	0.00	10.00	0.00	0.36
0.22	0.33	0.44	0.00	7.78	2.22	1.17
0.20	0.30	0.40	0.10	8.00	2.00	1.44
0.18	0.27	0.36	0.20	8.22	1.78	1.70
0.16	0.23	0.31	0.30	8.44	1.56	1.96
0.13	0.20	0.27	0.40	8.67	1.33	2.22
0.11	0.17	0.22	0.50	8.89	1.11	2.49
0.09	0.13	0.18	0.60	9.11	0.89	2.75
0.07	0.10	0.13	0.70	9.33	0.67	3.01
0.04	0.07	0.09	0.80	9.56	0.44	3.27
0.02	0.03	0.04	0.90	9.78	0.22	3.54
0.00	0.00	0.00	1.00	10.00	0.00	3.80

Table 4-10 (b) Global scale overall values with varying weights

w_1	w_2	w_3	w_4	$V(a_9)$	$V(a_{12})$	$V(a_{19})$
0.00	0.32	0.43	0.26	10.00	8.06	8.47
0.10	0.29	0.38	0.23	9.97	8.25	8.61
0.20	0.26	0.34	0.20	9.94	8.45	8.76
0.30	0.22	0.30	0.18	9.90	8.64	8.90
0.40	0.19	0.26	0.15	9.87	8.84	9.05
0.50	0.16	0.21	0.13	9.84	9.03	9.19
0.60	0.13	0.17	0.10	9.81	9.22	9.33
0.70	0.10	0.13	0.08	9.78	9.42	9.48
0.80	0.06	0.09	0.05	9.74	9.61	9.62
0.90	0.03	0.04	0.03	9.71	9.81	9.77
1.00	0.00	0.00	0.00	9.68	10.00	9.91
0.24	0.00	0.48	0.29	9.92	8.37	8.80
0.21	0.10	0.43	0.26	9.93	8.38	8.77
0.19	0.20	0.38	0.23	9.94	8.39	8.74
0.17	0.30	0.33	0.20	9.95	8.40	8.71
0.14	0.40	0.29	0.17	9.95	8.41	8.68
0.12	0.50	0.24	0.14	9.96	8.43	8.65
0.10	0.60	0.19	0.11	9.97	8.44	8.63
0.07	0.70	0.14	0.09	9.98	8.45	8.60
0.05	0.80	0.10	0.06	9.98	8.46	8.57
0.02	0.90	0.05	0.03	9.99	8.47	8.54
0.00	1.00	0.00	0.00	10.00	8.48	8.51
0.27	0.41	0.00	0.32	9.91	8.99	9.15
0.24	0.36	0.10	0.29	9.92	8.83	9.03
0.22	0.32	0.20	0.26	9.93	8.66	8.91
0.19	0.28	0.30	0.23	9.94	8.49	8.78
0.16	0.24	0.40	0.19	9.95	8.32	8.66
0.14	0.20	0.50	0.16	9.96	8.15	8.54
0.11	0.16	0.60	0.13	9.97	7.98	8.42
0.08	0.12	0.70	0.10	9.97	7.81	8.30
0.05	0.08	0.80	0.06	9.98	7.64	8.18
0.03	0.04	0.90	0.03	9.99	7.47	8.06
0.00	0.00	1.00	0.00	10.00	7.30	7.94
0.22	0.33	0.44	0.00	9.93	8.29	8.57
0.20	0.30	0.40	0.10	9.94	8.34	8.64
0.18	0.27	0.36	0.20	9.94	8.39	8.71
0.16	0.23	0.31	0.30	9.95	8.45	8.79
0.13	0.20	0.27	0.40	9.96	8.50	8.86
0.11	0.17	0.22	0.50	9.96	8.55	8.94
0.09	0.13	0.18	0.60	9.97	8.60	9.01
0.07	0.10	0.13	0.70	9.98	8.65	9.09
0.04	0.07	0.09	0.80	9.99	8.70	9.16
0.02	0.03	0.04	0.90	9.99	8.75	9.24
0.00	0.00	0.00	1.00	10.00	8.80	9.31

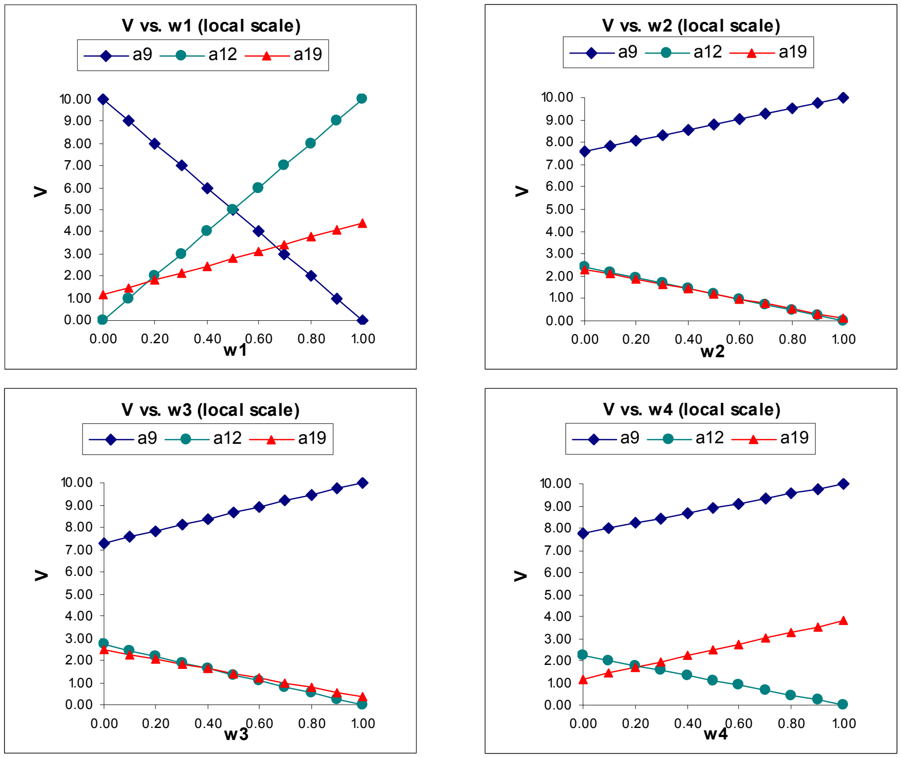


Figure 4-3(a)~(d) Sensitivity analysis for weights in local scale

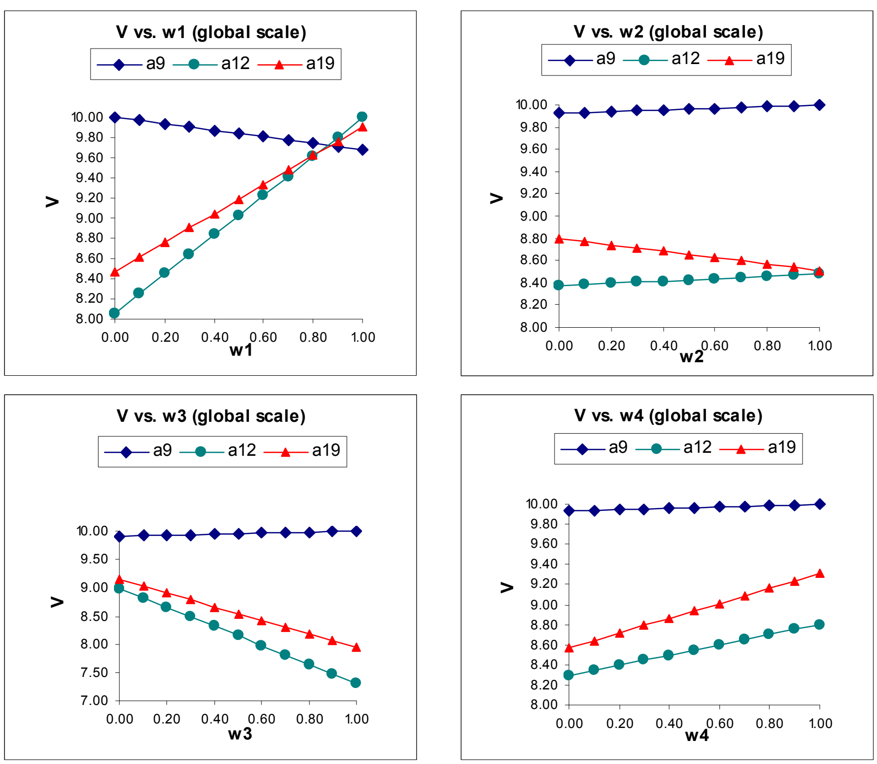


Figure 4-4(a)~(d) Sensitivity analysis for weights in global scale

CHAPTER 5

SOLVING MULTIPLE OBJECTIVE DECISION MAKING

5.1 SOLVING MODM

A Multiple Objective Decision Making (MODM) problem is also known as Multiple Objective Programming (MOP) or Vector Maximum Problem (VMP). The ultimate goal of solving such a problem is to find a single solution $\mathbf{x}^*=[x_1^*, x_2^*, \ldots, x_{nx}^*]^T$ that satisfies all the constraints and possesses the most "preferred" (by the DM) values on the vector objective function $\mathbf{f}(x^*)=[f_1(x^*), f_2(x^*), \ldots, f_{nf}(x^*)]^T$. Mathematically, a typical MODM problem can be represented as:

$$\begin{aligned}
&\text{Minimize} \quad \mathbf{f}(\mathbf{x}) \qquad \mathbf{f} = [f_1, f_2, \ldots, f_{nf}]^T \quad \mathbf{x} = [x_1, x_2, \ldots, x_{nx}]^T \qquad (5.1)\\
&\text{s. t.} \quad \mathbf{x} \in \mathbf{F}\\
&\qquad \mathbf{F} = \{\mathbf{x} \mid \mathbf{g}(\mathbf{x}) \le 0 \qquad g = [g_1, g_2, \ldots, g_{ng}]^T;\\
&\qquad\qquad \mathbf{h}(\mathbf{x}) = 0 \qquad h = [h_1, h_2, \ldots, h_{nh}]^T;\\
&\qquad\qquad x_{il} \le x_i \le x_{iu} \qquad i = 1, 2, \ldots, nx\ \}
\end{aligned}$$

There are numerous methods for solving MODM problems. Many dedicated books and monographs have been published, such as (Hwang & Masud, 1979; Sawaragi et al., 1985; Steuer, 1986; Miettinen, 1999; Collette & Siarry, 2003). Several points should be noted before specific solution methods are presented.

First of all, from a decision-making standpoint, infinite alternative space and multiple competing objectives are two fundamental difficulties in a MODM. Accordingly, two distinct sub-processes are imperative in solving a MODM. On the one hand, a search mechanism explores the possible solutions by iteratively sampling the alternative space. Past studies on optimization have produced abundant techniques for searching a given space in a theory-guided, heuristic, patterned, or simply random manner. On the other hand, as addressed in Chapter 3 and 5, a decision method is needed to evaluate a finite collection of intermediate solutions against conflicting objectives, which requires the human decision maker to be involved sooner or later.

Second, finding the Pareto optimal set (often containing infinite solutions) is sometimes considered the mathematical endpoint of a solution process, especially for the approaches referred to as "vector optimization." However, the problem is still not completely solved, because real world applications would always require only one solution.

Third, as an infinite number of candidates are to be decided, it is important to (theoretically or empirically) ensure that the achieved final solution is globally "optimal" or "preferred" (compared with all other possible candidates) rather than just "local" (compared with the very limited number of alternatives that are examined during the solution process). However, as a matter of fact, very few algorithms present completely satisfactory performance in this regard. A looser criterion, as mentioned in Chapter 3, is that an overall preferred solution has to be Pareto optimal. However, globally Pareto optimality is also hard to verify as far as an infinite set is concerned.

5.1.1 Different Solution Strategies

MODM Solution techniques can be classified in a variety of different ways (Miettinen, 1999). A taxonomy that gained the most recognition was first proposed in (Cohen & Marks, 1975) and formulated by Hwang and Masud (1979) into the later widespread discourse. According to this scheme, different methods are sorted by the timing for the DM to be involved (i.e. decision sub-process) relative to the search sub-process. As a result, three fundamentally different solution strategies can be distinguished:

- A priori preference articulation (decision ⇒ search)
- A posteriori preference articulation (search ⇒ decision)
- Progressive preference articulation (search ⇔ decision)

Both search and decision-making have been very active research areas over the past years. However, the simultaneous attainment of both seems not as successful. On the one hand, multiple attribute decision-making (MADM) assuming a "countable" or "easily searchable" alternative space has been extensively studied, in which preference is handled variously. On the other hand, many robust algorithms exist capable of searching intractably large and complex spaces. However, their applications to multi-objective cases are less reported (Horn, 1997a).

5.1.2 "A Priori" Methods

This traditional class of methods seeks to convert a MODM to a single objective programming (SOP) problem (or a sequence of SOPs), so that a large number of long-standing numerical optimization techniques can be applied. Though there exist widely different ways of constructing a scalar objective function (Ehrgott, 2005; Parsons & Scott, 2004; Marler & Arora, 2004), preference from the decision maker is always needed (sometimes implicitly) ahead of time. However, operational difficulties may arise, which most likely originate from acquiring legitimate preference and justifying its validity for a particular method. Table 5-1 contains an inexhaustive list of methods sorted according to distinct scalarization mechanisms. Hwang & Masud (1979) and Ehrgott (2005) provide more complete surveys. Several most widespread methods are introduced in brief next.

Table 5-1 Different methods using a priori preference strategy

Category	Explanation	Approaches
Value function-based	Based on the existence of an explicit value function that can reliably convey the DM's global preference	Weighted sum Weighted t-th power Multiplicative value function
Constraint-based	Reserving one objective function to be optimized while converting all the others to constraints	ε-constraint Proper equality constraint Elastic constraint
Reference point (Distance function)	Minimizing the distance function constructed to measure the closeness to a reference point	Compromise programming Achievement function Weighted geometric mean Goal programming
Direction-based	Searching along a direction in the objective space with a pre-specified base point	Goal-attainment Reference direction Normal boundary intersection
Other	Miscellaneous scalarization	Benson approach Gauge-based Min-Max

5.1.2.1 Weighted Sum Method

$$\text{Minimize} \qquad f' = \sum_{i=1}^{nf} w_i f_i \qquad (5.2)$$

The scalar objective function is obtained from the simple additive formula as shown in (5.2). This method can be applied when the DM's value judgement on each attribute is linear and his/her preference can be encoded or assumed in an additive form. As seen in Chapter 5, a necessary condition for a value function to be additive is that all the partial value functions (i.e. f_i) are mutually preferential independent. The weights w_i in (5.2) should be interpreted and elicited as marginal rate of substitution (i.e. swing), which essentially stands for how many units of decrease in f_i compensate one unit of increase in another criteria f_j. Though this method appears simple, many difficulties, particularly those associated with weights, have been recognized. First, weights in practice are prone to misinterpretation, debatable elicitation, and alteration with time (Marler & Arora, 2004). Second, though theorems have been proved that positive weights guarantee a Pareto optimal solution and vice versa (Miettinen, 1999), this method is impossible to find Pareto optimal solutions locating in a non-convex region (Das & Dennis, 1997). Third, consistent and continuous variation in weights does not necessarily lead to an even distribution of Pareto optimal solutions (Das & Dennis, 1997; Marler & Arora, 2004).

5.1.2.2 ε-Constraint Method

This method performs the MOP-to-SOP conversion by retaining one objective function while treating the others as constraints (Haimes et al., 1971), which is shown in (5.3).

$$\text{Minimize} \quad f_k \qquad (5.3)$$

$$\text{s.t.} \qquad f_i \le \varepsilon_i,\ i \ne k,\ i = 1, 2, \ldots, nf$$

The solution to (5.3) has been proven "weakly" Pareto optimal if exist and Pareto optimal if unique (Miettinen, 1999). The difficulties primarily arise from selecting the objective function as well as an appropriate bound for each constraint. In addition, this method is computationally laborious, as extra calculations often have to be spent on those bound values that yield no feasible solution and also on verifying the uniqueness of a solution. The increased number of constraints would cost even more computation.

5.1.2.3 Distance Function Methods

This name actually refers to a school of methods with a common root that lies in the construction of a scalar distance (achievement) function, which essentially offers a meaningful measure of the closeness to an identified reference point in the objective space.

$$\text{Minimize or maximize} \quad d(\mathbf{f}, r) \qquad (5.4)$$

In literature, different distance metrics and reference points lead to various methods. The representing methods for this class include: goal programming (GP) (Charnes & Cooper, 1977) and Compromise programming (CP) (also referred to as global criterion or weighted metric with slightly different formulations) (Zeleny, 1973). The conditions for these methods to yield Pareto optimal solutions were discussed in (Miettinen, 1999). Romero and coworkers (1999) attempted establishing theoretical inter-connection among various methods. The different characteristics of these methods are summarized in Table 5-2.

Table 5-2 Distance function methods for solving a MODM

Method	Reference point	Distance metric	
GP	Vector of goals on attributes	Weighted	$\sum_{i=1}^{nf}(w_i^- \delta_i^- + w_i^+ \delta_i^+)$
		lexicographic	Minimize $\lvert\delta_i\rvert$
		Min-max	Minimize (max δ_{i+})
CP	Vector of optimal attribute values	Non-weighted	$(\sum_{i=1}^{nf} \lvert f_i - r_i \rvert^p)^{1/p}$
		Weighted	$(\sum_{i=1}^{nf} w_i \lvert f_i - r_i \rvert^p)^{1/p}$

5.1.3 "A Posteriori" Methods

A major criticism on a priori methods lies in that it is very difficult, if not impossible, to precisely elicit preference only in terms of criteria (i.e. objective functions) without associating them with specific solutions. This, however, is just the most prominent advantage of a posteriori methods. A posterior methods tend to generate or approximate (part of) the Pareto optimal solutions, so that the infinite candidate set can be narrowed down to a reasonable finite subset, which, as a consequence, allows the human DM to make further decisions. These methods are criticized for their computational burden in generating the entire efficient set and their cognitive burden on the decision maker in selecting one solution from a still considerable number of alternatives (Shin & Ravindran, 1991).

5.1.3.1 Traditional Generation Techniques

In a rather long time, the only way of generating multiple Pareto optimal solutions seemed to be solving a sequence of SOP iteratively. An apt SOP formulation can be obtained from any a priori method mentioned in the subsection 5.1.2, such as weighted sum, ε-constraint, etc. However, the tricky part is how to efficiently attain distinct yet well representative Pareto optimal solutions (usually depicted by the uniform spread in the objective space). Most methods have questionable ability to fulfill this task in a systematic and well-perceived way (Miettinen, 1999). It is also important to note that the traditional methods to a great extent are beholden to the success and efficiency of the SOP solver.

5.1.3.2 Multiobjective Evolutionary Algorithms (MOEAs)

Differing from those generation methods, this class of methods are new and based on a totally different philosophy of search. Research has indicated that MOEAs, depending on applications, are able to generate a satisfactory set of solutions (globally Pareto optimal and evenly distributed) in a single run (Deb, 2001; Coello Coello et al., 2002). The in-depth discussion on MOEAs is provided later.

5.1.4 Interactive Methods

All MCDA methods are essentially interactive (Stewart, 1999; Korhonen, 2005), since the intervention of a DM, though occurring at different timings (in advance, during the search, or afterwards), is always requisite. The term "interactive" is used here in a relatively narrower sense referring to the methods in which the DM's global preference structure is evaluated progressively from making local choices. As a result, the dialogue about the current situation between a "consistent" DM and an analyst (who performs the search) are iterated during the entire solution process. A typical interactive procedure is as follows: “initial solution(s) – preference from the DM – update the solution(s) – repeat until satisfaction or termination” (Miettinen, 1999).

In literature, most interactive MOP techniques were generally presented rather than computationally applied. Numerical comparative studies that test different methods are even less. This may be partially attributed to: 1) the complicating fact working with real decision makers, in particular, the nonequivalence of variously articulated preference; 2) the lack of benchmark test MOP problems (Shin & Ravindran, 1991; Miettinen, 1999). Shin & Ravindran (1991) in their comprehensive survey differentiated the interactive methods into ten categories, while Stewart (1999) and Korhonen (2005) both presented different rougher taxonomies. In this study, two general classes of methods are distinguished.

5.1.4.1 Implicit Value Function-Based

This class of methods assumes the existence of a value function, which can represent the DM’s global preference. However, no effort is made to pursue the explicit form of the value function. Instead, certain mild functional characteristics (e.g. pseudoconcavity) are hypothesized and applied in a local sense. The class includes the methods using tradeoff information (Geoffrion et al., 1972) and using direct alternative comparison (Zoints & Wallenius, 1976 ; Steuer, 1977).

5.1.4.2 None Value Function-Based

Without value function assumption, most of these methods are conceptually based on iteratively adjusting the DM's aspiration. Different ways of expressing aspiration as well as manipulating adjustment essentially give rise to a variety of distinct methods. Among various methods, STEM (Banayoun et al., 1971), Light Beam Search (Jaszkiewicz & Slowinski; 1999), Tchebycheff method (Steuer, 1986), and Reference Point method (Wierzbicki, 1980, Wierzbicki, 1998,) are notable representatives.

5.1.5 Interest of This Work

The behavioral foundation underlying a priori methods appears unrealistic for most of the real-world decision contexts, attributed to its demand for an assured global preference at the very beginning of a decision process even before any local preference is explored. Interactive methods, on the other hand, are conceptually very attractive, mainly because of their "learning" capacity, local preference requirement and the adequate involvement of the decision maker (Miettinen, 1999; Hwang et al., 1980). However, these advantages could also be their shortcomings, if examined from a different perspective. For instance, higher burdens are imposed on the DM, not only cognitively (i.e. to keep psychological consistency) and physically (e.g. to interact with the analyst at each iteration). In addition, the computerized search algorithm has to pause at each iteration to allow for incorporating updated preference. This further requires a friendly computer-man interface and more importantly lowers the efficiency of solution process. To this end, the methods adopting a posterior solution strategy turn out to be practically more desired, as it split the rigorous search (which can be efficiently accomplished by a computer) and the interactive human-dependent decision (which may involve rather tedious preference elicitation and refining) and perform them in sequence. The issues on multiple attribute decision making have been extensively discussed in Chapter 4. Hence, the succeeding sections cast focus on MOEAs, a recently emerged a posterior method that has been claimed to be "well adapted" to tackling the search task in a MODM (Collette & Siarry, 2003; Chipperfield et al., 1999).

5.2 EVOLUTIONARY ALGORITHMS

5.2.1 Introduction

Evolutionary Algorithms (EAs) refer to a class of stochastic search techniques with natural evolution and Darwin's survival-of-the-fittest theory as the underlying inspiration. The backbone of EAs consists of genetic algorithms (GAs) (Holland, 1975, Goldberg, 1989), evolution strategies (ESs) (Rechenberg, 1965), and evolutionary programming (EP) (Fogel et al., 1966), which all stemmed in the 1960s and the 1970s and have developed almost independently in history. In recent years, the boundaries between GAs, ESs, and EP have broken down considerably (Mitchell, 1996). The majority of today's EAs exhibit more or less hybrid characteristics and dramatic difference from their ancestors. Therefore, the succeeding discussions are predominantly focused on Genetic Algorithms, which are most well known and widespread.

EAs differ in principle from those "traditional" search methods. As a result, some difficulties inherent in traditional optimization methods can be easily overcome by EAs. Several authors have pointed out the strength of EAs in comparison with traditional optimization methods (Deb, 2001; Goldberg, 1989). However, some obvious shortfalls also exist. Below listed are several points to which this author attached the most importance.

- EAs evolve a population of solutions at a time, instead of jumping from one individual solution to the other. This is of particular advantage for three cases: 1) to attain more than one solution in a single run, for instance, to approximate Pareto optimal front, 2) to utilize parallel computation, and 3) to avoid getting stuck in a local optimum.
- EAs apply metaheuristics and therefore require less auxiliary information (such as derivatives, Hessian matrix for indirect optimization algorithms). This makes EAs more robust than most conventional deterministic methods, which usually have trouble solving such problems with nonlinear, multimodal or even blackbox (no analytical expression) objective function(s) as well as discrete or mixed type of decision variables (Mixed Integer Linear/Nonlinear Programming).
- Due to their stochastic nature and absence of solid theoretical foundation, EAs can not guarantee that an optimal-enough or even bearable solution is found in each run (within finite time). Also, the computational cost of EAs is usually high.

5.2.2 Construction of a Genetic Algorithm

As originally formulated by John Holland (1975), GAs work in a parallel and iterative fashion by discovering, emphasizing, and recombining the "schemas" (building blocks) of good solutions (Mitchell, 1996). Figure 5-1 presents the flowchart of a generic GA. In general, a GA starts with a random population of solutions, if no prior domain knowledge is available. Each solution is encoded as an artificial chromosome ("genotype") mimicking the natural chromosomes carrying genetic information for organisms. How a particular solution performs in terms of the interested goals of search is evaluated in terms of its fitness corresponding to organisms' biological characteristics ("phenotype"). If the stopping criteria are met, the solution process comes to an end. Otherwise, the solutions go through a sequence of genetic operations to hopefully update the current population to a better composition. Various genetic operators have been developed and applied. The majority of them fall in three basic types: 1) selection, 2) crossover, and 3) mutation. Some working steps pivotal to implementing a GA are discussed briefly in the following subsections.

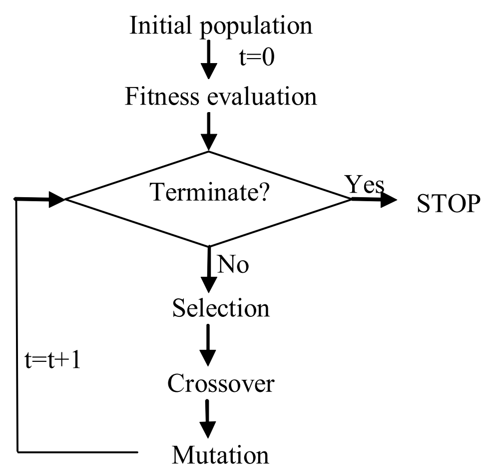


Figure 5-1 Flowchart of a generic GA

5.2.2.1 Representation

Partly attributed to historical reasons as well as intuitive metaphor of natural chromosomes, binary-encoding GAs in which solutions are represented by bit strings (length may be fixed or varying with precision) are most common (Mitchell, 1996). However, it has been proven that GAs' effectiveness does not stem from using bit strings

(Herrera et al., 1998). Other encoding methods, such as real-valued encoding (Herrera et al., 1998), tree encoding (Koza, 1992), and permutation encoding (Ronald, 1997) are more wieldy than binary encoding for some particular problems. The best philosophy of choosing the correct encoding so far seems to be applying the one that is most natural to the specific problem under consideration (Davis, 1991). Robust (Ronald, 1997) and adapting encoding (Mitchell, 1996) were also elaborated in literature for complex problems.

5.2.2.2 Fitness Evaluation

Fitness plays a key role in guiding the evolution through future generations. It is essentially a measure of how good a solution is, either relative to the others in the current population or according to certain pre-defined universal standards. Fitness could involve mathematical models (e.g. objective and constraint functions), human judgement, or even ecology-like process (Goldberg, 2002). In most mathematical optimization settings, either objective function(s) itself or the relevant variations (e.g. sorting, ranking, combination) are taken as fitness.

5.2.2.3 Selection

Selection is an operator emulating survival-of-the-fittest mechanism. The basic idea is to drive the evolution by emphasizing fitter individuals in hopes that their offspring will in turn have even higher fitness. Among a number of selection operators, proportionate selection including roulette wheel (Holland, 1975) and stochastic universal sampling (Baker, 1987), rank selection (Baker, 1985), tournament selection (Goldberg &

Deb, 1991) are widely applied. The selection pressure of a selection operator needs to be balanced with successive crossover and mutation (i.e. exploitation/exploration balance) in order to obtain successful behavior of a GA (Blickle & Thiele, 1996).

5.2.2.4 Crossover and Mutation

Crossover shuffles pieces of fit schemas, which possibly will result in the offspring with good or even better combined parental traits. Mutation, on the other hand, modifies a single individual in order to introduce new genes into the current population. Again, there are a variety of ways to accomplish crossover and mutation. The specific operators to be applied depend on many considerations, including encoding strategy, fitness function, and other details in a particular GA (Mitchell, 1996). The existing guidance regarding what and how (e.g. probabilities) operators should be utilized is very limited and was mostly achieved from empirical studies on small suites of test problems.

5.3 MULTI-OBJECTIVE EVOLUTIONARY ALGORITHMS

5.3.1 Overview

The transformation of EAs to multiple objective programming (MOP) fields was not long ago. Schaffer (1985) and his vector evaluated GA (VEGA) was widely regarded as the first attempt to implement EAs to MOPs in such a different manner that EAs' population-based characteristics were exploited to keep multiple objectives in parallel without scalarization. Based on Schaffer's pioneering work, non-dominated sorting proposed by Goldberg (1989) further laid the foundation of dominance-based fitness assignment and selection, which stay central to most MOEAs developed thereafter.

A large number of MOEAs emerged in the 1990s. Some notable representatives are multi-objective GAs (MOGAs) (Fonseca & Fleming, 1993), niched Pareto GAs (NPGAs) (Horn et al., 1994), non-dominated sorting GAs (NSGAs) (Srinivas & Deb, 1994), Strength Pareto EAs (SPEAs) (Zitzler & Thiele, 1998a), and Rank-Density-Based GAs (RDGAs) (Lu & Yen, 2002). Some of them have been developed to newer versions and multiple variations. These methods differ in the mechanism of fitness assignment, diversity preservation, as well as elitism strategy. Good overview books and survey articles on MOEAs include (Deb, 2001), (Coello et al., 2002), (Fonseca & Fleming, 1995a), (Coello Coello, 2000a), (Van Veldhuizen & Lamont, 2000), (Tan et al., 2002).

Coello and coauthors (2002) stated that the classification scheme described in 5.1.1 (i.e. a priori, a posteriori, progressive) also apply to MOEAs. In addition, the majority of MOEAs fall in the "a posteriori" class. This was justified by the survey by Van Veldhuizen & Lamont (2000). As pointed out in (Lu & Yen, 2002), the intention of "a posteriori" MOEAs is to find a uniformly distributed set of samples of a near-complete and near-optimal Pareto front. Deb (2001) argued that finding multiple Pareto optimal solutions is motivated by the fact that the DM's definite preference among criteria is unavailable. Therefore, from a perspective of MCDA, a MOEA itself cannot completely solve a MOP problem (locating a single "best" solution) and must require extra preference information to tackle the conflict among criteria. However, as stated in 3.5.3, a preferred solution to a choice problematic has to be one of Pareto optimal solutions. To this end, MOEAs, particularly those adopting dominance-based fitness assignment, played an important role in solving MOP. They help to reduce significantly the size of the interested set of solutions in a rational way and without a risk of choosing non-Pareto-optimal solutions. Hence, the following discussions on implementation issues are restricted to those MOEAs applying dominance-based fitness assignment.

5.3.2 Fitness Assignment

Determining the fitness of an individual is not straightforward in the presence of multiple criteria. The concept of dominance was first applied by Goldberg (1989) to fitness assignment. Various fitness assignment methods have emerged in the past decade based on the similar philosophy, which assigns non-dominated solutions more desirable fitness (i.e. rank) than dominated ones in the population. Three categories can be loosely defined to sort different methods (Zitzler, 2002; Raghuwanshi & Kakde, 2004):

- Dominance rank: The fitness of an individual is related to the number of individuals by which it is dominated.
- Dominance count: the fitness of an individual is related to the number of individuals it dominates.
- Dominance depth: the fitness of an individual is related to which front it belongs to (the current population is divided into several fronts by non-dominated sorting).

Table 5-3 contains a list of different fitness assignment methods adopted in several popular MOEAs. There is no clear evidence that could favor any of those methods over the others in a general sense. The mathematical complexity of several methods was analyzed in (Van Veldhuizen & Lamont, 2000).

Table 5-3 Different fitness assignment techniques in several popular MOEAs

MOEA	Classification	Fitness assignment technique
MOGA	Dominance rank	Rank-based fitness assignment $rank(x_i, t)=1+p_i(t)$ x_i: The individual to be considered at generation t $p_i(t)$: The number of individuals that dominate x_i
NPGA	Dominance rank	Pareto domination tournaments
NSGA	Dominance depth	Non-dominated sorting Iteratively assign increased rank to non-dominated individuals and extract them from unclassified solutions.
NSGA-II	Dominance depth	Fast non-dominated sorting Same mechanism as that in NSGA, but with a better book-keeping strategy to accelerate calculation.
SPEA	Dominance count & rank	$S(\overline{x_i}, t) = n_i/(N+1)$ $\quad F(x_j, t) = 1 + \sum_{i=1}^{p_j^{(t)}} S(\overline{x_i}, t)$ x_j: The individual in the population at generation t $F(x_j, t)$: Fitness of xj at generation t $\overline{x_i}$: The ith (i=1,2,…$p_j(t)$) archive member dominates x_j $p_j(t)$: The number of archive members that dominate x_j $S(\overline{x_i}, t)$: Strength of $\overline{x_i}$ at generation t n_i: The number of population members $\overline{x_i}$ dominates N: The size of the current population
SPEA-II	Dominance count & rank	$R(x_j, t) = \sum_{i=1}^{p_j^{(t)}} S(x_i, t)$ $S(x_i, t)$ = Number of individuals x_i dominates at generation t x_j: The individual to be considered at generation t $R(x_j, t)$: Raw fitness of x_j at generation t x_i: The ith (i=1,2,…$p_j(t)$) individual that dominates x_j $p_j(t)$: The number of individuals that dominate x_j $S(x_i, t)$: Strength of x_i at generation t
RDGA	Dominance count & rank	Automatic Accumulated Ranking Strategy (AARS) $Rank(x_j, t)=1+\sum_{i=1}^{p_j^{(t)}} rank(x_i, t)$ x_j: The individual to be considered at generation t x_i: The ith (i=1,2,…$p_j(t)$) individual that dominates x_j $P_j(t)$: The number of individuals that dominate x_j

Figure 5-2 illustrates a two-dimensional objective space containing nine distinct solutions whose fitness are to be determined. The fitness of these points yielded from the selected MOEAs are summarized in Table 5-4.

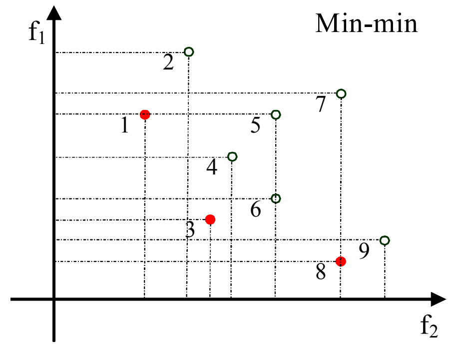


Figure 5-2 Determining the fitness for a population of solutions

Table 5-4 Fitness assigned by different methods

	Non-dominated individual			Dominated individual					
	#1	#3	#8	#2	#4	#5	#6	#7	#9
MOEA	1	1	1	2	2	5	2	7	2
NSGA	1	1	1	2	2	3	2	4	2
NSGA-II	1	1	1	2	2	3	2	4	2
SPEA-II	0	0	0	3	4	11	4	14	2
RDGA	1	1	1	2	3	7	2	13	2

5.3.3 Diversity Preservation

Using EAs to solve optimization problems, particularly those with vector-valued or multi-modal objective function, has been suffering from the so-called "genetic drift" (losing genes due to stochastic selection on a finite-size population) as well as "premature convergence" (trapped at a single solution). Researchers have developed a variety of techniques to combat these negative effects. Most of them are based on maintaining diversity in the population (Coello et al., 2002; Landa Silva & Burke, 2004). These diversity preservation methods were loosely distinguished as either niching (Goldberg, 1989; Sareni & Krahenbuhl, 1998) /speciation (Darwen & Yao, 1996) or non-niching methods.

From the observation of natural evolution within an environmental niche (a portion of ecosystems to sustain competing species), Goldberg and Richardson (1987) proposed a niching technique named sharing, which was perhaps most widely applied (Deb and Goldberg, 1989; Mahfoud, 1995; Horn, 1997b). This technique works analogous to natural species exploiting and sharing a same resource. An individual's shared fitness (f') is equal to its original fitness (f) divided by its niche count (nc_i), which is the sum of sharing function (sh) values between the individual and every individual (including itself) in the population:

$$f'(i) = \frac{f(i)}{nc_i} \qquad nc_i = \sum_{j=1}^{n} sh(d(i,j)) \tag{6.5}$$

$$sh\ (d(i,j)) = \begin{cases} 1-(d(i,j)/\sigma_{share})^{\alpha}, & if\ d < \sigma_{share} \\ 0, & otherwise \end{cases}$$

d(i,j) stands for a distance measure between solution i and j. Sharing tends to encourage the proliferation of solutions in unexplored regions by reducing the payoff of densely populated individuals. There are many fitness sharing variants differing from one another in many aspects, such as distance metrics applied, genotypic or phenotypic sharing, restricted or non-restricted sharing, etc. Though fitness sharing methods enjoyed the most success (Mahfoud, 1995), particularly in solving multimodal problems, they have been criticized for their perplexity in determining an appropriate dissimilarity threshold σ_{share} as well as high cost in computing niche count (Sareni & Krahenbuhl, 1998).

More recently, measures of crowding and/or density have been applied as an auxiliary meter for comparing the individuals with identical fitness. This class includes crowding distance (size of largest cuboid enclosing the individual without including any other individual) in NSGA-II (Deb et al, 2000); density (an individual's distance to k-nearest neighbor) in SPEA-II (Zitzler et al., 2002), and adaptive density (a revised cell density estimation) in RDGA (Lu & Yen, 2002). Table 5-5 summarizes the diversity preservation methods used in several major MOEAs.

Table 5-5 Different diversity preservation techniques in several popular MOEAs

MOEAs	Classification	Diversity preservation technique
MOGA	Niching & non-niching	Fitness sharing in objective space Mating restriction
NPGA	Niching	Equivalent class sharing (fitness sharing) in objective space
NSGA	Niching	Fitness sharing in decision space
NSGA-II	Niching	Crowding distance comparison
SPEA	Niching	Average linkage clustering
SPEA-II	Niching	Density (k-nearest neighbor) in objective space D(xi) = 1/(σ_{ik}+2) k= $\sqrt{N+\overline{N}}$ D(xi): Density of individual i σ_{ik}: Distance to the k-th nearest neighbor N: Population size $\overline{N}$: Archive size
RDGA	Niching	Adaptive cell density in objective space D(xi) = Number of individuals located in the same cell $d(j) = \left\lfloor \max_{x \in X} f_j(x) - \min_{x \in X} f_j(x) \right\rfloor / K_j$ D(xi): Density of individual i d(j): Cell size in j-th dimension $f_j(x)$: Fitness function K_j: Number of cells in j-th dimension

The most frequently used non-niching method is restricted mating (Goldberg, 1989). Through this mechanism, the recombination of the individuals that do not satisfy predefined criteria is prevented. Usually, restrictions are imposed on the pair of genotypic or phenotypic similarity. In literature, various implementations exist (Kumar & Rockett, 2002; Loughlin & Ranjithan, 1997). However, at least two questions still remain open: first, no rationale holds for determining the threshold value σ_{mate} that kindles the mating restriction, though a common practice seems to be adopting $\sigma_{mate}=\sigma_{share}$. Second, extensive arguments exist on the actual benefits of performing such an action (Zitzler & Thiele, 1998b; Coello Coello et al., 2002).

In order to overcome the possible deterioration of convergence ability resulting from pursuing a good spread, Laumanns and coworks (2002) applied ε-dominance that aims to achieving a combined convergence and diversity. Lu and Yen (2002) as well as Affolo and Benini (2003) both proposed to treat diversity as an extra objective to be maximized in parallel with maximizing the fitness.

5.3.4 Elitism

Elitism is a mechanism that helps to improve search convergence and effectiveness by ensuring that the maximum fitness never deteriorates as the evolution goes along. To achieve this goal, the highly fit member(s) are passed on to the next generation without being altered. As many authors have pointed out (Laumanns et al., 2000; Deb, 2001), there is a great variety in the implementation of elitism to EAs. (Deb, 2001) introduced several different versions of popular elitist MOEAs, for instance, SPEA by Zitzler and Thiele (1998) and PAES by Knowles and Corne (1999). As a result, the evaluation of the effects of elitism should not be independent with the way it is applied. Specifically, in the multi-objective case, the following considerations need to be taken. Some of these questions remain open to date and require extensive further exploration:

- How to define elite solutions with conflicting objectives?
- What is the appropriate intensity of elitism (i.e. proportion of elites)?
- How to effectively incorporate elites into search?
- What are the real effects of elitism on different algorithms?
- How does a given elitist strategy perform on different problems?

5.4 MOEA ISSUES IN CHEMICAL PROCESS DESIGN

5.4.1 Difficulties

Chemical engineers have, since a long time ago, realized the necessity to take into account various design goals beyond just profit, to cite a few, operability and reliability (Umeda et al., 1980), controllability (Vasbinder & Hoo, 2003), safety (Kim et al., 2004), environmental risk (Thurston & Srinivasan, 2003; Chen & Shonnard, 2004; Fu, 2000), and more recently sustainability (Jin & High, 2004a; Jin & High, 2005). However, restricted by algorithmic and computing capacity, virtually all the chemical process optimizations were conducted with a single scalar objective before the 1980s. There were only two comprehensive reviews on multiobjective optimization in the areas of chemical engineering (Bhaskar et al., 2000; Clark & Westerberg, 1983). From (Bhaskar et al., 2000), it can be seen that ε-constraint, goal programming, and surrogate trade-offs are among the solution techniques of the widest utilization. MOEAs appeared to gain growing popularity from the later half of the 1990s.

However, the applications of EAs in general and MOEAs in particular were relatively less reported in chemical engineering fields, compared with other engineering disciplines, such as mechanical, industrial, and electrical engineering (Miettinen et al., 1999; Dasgupta & Michalewicz, 1997a). This phenomenon may be explained by the following reasons.

First, a chemical process typically consists of a number of interconnected equipment (i.e. unit operations), each of which is modeled in a different way. Rigorous models of these operating units (kinetic and thermodynamic models in particular) often contain high nonlinearity. All together, the overall process model often ends up to be very complex, large-scaled and highly nonlinear (Biegler et al., 1997; Edgar & Himmelblau, 2001). Lowery and coworkers (1993) reported the optimization of a bisphenol-A plant model that involves 41147 variables, 37641 equality constraints, 212 inequality constraints, and 289 plant measurements. To solve the problems of such high complexity, MOEAs require an improved computational capacity due to their population-based inherency.

Second, attributed to their heuristics-based nature, the EAs and MOEAs developed over the past years exhibit enormous variety. Each algorithm was tailored and tested against the purpose of solving a particular type of problems (e.g. single or multiple objectives; unconstrained or constrained). As a consequence, a non-expert chemical engineer may experience a hard time trying to find such an algorithm that could be capable for solving a range of different problems.

Third, chemical process models are highly constrained. There usually exist a large number of equations (algebraic, ordinary differential, and partial differential). Some equations ensure that fundamental mass, energy and momentum conservation laws are not violated, while the others describe the process behavior under either steady-state or dynamic conditions. Attaining roots to a nonlinear system of equations (i.e. a feasible solution) per se is numerically very challenging (Dennis & Schnabel, 1996; Nocedal & Wright, 1999). In an optimization setting, the presence of equations essentially gives rise to equality constraints. Those nonlinear equality constraints may result in rare, disjoint, intricately scattered, or even the worst case: void feasible solutions. Evolutionary algorithms have no default mechanism to handle constraints, as they were originally developed as a sort of non-constrained search technique. Though various constraint handling methods have been developed recently (Michalewicz, 1995a; Coello Coello, 2002), not a single robust technique virtually exists. As a matter of fact, the majority of EA or MOEA test problems exclude equality constraints, because one of the philosophic pillars of solving constrained EAs rests on relaxing equality constraints and converting them to inequality constraints. However, the extent to which an equality constraint can be loosened, from a design perspective, is extremely limited.

From the above discussion, it can be concluded that the biggest challenge of applying MOEAs to chemical process design lies in effective incorporation of constraint handling into a robust algorithmic searching framework. Certainly, computational efficiency is important, but it can be eventually overcome by improved computing capacity. Therefore, in the next subsections, focus is cast on constraint handling in MOEAs, with intention to accommodate chemical engineers' practical needs.

5.4.2 Constraint Handling

Real-world optimization problems are hardly free from constraints. Consequently, growing efforts has been made to remedy the shortage in constraint handling of those EAs developed aforetime. In literature, an extensive variety of techniques have been proposed, which were surveyed in (Michalewicz, 1995a), (Michalewicz & Schoenauer, 1996) and (Ceollo Coello, 2002). For a typical constrained MOP in (5.1), the presence of equality and/or inequality constraints splits the search space **S** into two distinct regions, namely, feasible region **F** and infeasible region **I**. Violating one or many constraints leads to an infeasible solution, though whose extent of infeasibility may vary.

5.4.2.1 Approaches Using Penalized Objective Functions

The popularity of penalty functions in constrained EAs was obviously inherited from its success in conventional optimization fields. In penalty function methods (only referring to "exterior" kind of penalties by default in this dissertation), the objective function value of an infeasible solution is modified by a penalty term, so that a constrained problem can be converted to and solved as an unconstrained problem. Hence, the constrained MOP given in (5.1) can be converted to:

Minimize $\mathbf{f}_p(x)$ $\qquad \mathbf{f}_p(\mathbf{x}) = [f_{p,1}, f_{p,2},\ldots, f_{p,nf}]^T \quad \mathbf{x} = [x_1, x_2,\ldots, x_{nx}]^T$ (5.6)

$$\mathbf{f}_p(\mathbf{x}) = \begin{cases} \mathbf{f}(\mathbf{x}), & \text{if } \mathbf{x} \in \mathbf{F} \\ \mathbf{f}(\mathbf{x}) + \text{penalty}, & \text{if } \mathbf{x} \in \mathbf{I} \end{cases}$$

$\mathbf{f}_p(\mathbf{x})$: Penalized objective functions

A penalty can be constructed in a variety of ways. There are at least three different schemes of devising a penalty function (Dasgupta & Michalewicz, 1997b; Coello Coello, 2002):

- An infeasible individual is penalized anyway just for violating the constraints
- Penalty is related to the degree of constraint violation
- Penalty is related to the cost of repairing a solution (i.e. force it into **F**).

Over the past years, many heuristics on penalty function design have been suggested, for instance, the guidelines formulated in (Richardson et al., 1989) and minimal penalty rule in (Le Riche et al., 1995). However, difficulties were often encountered in implementing those heuristics, owing to diverse and sometimes even unknown characteristics of specific problems.

1. Death Penalty – This heuristic simply rejects infeasible individuals. Therefore, in a strict sense, it should not be classified as a penalty method. However, this naive algorithm offers acceptable performance when the feasible region is convex and takes a reasonable portion of the entire search space (Dasgupta & Michalewicz, 1997b).

Nevertheless, this method has serious limitations on both efficiency and effectiveness, especially in the case of very low ratio of feasible individuals (Venkatraman, 2004).

2. Static Penalty – Under this strategy, the penalty depends on the degree of constraint violation. Moreover, how the original objective function is penalized does not change as the algorithm proceeds. A typical statically penalized objective function may be seen as either one of the following forms:

$$f_{p,i}(x) = f_i(x) + r_i\Omega(x) \qquad (5.7a)$$

$$f_{p,i}(x) = f_i(x) + \sum_{j=1}^{nh+ng} r_{i,j}cv_j(x) \quad (5.7b)$$

$r_{i,j}$: Penalty parameter of the jth constraint for the ith objective function

r_i: Penalty parameter for the ith objective function

Ω: Overall measure of feasibility

cv_j: Violation of the j constraint

Many authors have applied different metrics for measuring constraint violation as well as one or more fixed penalty parameters (also seen as factors, coefficients) in formulating penalized objective functions (Homaifa et al., 1994; Michalewicz, 1995b). Difficulties in determining and tuning the optimal penalty parameter(s) constitute one major weakness for static penalty methods. This can be attributed to a dilemma (Runarsson & Yao, 2000): a large r_i favors finding a feasible solution but discourages the exploration of infeasible region; while a small r_i may result in large computational resources spent on evolving infeasible solutions. The solution to such a dilemma has to be problem dependent.

3. Dynamic/Adaptive Penalty – This class involves those methods in which the penalty parameters are updated constantly during the search process, based on either generation number or certain information detected from the previous and/or current population. The noted representatives for this class include (Joines & Houck, 1994), (Kazarlis & Petridis, 1998), (Hadj-Alouane & Bean, 1997) and (Smith & Tate, 1993). Through introducing extra sophisticated parameters, an algorithm may gain an improved response to varying situations during the search process. Certain test results, though limited, were cited as proof of the superiority of dynamic/adaptive over stationary penalties. However, those parameters themselves are sometimes hard to be obtained. In addition, the pursuit of instantaneous population information will severely reduce the efficiency of the algorithm.

5.4.2.2 Approaches Using Augmented Objective Functions

Seeking a feasible solution in many real world problems constitutes a challenging task. In a MOP setting, it presents a simultaneous goal besides optimizing objective functions. Hence, it is conceptually attractive that feasibility can be treated as extra objective function(s) in parallel with original objective functions. This has been made realizable particularly after the recent development of MOEAs. Therefore, the MOP problem in (5.1) can be augmented and solved as follows:

$$\text{Minimize} \quad \mathbf{f}_a(\mathbf{x}) \qquad (5.8)$$

$\mathbf{f}_a = [f_1, f_2, \ldots, f_{nf}, \Omega]^T$ or $\mathbf{f}_a = [f_1, f_2, \ldots, f_{nf}, cv_1, cv_2, \ldots cv_{ng+nh}]^T$

$\mathbf{x} = [x_1, x_2, \ldots, x_{nx}]^T$

$\mathbf{f}_a$: Augmented objective functions

cv_j: Violation of the constraint j

Ω: Overall measure of infeasibility

Surry and Radcliffe (1997) proposed an approach called COMOGA, in which Pareto ranking and VEGA were used to handle constraints. In this method, part of the solutions is selected based on their ranked objective functions, while the others are based on constraint violation. Credible evidences for this algorithm's steady good performance are lack even in its authors' tests (Surry & Radcliffe, 1997). Ray and coworker (2001) proposed a more sophisticated constraint handling technique. In this method, each constraint stands on its own without combination and selection is performed using carefully designed heuristics with three different non-dominated ranks, namely, constraint violation rank, objective rank, and a rank for combined objective functions and constraint violations. This technique was studied and compared in (Deb et al., 2001) along with other techniques. Mezura-Montes (2004) performed numerical experiments on four multiobjective-based constraint handling techniques with an expanded set of single objective test problems. His results further revealed some major difficulties facing essentially all constraint handling techniques, which include large feasible regions, low percentage of feasible solutions, and existence of nonlinear equality constraints.

5.4.2.3 Approaches Using Heuristics on Different Solutions

This class of techniques is based on an assumption that feasible solutions are superior over infeasible ones. Powell and Skolnick (1993) proposed a penalty-like method that incorporates the heuristic rule suggested in (Richardson et al., 1989). Through distinct mapping schemes applied to feasible and infeasible solutions, the feasible solutions always possess higher fitness than infeasible solutions. Deb (2000) proposed a tournament selection method with pairwise comparison using a new binary relation "constrain dominance." This method makes explicit use of some customized heuristics that favor feasible solutions. However, as pointed out in (Coello Coello, 2002), this technique would fail in the cases when the ratio between feasible region and the entire search space is very low.

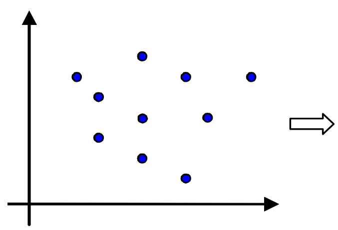
5.4.2.4 Other Approaches

There exists a large body of different constraint handling techniques for EAs other than those mentioned above. Some of them originate from classical numerical optimization, such as Lagrangian multipliers. The others are either nature inspired, such as co-evolution and immune systems, or based on special representation and operators, such as decoders.

5.5 AN ORDINAL RANKING-BASED GENETIC ALGORITHM

5.5.1 An ORGA Framework

Placing a MOEA in a general framework of MCDM helps to establish the insight to its essence. The solution course of a MOEA can be dissected in a generation-by-generation manner and examined closely at each generation. Apparently, a Multi-Attribute Decision Making (MADM) problem is faced at every generation. As illustrated in Figure 5-3, solutions need to be decided not only against multiple objective functions, but also with respect to their feasibility and diversity. However, what decisions need to be made on this finite set consisting of n (population size) individuals? Is this a choice, sorting, or ranking problematic (see section 3.3)? EAs' analog to natural evolution clearly indicates that relative "fitness" or survival capacity is to be determined within the given collection of candidates.



	f_1	f_2	…	f_{nf}	Ω	Δ
$\mathbf{x}_1$	$f_1(\mathbf{x}_1)$	$f_2(\mathbf{x}_1)$	$\ldots(\mathbf{x}_1)$	$f_{nf}(\mathbf{x}_1)$	$\Omega(\mathbf{x}_1)$	$\Delta(\mathbf{x}_1)$
$\mathbf{x}_2$	$f_1(\mathbf{x}_2)$	$f_2(\mathbf{x}_2)$	$\ldots(\mathbf{x}_2)$	$f_{nf}(\mathbf{x}_2)$	$\Omega(\mathbf{x}_2)$	$\Delta(\mathbf{x}_2)$
…	$f_1(\ldots)$	$f_2(\ldots)$	$\ldots(\ldots)$	$f_{nf}(\ldots)$	$\Omega(\ldots)$	$\Delta(\ldots)$
$\mathbf{x}_n$	$f_1(\mathbf{x}_n)$	$f_2(\mathbf{x}_n)$	$\ldots(\mathbf{x}_n)$	$f_{nf}(\mathbf{x}_n)$	$\Omega(\mathbf{x}_n)$	$\Delta(\mathbf{x}_n)$

Figure 5-3 Multiple attribute decision making at each generation of MOEAs

A simple elitism GA framework developed in this study is summarized in Box 5-1. The underlying idea is straightforward: At each generation, a one-to-one correspondence is somehow established between the n individuals and the first n natural numbers. The consequent rank of each individual represents its comprehensive quality (usually assessed with respect to a wealth of criteria). Tournament selection is performed iteratively on the current population until the mating pool is filled. The first n_{elite} (number of eiltes) highest ranked individuals are preserved, while all the others are replaced by the new individuals produced from a series of genetic operations (parent selection, crossover, mutation).

Obviously, how to come up with an ordinal ranking at every updated generation is most crucial. This rank is expected to be consecutive and complete, which means that any individual could only be ranked between 1 to n. No "tie" (i.e. equally good) is allowed. However, achieving such a rank is difficult, particularly with multi-dimensional ranking criteria such as multiple objective functions $\mathbf{f} = [f_1, f_2, \ldots, f_{nf}]^T$, feasibility ($\Omega$), diversity ($\Delta$), and so forth. Ordinal ranking will be further discussed in the next subsection. This proposed GA algorithmic framework was predominantly motivated by the following considerations:

Box 5-1 Algorithmic framework of the proposed Ordinal Ranking-based GA

GENERATE INITIAL POPULATION
  $g = 0$
  $p^0 = [p_1^0, p_2^0, \ldots, p_n^0]^T$

DO
  PERFORM ORDINAL RANKING
  $\mathbf{R} = [R(p_1^g), R(p_2^g), \ldots, R(p_n^g)]^T \quad R \in (1, 2, \ldots, n)$

IF (stopping criteria satisfied) EXIT
  CREATE MATING POOL
    Set tournament size $n_{tournament}^g$
    Randomly pick $n_{tournament}^g$ individuals from the current population
    Highest ranked individual → mating pool

  PRESERVE ELITES
    Do i = 1, n
      If ($\mathbf{R}(p_i^g) \le n_{elite}^g$) then
        p_i^g → elite
      End if
    End do

  VARIANCE
    Random parent selection from the mating pool
    Crossover
    Mutation
    Replacement

  $g = g + 1$
END DO

First, such a framework is robust for essentially any problem. The ordinal ranking, once available, is virtually an ordering of the overall "goodness" of alternatives. Therefore, it offers an ordinal fitness instead of oft-seen cardinal one. To this end, no matter what problems are confronted (single or multiple objectives, constrained or not), this GA can be applied as long as an ordinal rank is attainable. On the other hand, this 1~n rank makes the MADM problem at each generation straightforward, because the higher ranked, the better.

Second, an ordinal order is intuitively more accordant with human's cognitive nature when facing the MADM problem at each generation of MOEA. In addition, ordering, in contrast with cardinal fitness measures, is practically more attainable. In many decision-making scenarios, people may not be able to quantify how good an individual performs or the extent by which one outperforms the other, especially under conflicting criteria. However, qualitative pair-wise comparisons or some sort of ordinal sequence turns out to be relatively easier. Therefore, adopting ordinal ranking potentially paved a smoother way for a human decision maker to interfere, if needed by any chance.

Third, certain selection operators for GAs, such as roulette wheel selection, are sensitive to the specific scale of fitness function. The tournament selection applied in this study works perfectly under this formulation, as it requires nothing more than relative comparison among alternatives. The ordinal ranking of alternatives, on the other hand, makes the implementation of tournament selection extraordinarily simple.

Last, but not the least, in the presence of multiple criteria, the dominance-based ranking often results in identical fitness among different individuals. For instance, all non-dominated solutions are ranked 0 or 1. This has given rise to the inconvenience in elitist preservation. As an example, in SPEA-II, an extra truncation operator was applied to break the tie among solutions with the same fitness (Zitzler et al., 2002). A complete ordinal ranking definitely eliminates the trouble in this regard.

5.5.2 Ordinal Ranking for Multi-Objective Problems

Like most MOEAs, ORGA aims to obtaining a collection of feasible and globally nondominated solutions that are evenly distributed. These simultaneous search goals give rise to three aspects of concerns in assessing the comprehensive quality of any solution: feasibility (Ω), objective functions (**f**), and diversity (Δ).

Feasibility (i.e. constraint violation) in this algorithm is measured using a scalar function Ω:

$$\Omega(x_i) = \sum_{j=1}^{nh+ng} cv_j(x_i) \qquad (5.9)$$

$$cv_j(\mathbf{x}_i) = \begin{cases} Max(g_j(\mathbf{x}_i), 0), & \text{for inequality constraints} \\ Max(|h_j(\mathbf{x}_i)| - h_{j,threshold}, 0), & \text{for equality constraints} \end{cases}$$

g_j: Inequality constraint

h_j: Equality constraint

$h_{j,\ threshold}$: Threshold value for an equality constraint

cv_j: Violation of each constraint

Ω: Total constraint violation

The threshold value $h_{threshold}$ sets a limit for each equality constraint, beyond which (i.e. $|h|>h_{threshold}$) the constraint is considered violated. In a strict sense, the threshold for each individual equality constraint should be assessed with respect to its physical meaning. This study adopts $h_{threshold}$=0.001 for all equality constraints. As a result, the solutions with a total violation of all constraints that is less than 0.001 is regarded feasible and assigned a zero-valued Ω. The Ω value for infeasible solutions varies with their specific extent of infeasibility.

The diversity measure of an arbitrary solution x_i is the arithmetic mean of the distances from this solution to its k-th first nearest neighbors. Therefore, the diversity measure can be calculated with the formula shown in (5.10).

$$\Delta(x_i) = \frac{\sum_{j=1}^{k} D(i,j)}{k} \tag{5.10}$$

D(i,j): Distance of x_i to its j-th closest neighbor, j=1,2,…,k

k: Parameter, k=$\sqrt{n}$, n is the population size

Δ: Diversity measure

Obviously, a ranking MADM (see section 3.3 and Figure 5-3) is faced at each generation of ORGA. Solving this MADM tends to derive a complete alternative permutation from a typical decision matrix. However, achieving a complete and meaningful ordinal ranking is not easy because cross-attribute conflicts arise. Discussions in previous chapters vetoed the possibility of making any multi-criteria decision (including ranking) in a hundred-percent absence of human judgements. It is not hard to observe that these attributes F, Ω, and Δ are neither compensatory nor of equal priority. Therefore, based on these observations, an ordinal ranking mechanism is proposed below, as illustrated in Figure 5-4.

	f_1	f_2	…	f_{nf}	Ω	Δ
$\mathbf{x}_1$	$f_1(\mathbf{x}_1)$	$f_2(\mathbf{x}_1)$	$\ldots(x_1)$	$f_{nf}(\mathbf{x}_1)$	$\Omega\,(\mathbf{x}_1)$	$\Delta\,(\mathbf{x}_1)$
$\mathbf{x}_2$	$f_1(\mathbf{x}_2)$	$f_2(\mathbf{x}_2)$	$\ldots(x_2)$	$f_{nf}(\mathbf{x}_2)$	$\Omega\,(\mathbf{x}_2)$	$\Delta\,(\mathbf{x}_2)$
…	$f_1(\ldots)$	$f_2(\ldots)$	$\ldots(\ldots)$	$f_{nf}(\ldots)$	$\Omega\,(\ldots)$	$\Delta\,(\ldots)$
$\mathbf{x}_n$	$f_1(\mathbf{x}_n)$	$f_2(\mathbf{x}_n)$	$\ldots(x_n)$	$f_{nf}(\mathbf{x}_n)$	$\Omega\,(\mathbf{x}_n)$	$\Delta\,(\mathbf{x}_n)$

$\Downarrow$

	$r_{\Omega F}$	Δ
$\mathbf{x}_1$	$r_{\Omega F}\,(\mathbf{x}_1)$	$\Delta\,(\mathbf{x}_1)$
$\mathbf{x}_2$	$r_{\Omega F}\,(\mathbf{x}_2)$	$\Delta\,(\mathbf{x}_2)$
…	$r_{\Omega F}\,(\ldots)$	$\Delta\,(\ldots)$
$\mathbf{x}_n$	$r_{\Omega F}\,(\mathbf{x}_n)$	$\Delta\,(\mathbf{x}_n)$

$\Downarrow$

1	*2*	*3*	*4*	*5*	…	*n*
$\mathbf{x}_3$	$\mathbf{x}_7$	$\mathbf{x}_5$	$\mathbf{x}_1$	$\mathbf{x}_4$		$\mathbf{x}_2$

Figure 5-4 Derivation of an ordinal ranking from a decision matrix

Two techniques essentially form the cornerstones of this proposed ranking scheme. First, the concept of "constrain-dominance" suggested by Deb (2000) is applied to generate a constrained-objective ranking $r_{\Omega F}$. This binary relation virtually extends the dominance relations to constrained cases. An alternative x_i is said to constrain-dominate another alternative x_j, if any of the following conditions is met:

- x_i is feasible and x_j is infeasible.
- x_i and x_j are both feasible, and x_i (weakly) dominates x_j with respect to objective functions.
- x_i and x_j are both infeasible, and x_i has a less extent of constraint violation.

Box 5-2 contains the pseudocode of deriving $r_{\Omega F}$ from pairwise comparison using the constrain-dominance relation, where $r_{\Omega F}(x_i)$ is defined as the number of solutions that "constrain-dominate" x_i.

Box 5-2 Pseudocode for obtaing constrained objective ranking $r_{\Omega F}$

```
rΩF (x1:n) =0
Do i = 1, n-1
    Do j = i+1, n
        If (Ω(xi)=0 and Ω(xj)≠0)
            rΩF(xj) = rΩF(xj) + 1
        Else if (Ω(xi)≠0 and Ω(xj)=0)
            rΩF(xi) = rΩF(xi) + 1
        Else if (Ω(xi)=0 and Ω(xj)=0)
            If (f(xi) ≻d f(xj))
                rΩF(xj) = rΩF(xj) + 1
            Else if (f(xj) ≻d f(xi))
                rΩF(xi) = rΩF(xi) + 1
            End if
        Else
            If (Ω(xi) > Ω(xj))
                rΩF(xj) = rΩF(xj) + 1
            Else if (Ω(xi) < Ω(xj))
                rΩF(xi) = rΩF(xi) + 1
            End if
        End if
    End do
End do
```

The second cornerstone technique is lexicographic method (Yoon & Hwang, 1995), a noncompensatory technique of multi-attribute decision making. Through this method, for any pair of alternatives (x_i, x_j), multiple attributes are evaluated sequentially in the order of descent importance until one alternative is chosen over the other. Specifically for the MADM in Figure 5-4, if x_i ranks higher on $r_{\Omega F}$ than x_j, then x_i is better. However, if they tie, comparison moves on to the next attribute Δ, the one with greater diversity gets selected. The overall ordinal ranking $R(x_i)$ is obtained by counting the number of individuals in the population that outperform x_i in terms of the two attributes in the aforementioned lexicographic ordering. The pseudocode implementing the above algorithm is illustrated in Box 5-3.

Box 5-3 Pseudocode for constructing ordinal ranking with lexicographic method

```
R(x_{1:n}) =0
Do i = 1, n-1
    Do j = i+1, n
        If (r_ΩF(x_i) < r_ΩF(x_j))
            R(x_j) = R(x_j) + 1
        Else if (r_ΩF(x_i)  > r_ΩF(x_j))
            R(x_i) = R(x_i) + 1
        Else
            If (Δ(x_i) > Δ(x_j))
                R(x_j) = R(x_j) + 1
            Else if (Δ(x_j) > Δ(x_i))
                R(x_i) = R(x_i) + 1
            End if
        End if
    End do
End do
```

It is evident that the proposed mechanism of constructing a MOEA is unique. This can be seen in contrast to the Table 5-3 and Table 5-5. More importantly, the proposed ORGA is robust for both unconstrained and constrained problems. The algorithm shown in Box 5-2 and 5-3 can be applied to most problems without modification. In unconstrained cases, the way in which the ordinal ranking is derived virtually coincides with that in most traditional MOEAs, in which the dominance-based fitness is complemented by diversity or density measures. On the other hand, for constrained problems, constraints are handled through the heuristics implied in the definition of constrain-dominance. This technique has proven effective on a wide range of problems (Deb, 2000; Deb et al., 2001).

5.5.3 Implementation Details

Real-valued encoding – The real-valued representation is intuitively straight-forward to tackle optimization with real variables. In this study, vectors of floating point numbers are applied as artificial chromosomes to encode real decision (genotype) variables in an optimization problem.

Population size – Except for certain problems that require more points to display the complete shape of a geometrically complicated Pareto front, the population size is fixed at 100. However, a smaller population size should be used in practice wherever sufficient, as that will significantly reduce the computational time.

Stopping criteria – The proposed algorithm is run for 1000 generations for all problems, though for certain problems much less number of generations may be sufficient to converge to the true Pareto front.

Elitist preservation – The first n_{elite} highest ranked individuals at each generation are identified as elitists and carried over intact to the next generation. In this implementation, the last n_{elite} seats ($x_{n-nelite+1}$~x_n) are reserved to retain the elites, which, however, are updated at each generation. The elitsim size n_{elite} in this study is fixed at n/10 (n: size of population). Doing that is empirical: as too many elites are likely to cause loosing the evolutionary driving force and jeopardize the search in either going nowhere or premature convergence. On the other hand, genetic drift or poor preservation effect will occur in the case that the portion of elites is too low with respect to the total number of population.

Tournament selection – Mating pool is created by selecting individuals from the current population (including both elite and regular members) via tournament selection. Tournament selection is theoretically simple: Randomly pick $n_{tournament}$ individuals from the current population. The one with highest rank wins the tournament and enters the mating pool. The selection pressure is controllable by adjusting the tournament size. Tournament size is set at 5 in solving most test problems.

BLX-α crossover – BLX-α crossover was first suggested in (Eshelman & Schaffer, 1993). Herrera and coworkers (1998) performed a systematic study on various genetic operators and identified the BLX-α as one of the superior crossover operators in real-coded applications. In this study, the only parameter α is set at 0.5, while the crossover rate remains 1. The BLX-α is operated as summarized in Box 5-4:

Box 5-4 BLX-α crossover operator

$c_{max}(i)$ = MAX(offspring1(i), offspring2(i))
$c_{min}(i)$ = MIN(offspring1(i), offspring2(i))
$q(i) = c_{max}(i) - c_{min}(i)$
$l(i) = \mathrm{MAX}(c_{min}(i) - q(i)^* \alpha, x_l(i))$
$u(i) = \mathrm{MIN}(c_{max}(i)+q(i)^* \alpha, x_u(i))$
offspring1(i) = (u(i) – l(i))*rannum1(i) + l(i)
offspring2(i) = (u(i) – l(i))*rannum2(i) + l(i)
i = 1,2,…n

$x_l(i)$, $x_u(i)$: lower and upper bound of x(i)
rannum1, rannum2: random numbers
α: parameter

Random mutation –This study uses a fixed mutation rate of 0.1. Every time mutation is activated, only one random dimension i of the given offspring takes on a new value randomly generated between the range $[x_l(i), x_u(i)]$.

5.5.4 Solving Test Problems

In order to evaluate the performance of the proposed ORGA, this algorithm is applied to solve a series of test problems. The selected test problems essentially fall in three classes: unconstrained MOPs (UNMOPs), side-constrained MOPs (SCMOPs), and equality constrained MOPs (ECMOPs). Detailed descriptions on those problems are provided in Appendix B. The selected test problems offer a wide coverage of various difficult characteristics, which is summarized in Table 5-6.

Table 5-6 Characteristics of the test problems

	nf	nx	ng	nh	Feature
UCMOP-1	2	30	0	0	Convex Pareto optimal front
UCMOP-2	2	30	0	0	Non-convex Pareto optimal front
UCMOP-3	2	30	0	0	Multiple discontinuous Pareto optimal fronts
UCMOP-4	2	10	0	0	Non-convex Pareto optimal front and non-uniform search space
UCMOP-5	2	1	0	0	Historical, Large search space
UCMOP-6	2	3	0	0	Non-convex Pareto optimal front, independence of optimum
UCMOP-7	2	2	0	0	Non-convex and disconnected Pareto fronts and convoluted mapping
UCMOP-8	2	3	0	0	Three disconnected Pareto fronts and convoluted mapping
UCMOP-9	3	2	0	0	Convoluted three dimensional Pareto fronts
SCMOP-1	2	2	2	0	Convex Pareto front
SCMOP-2	2	2	2	0	Straight line Pareto front
SCMOP-3	2	2	2	0	Discontinuous and concave Pareto optimal sets
SCMOP-4	2	6	6	0	Pareto front is a concatenation of five connected line segments
SCMOP-5	2	2	2	0	Convex Pareto optimal front
ECMOP-1	2	2	0	1	Low feasible ratio and unknown Pareto optimal front
ECMOP-2	2	5	0	3	Low feasible ratio and unknown Pareto optimal front
ECMOP-3	2	4	2	3	Low feasible ratio and unknown Pareto optimal front
ECMOP-4	2	12	0	8	Low feasible ratio and unknown Pareto optimal front

5.5.4.1 Unconstrained MOPs

Nine unconstrained test MOPs are solved in this study. All these problems are classical, which have been extensively studied and widely applied in various algorithmic researches (Deb, 2001, Coello Coello et al., 2002). The difficulties associated with those problems vary from high dimensionality to concave, discontinuous, convoluted Pareto front. The nondominated solutions to each problem generated from the ORGA are plotted in Figure 5-5 ~ Figure 5-13. They are further compared to the true Pareto fronts to visualize how the proposed algorithm performs.

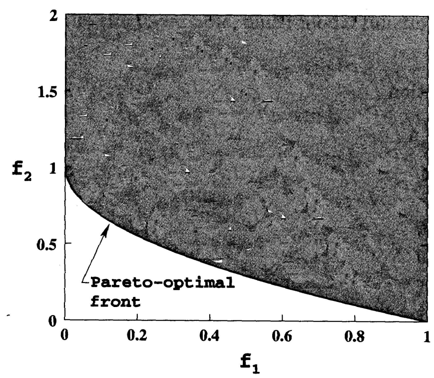


Figure 5-5a True Pareto optimal front of UCMOP-1 (Deb, 2001)

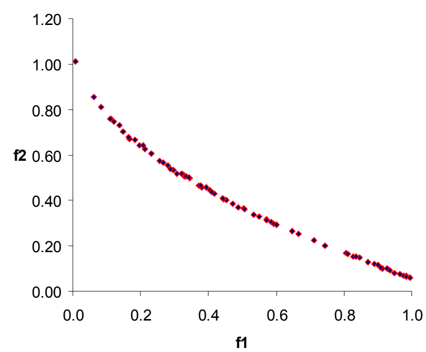


Figure 5-5b The Pareto optimal front of UCMOP-1obtained from ORGA

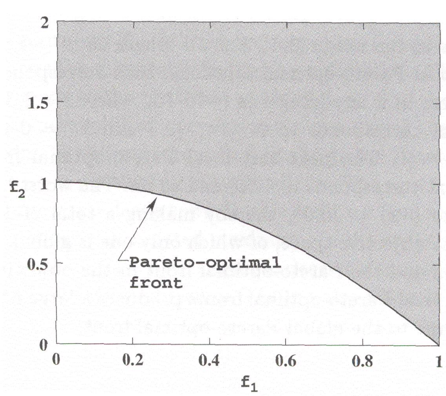


Figure 5-6a True Pareto optimal front of UCMOP-2 (Deb, 2001)

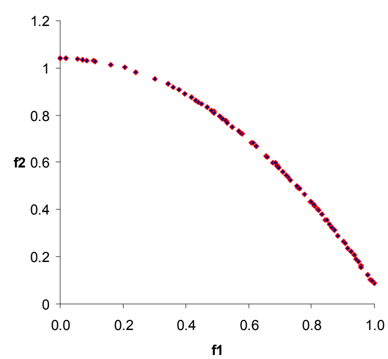


Figure 5-6b The Pareto optimal front of UCMOP-2 obtained from ORGA

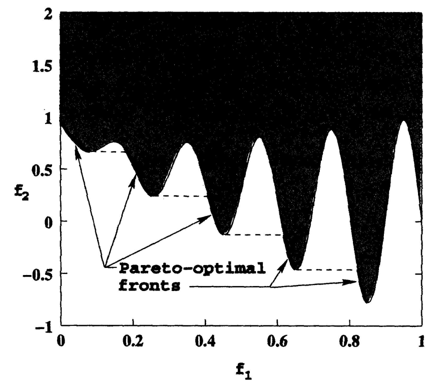


Figure 5-7a True Pareto optimal front of UCMOP-3 (Deb, 2001)

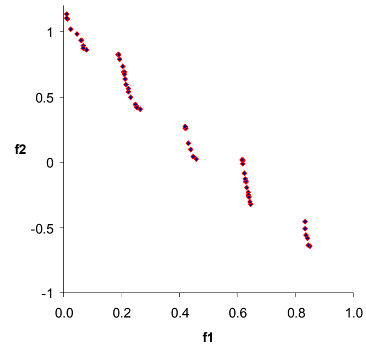


Figure 5-7b The Pareto optimal front of UCMOP-3 obtained from ORGA

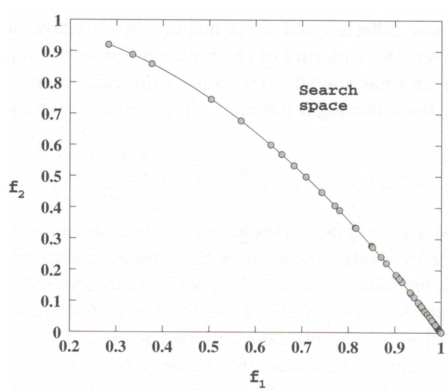


Figure 5-8a True Pareto optimal front of UCMOP-4 (Deb, 2001)

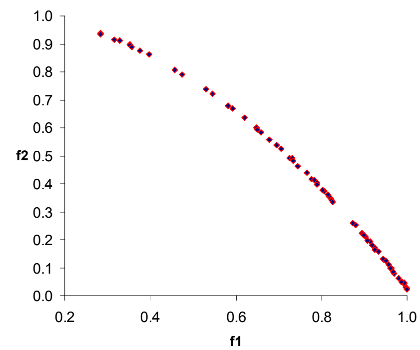


Figure 5-8b The Pareto optimal front of UCMOP-4 obtained from ORGA

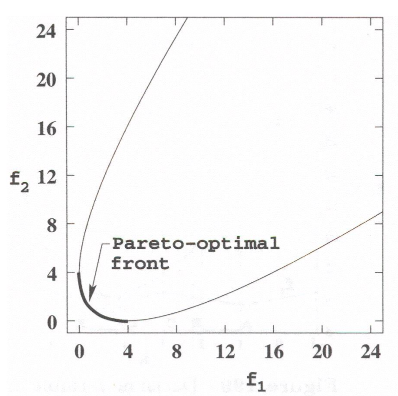


Figure 5-9a True Pareto optimal front of UCMOP-5 (Deb, 2001)

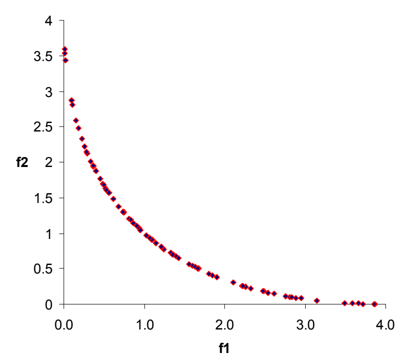


Figure 5-9b The Pareto optimal front of UCMOP-5 obtained from ORGA

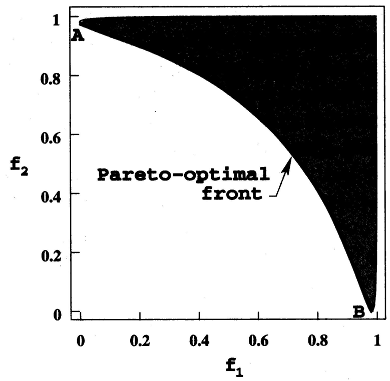


Figure 5-10a True Pareto optimal front of UCMOP-6 (Deb, 2001)

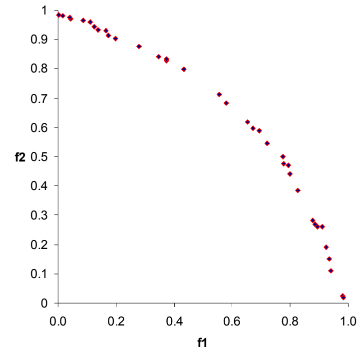


Figure 5-10b The Pareto optimal front of UCMOP-6 obtained from ORGA

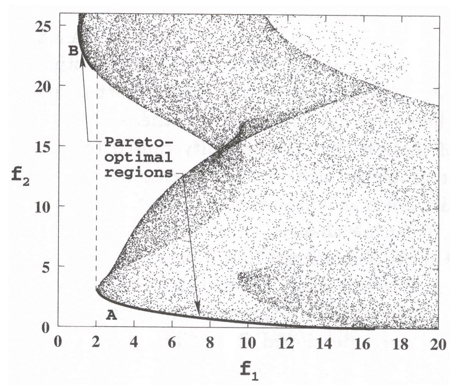


Figure 5-11a True Pareto optimal front of UCMOP-7 (Deb, 2001)

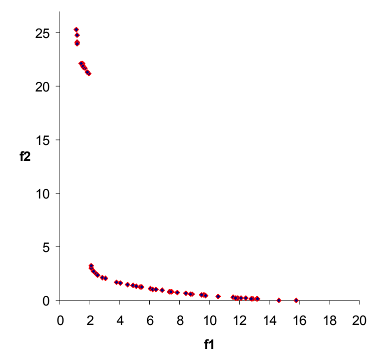


Figure 5-11b The Pareto optimal front of UCMOP-7 obtained from ORGA

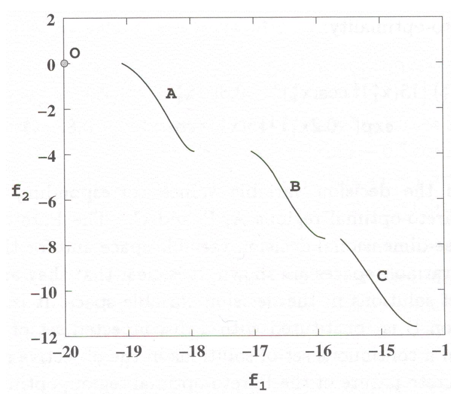


Figure 5-12a True Pareto optimal front of UCMOP-8 (Deb, 2001)

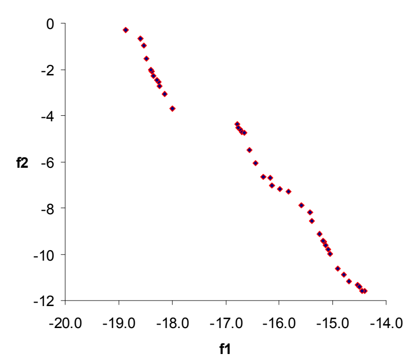


Figure 5-12b The Pareto optimal front of UCMOP-8 obtained from ORGA

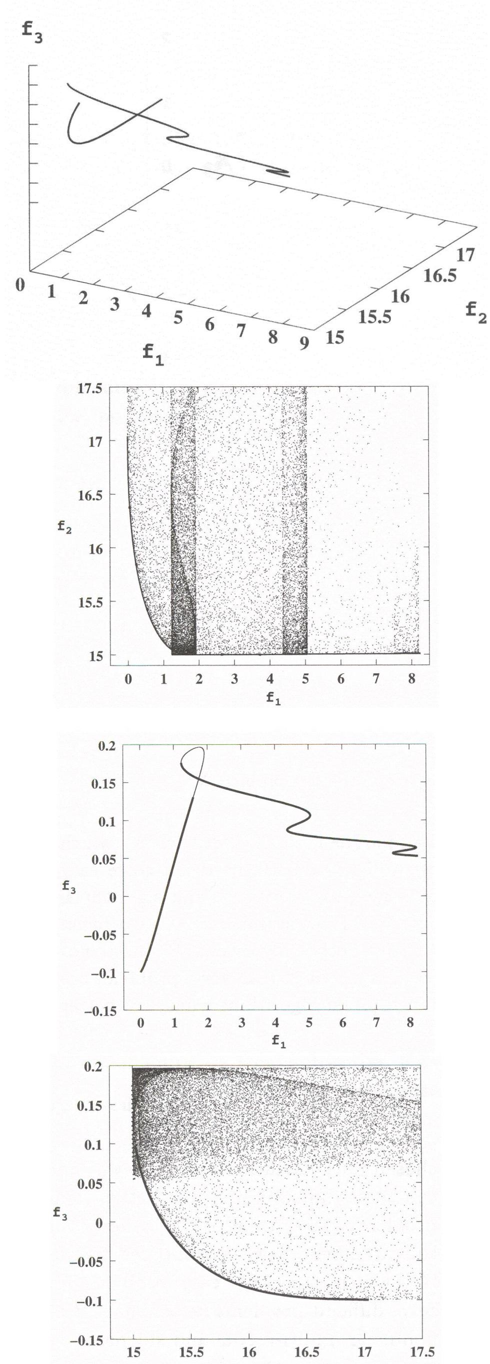


Figure 5-13a,b,c,d True Pareto optimal front of UCMOP-9 (Deb, 2001)

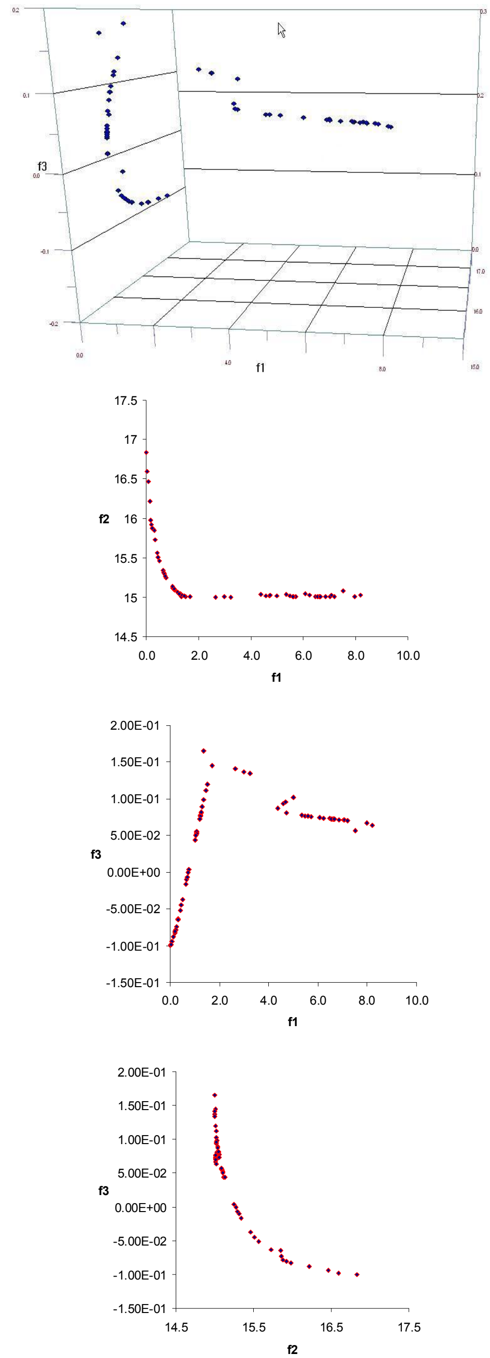


Figure 5-13e,f,g,h The Pareto optimal front of UCMOP-9 obtained from ORGA

5.5.4.2 Side-Constrained MOPs

"Side-constrained" here means only inequality constraints exist. Five problems are selected from (Deb, 2001) and (Coello Coello et al., 2002). The nondominated solutions to each problem obtained from the proposed ORGA are plotted and compared to the true Pareto front in Figure 5-14~Figure 5-18.

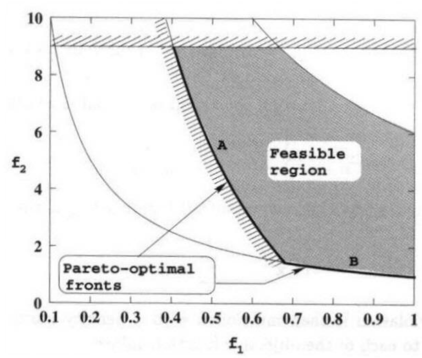


Figure 5-14a True Pareto optimal front of SCMOP-1 (Deb, 2001)

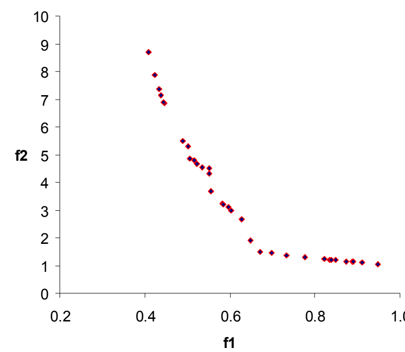


Figure 5-14b The Pareto optimal front of SCMOP-1 obtained from ORGA

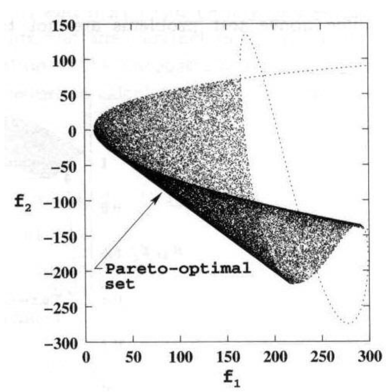


Figure 5-15a True Pareto optimal front of SCMOP-2 (Deb, 2001)

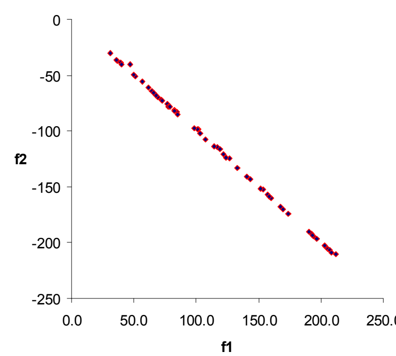


Figure 5-15b The Pareto optimal front of SCMOP-2 obtained from ORGA

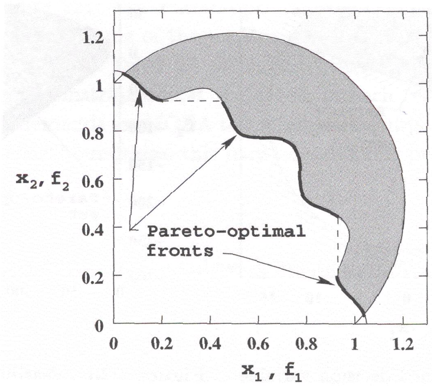


Figure 5-16a True Pareto optimal front of SCMOP-3 (Deb, 2001)

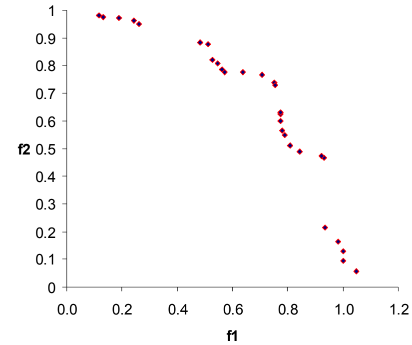


Figure 5-16b The Pareto optimal front of SCMOP-3 obtained from ORGA

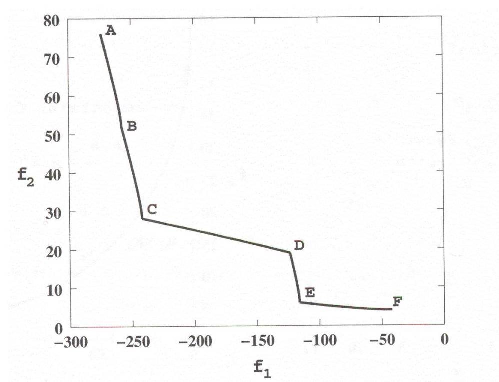


Figure 5-17a True Pareto optimal front of SCMOP-4 (Deb, 2001)

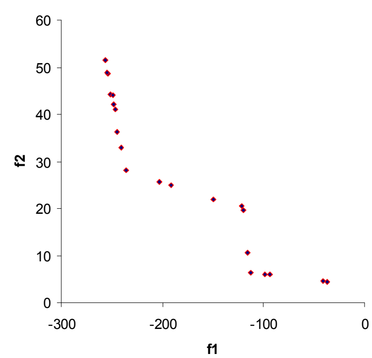


Figure 5-17b The Pareto optimal front of SCMOP-4 obtained from ORGA

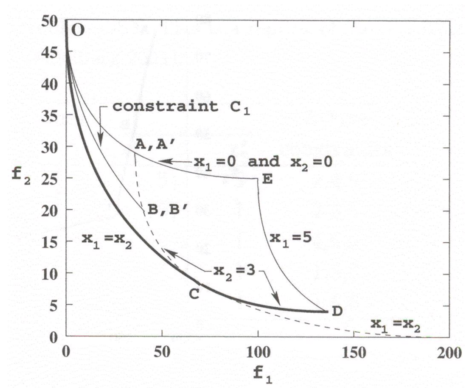


Figure 5-18a True Pareto optimal front of SCMOP-5 (Deb, 2001)

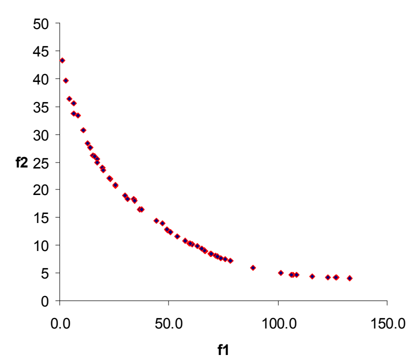


Figure 5-18b The Pareto optimal front of SCMOP-5 obtained from ORGA

5.5.4.3 Equality Constrained MOPs

Unfortunately, equality constrained MOPs are not as often seen in numerical studies as they occur in reality. Standard MOEA test suites always exclude equality constraints. This has led to very rare, if not inexistent, equality constrained MOP test problems, particularly those with a number of highly nonlinear equality constraints. In this study three equality constrained SOP problems from (Runarsson & Yao, 2000) and the classical Williams-Otto SOP (a classical chemical engineering problem) are revised into MOP problems to test ORGA's performance on these problems. These test problems are given in Appendix B. The background and derivation of the Williams-Otto model is further elaborated in Appendix C. All those self-made test problems have some difficulties in common: 1) At least one nonlinear equality constraint is present. 2) Feasible solutions take very low portion over the whole search space. (0.0000% according to feasible ratio defined in (Koziel & Michalewicz, 1999)). 3) No information is available regarding either feasible or true Pareto optimal solutions.

In Figure 5-19~Figure 5-21, the feasible as well as nondominated solutions generated from the proposed ORGA are plotted respectively. It should be noted that for ECMOP-2 and ECMOP-3, ORGA was iteratively applied instead of a single run in order to achieve multiple feasible solutions. For ECMOP-4, not a single feasible solution was obtained even after the pre-specified stopping criteria is met (1000 generations).

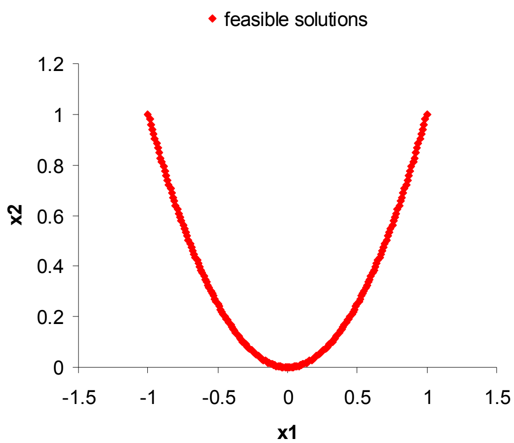


Figure 5-19a Feasible solutions to ECMOP-1 in the decision space

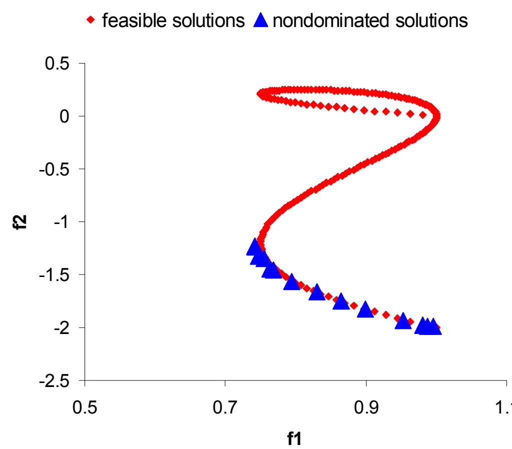


Figure 5-19b Feasible and Pareto optimal solutions to ECMOP-1 obtained from ORGA

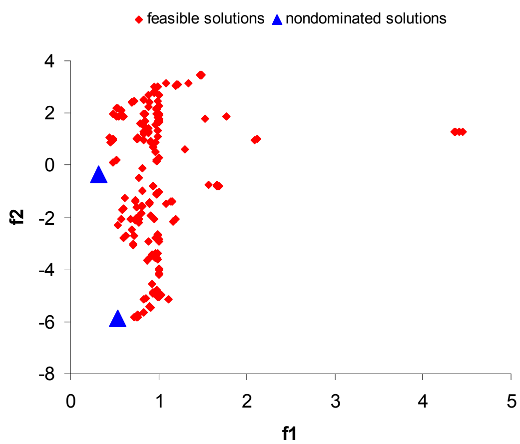


Figure 5-20 Feasible and Pareto optimal solutions to ECMOP-2 in the objective space obtained from ORGA

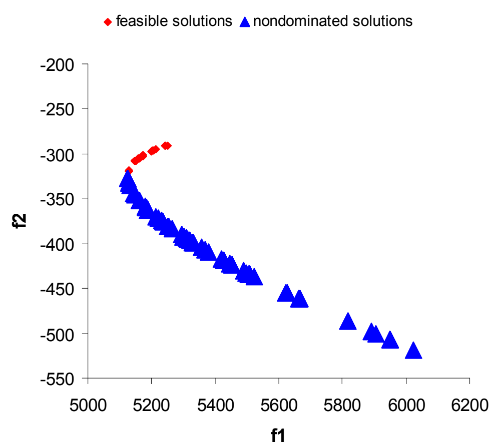


Figure 5-21 Feasible and Pareto optimal solutions to ECMOP-3 in the objective space obtained from ORGA

5.5.4.4 Discussions

The test problems solved in this study are able to offer a large coverage of the problems of different categories and different levels of difficulties. To gain a more concrete and convincing evaluation of this new algorithm, further in-depth tests are needed, which include comparative studies with peer algorithms, like the experiments in (Lu & Yen, 2002) as well as intense numerical and statistical studies with sophisticated metrics as described in (Deb, 2001; Coello Coello et al., 2002). Unfortunately, due to time limitation, those tasks could not be accomplished in this particular study.

By examining the Pareto front plots obtained, two assured conclusions can be drawn regarding ORGA's performance on unconstrained and side-constrained MOPs. First, this algorithm has a satisfactory capacity of achieving a close-enough, near-complete and evenly distributed set of nondominated solutions in a single run. In other words, the ORGA performs fairly well on all three aspects of intended search goals, namely, convergence, coverage, and distribution. Second, the proposed ORGA is robust for a wide range of different problems, both side-constrained and unconstrained.

However, for nonlinear equality constrained problems, the proposed ORGA didn't yield completely satisfactory results. In this study, ORGA succeeded in finding the Pareto front in a single run for ECMOP-1 which has only one nonlinear equality constraint. However, for the second and third test problems with multiple nonlinear equality constraints, the algorithm got stuck in one isolated feasible region and always converged to a set of locally nondominated feasible solutions. Within the finite simulation time, the algorithm could not even find just one feasible solution for ECMOP-4. These results can be attributed to the extremely low feasible ratio as well as the absence of relevancy from one feasible solution to the other. Also, the proposed algorithm, unlike many SOP solvers searching for a single optimum, always tends to seek a balance among multiple objectives. Therefore, the failure of the proposed algorithm in certain equality constrained problems should be explained by the level of difficulty as well as the particularity of those self-made ECMOPs. As a matter of fact, even today's most successful MOEAs are lack of tests on various equality-constrained MOP problems. In literature, no algorithm has been reported that could consistently offer satisfied performance on simultaneous obtainment of the entire Pareto front under multiple nonlinear equality constraints.

Therefore, for harder equality constrained problems to be solved, the way in which ORGA is implemented needs to be modified. Specifically, the ORGA is applied iteratively, instead of just once, to locate different feasible solutions. Doing this is equivalent to using ORGA to solve a nonlinear system of equations. Due to its stochastic nature, the ORGA is able to find diverse feasible solutions in multiple runs, if exist. Figure 5-20 and 5-21 illustrated the feasible solutions obtained from iterative execution of the ORGA. When sufficient and hopefully widely scattered feasible solutions are found, pairwise dominance check can readily identify those solutions that are nondominated among the located feasible solutions.

CHAPTER 6

CONCLUSION

6.1 ENDING REMARKS

The idea of sustainability has been taken very seriously by more and more people today. However, tremendous controversies still exist regarding sustainability definition and attainment. Certainly, the way sustainability is implemented relies on the perception of this concept, which varies with one's perspective and background. Engineers are typically not as enthusiastic as scientists or ethicists for the philosophical dispute about sustainability. Instead, they are more interested in making concrete and tangible commitments, such as building a cost-effective house or designing a combustor that reduces the fuel consumption by a specific percentage.

Such contributions are definitely very much needed. However, if different engineers all break down sustainability and picks only one fragment that best caters to his/her individual motivation, sustainability, in itself, then is nothing more than a rallying slogan. With this concern, the author investigated the conceptual and practical evolvement of the concept. Numerous evidences clearly indicate that it makes better sense to base sustainability on the synergy of various relevant issues, rather than each individual issue in isolation.

To this end, a sustainability-oriented design would require a different design procedure (see Figure 2-1 and Figure 1-3), which, in addition to regular design steps, needs to take care of the inherent conflict arising from the complex nature of sustainability. Sustainability-conscious engineers not only need an energy-saving technology or a novel environmental metric. More importantly, they need some sort of operational framework that could help perform different design steps systematically (particularly, systems thinking and conflict handling). This is exactly where Multiple Criteria Decision Analysis (MCDA) comes to their rescue.

Two points are essential for understanding MCDA. First of all, MCDA studies a series of systematic efforts (e.g. perception, formulation, analysis, solution) that are necessary for solving a MCDM, not only the brainwork of an individual decision maker. Secondly, MCDA is virtually a discipline, or a large collection of relevant techniques rather than any single method. Therefore, implementing MCDA in a sustainability-oriented design requires specific techniques to be developed or applied to accomplish different tasks.

Chapter 3 through 5 in this dissertation presents detailed discussion on how to design for sustainability with the framework of MCDA. Different techniques are developed to perform some key steps in MCDA, which are illustrated in Figure 6-1 and summarized in Table 6-1. Though various alternative techniques abound, it is critical for engineers to keep in mind that no technique works for all problems. Which technique to be applied has to be decided by carefully considering the specific scenario, including objectives and constraints, hypothesis and assumptions, interactions between the DM and the analyst, and uncertainties. Engineers tend to pursue the maximal objectivity and accuracy in their power, and sometimes think little of human judgement. However, the lesson learned from this study tells that people are always the most determinant factor in many value-laden engineering practices and this is particularly true for sustainability!

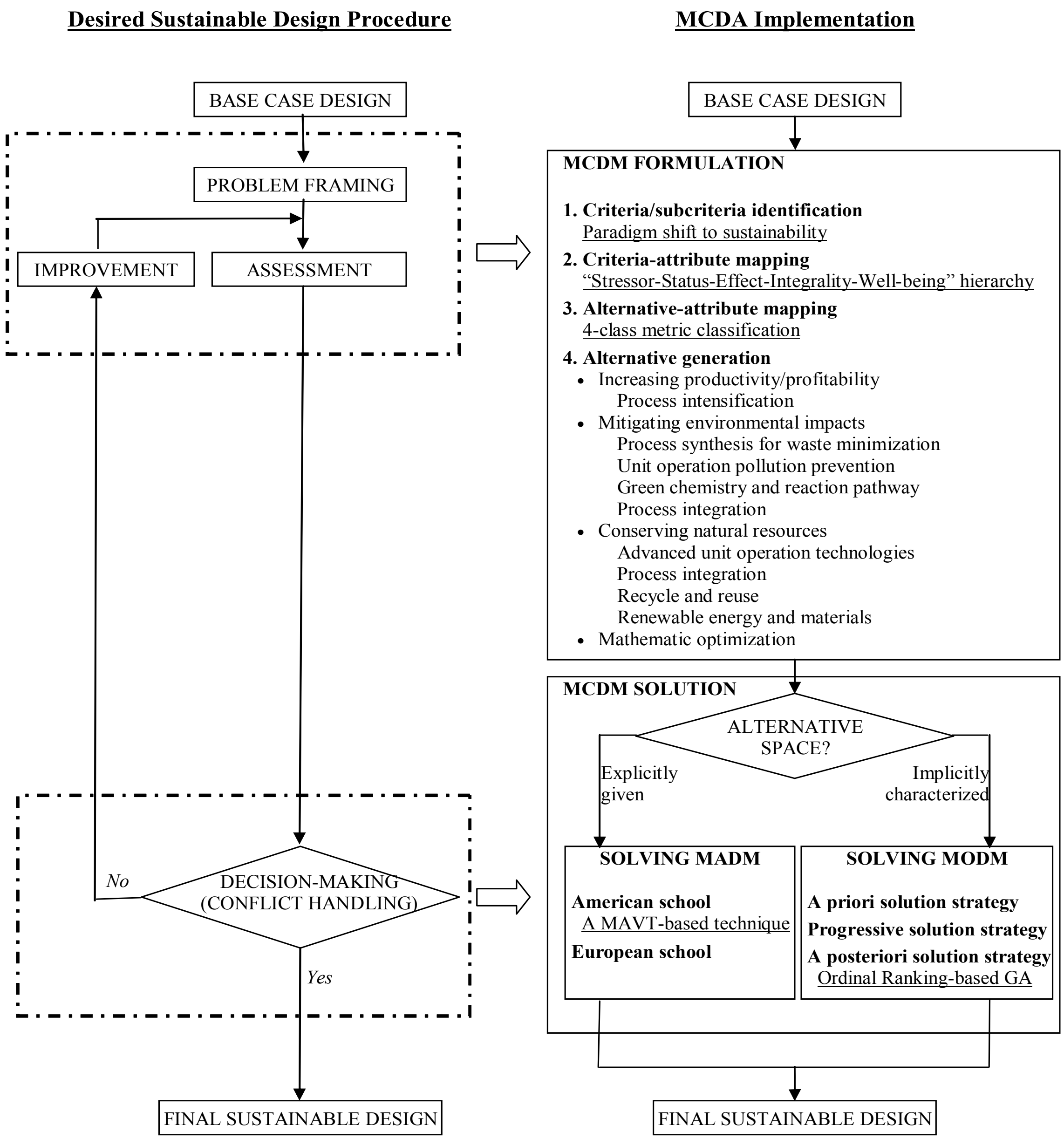


Figure 6-1 Implementing sustainability in design with multiple criteria decision analysis

Table 6-1 MCDA implementation of a sustainable design and the proposed techniques

Design Steps	Steps in MCDA	Technique proposed
Systems thinking	Criteria identification	None
	Criteria-attribute mapping	“Stress-Status-Effect-Integrality-Well-being”
Assessment	Alternative-attribute mapping	4-class metric classification
Improvement	Alternative generation	None
Conflict handling	MADM solution	A MAVT-base technique
	MODM solution	Ordinal Ranking based Genetic Algorithm

6.2 SUMMARY OF CONTRIBUTIONS

First of all, it was elaborated in this work that sustainability is neither an alluring catchword nor an alternate expression for environmental consciousness. In order to make a reality of sustainability in engineering practice, the key is to properly handle its complex nature and deeply rooted conflict.

Second, Multiple Criteria Decision Analysis (MCDA) was proposed as an overall methodological framework for conducting a sustainability-oriented design. In this study, MCDA has been proven ideal for filling the vacuum of a general operational framework for sustainability.

Third, a four-step procedure for formulating a sustainability-oriented design into a MCDM was proposed. Based on this proposed procedure, an attribute hierarchy “Stressor-Status-Effect-Integrality-Well-being” and a 4-class metric classification scheme were developed to help engineers in identifying appropriate environmental sustainability metrics.

Fourth, a MAVT-based technique was developed to make decisions from a discrete set of alternatives. This technique offers at least three advantages for making a sustainability-oriented decision: 1) well-shaped axiomatic foundation; 2) explicit and defendable processes to derive measurable partial value functions and weights; 3) uncertainty handling by sensitivity analysis.

Fifth, an Ordinal Ranking-based Genetic Algorithm (ORGA) was proposed to provide such a searching tool that could consistently produce well-distributed samples of globally Pareto optimal solutions in a single run. The proposed ORGA exhibits robustness in solving a variety of selcted test problems and performed excitingly well on unconstrained and side-constrained MOP problems.

6.3 RECOMMENDED FUTURE RESEARCH AREAS

Due to the limited time, the research for this particular project had to be ceased. However, the explorative work carried out in this study ignited the sparks of more promising research topics, which include but are not limited to:

- Model development for different case studies

  As mentioned before, the proposed MCDA framework allows different techniques that meet the users' specific needs to fit in. The entire process can be essentially viewed as constructing three layers of models (system, MCDM, and decision/preference models). Therefore, it would be interesting to find out the extent to which this framework can help in exploring suitable models, such as identifying an apt set of sustainability metrics or customizing a model that reflects the DM's real preference.

- Develop or identify "best practice" sustainability metrics

  With no doubt, any attempt to produce "best practice" metrics in a sustainability context would be debatable. This coincides with the ambiguous nature of the concept. However, for very specific occasions, for instance, assessing the sustainability performance of chemical manufacturing plants, there is a possibility to establish a set of metrics that are widely accepted by its particular group of users or audiences. A lesson can be learned from the existing efforts, such as the sustainability metrics developed by AICHE (CWRT, 1998) and IChemE (IChemE, 2001). Those metrics are obviously lack of convincing scientific elaboration and broad participation. Therefore, their acceptance was limited.

- Handle different uncertainties

  In this study, the prevalence and significance of the uncertainties in a sustainability-oriented design were elaborated. However, only the internal uncertainty arising in weight elicitation was handled in this research. Other uncertainties definitely require the same attention. Uncertainty handling techniques vary with different sources and characteristics. That is also why the related topics are so complicated and therefore deserve further exploration.

- Handle preference in MOEAs

  The application of the noncompensatory binary relations – dominance allows the MOEAs to proceed without specifying preference. However, preference still needs to be tackled after the nondomindated set are obtained. Therefore, efforts to incorporate preference into MOEAs have never stopped (Fonseca & Fleming, 1993; Coello Coello, 2000b). At least two benefits are expected from doing this: 1) the decision maker gets more involved; 2) the time for reaching a "preferred" solution can be reduced. Many existing researches, such as (Greenwood et al., 1997) (Cvetkovic & Parmee, 2002) (Branke & Deb, 2004), offered a good starting point for further exploration on this topic.

- Handle nonlinear equality constraints

  This is a tough mission! Varying with specific problems, the presence of nonlinear equality constraints could bring various difficulties, such as low feasible solution ratio, discrete feasible regions, even no solution (ill-conditioned). For certain equality constrained MOPs, MOEAs may not be a good choice. Further research could be focused on what ECMOP difficulties that MOEAs suffered the most or maybe the guidelines for the equality-constrained problems to which MOEAs should or should not be applied.

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APPENDICES

APPENDIX A VOC RECOVERY PROCESSES

A 170 °F and 1 atm gaseous waste flow originating from the drying step in a cellophane manufacturing plant contains equal mass percentage toluene and ethyl acetate. These Volatile Organic Compounds (VOCs) take 0.5% of the total volumetric flowrate (12,000 standard cubic feet per minute) of the waste stream, while the remainder is nitrogen. The chemical process under consideration aims to recover the VOCs from the given waste stream. Either adsorption- or absorption-based processes can perform recovery of the VOCs (Shonnard & Hiew, 2000). A simplified process flow diagram (PFD) of an absorption-based VOC recovery process is given in Figure A-1.

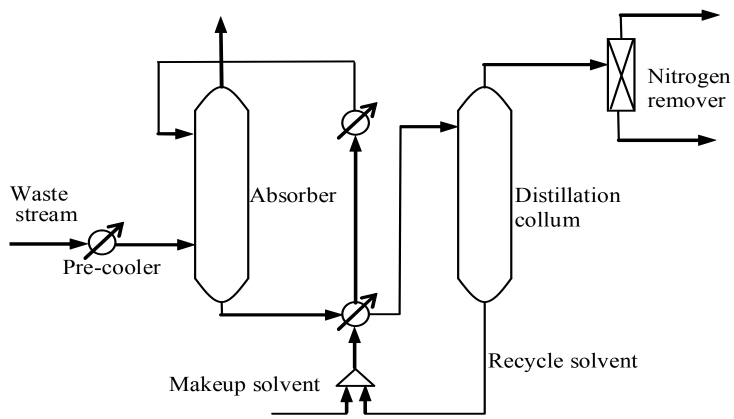

Figure A-1 Process Flow Diagram of an absorption-based VOC recovery process

In Table A-1, five different technologies are summarized. Those technologies differ significantly in the magnitude of chemical releases and consequently in the potential environmental impacts. This can be seen from Table A-2. The major sources of emission include equipment vents, utility consumptions, and fugitive emissions.

Table A-1 Different technologies of VOC recovery

Process	Features	Type
1	Steam stripping regeneration	Adsorption
2	Pressure swing regeneration	Adsorption
3	n-C_{23} solvent, no heat integration	Absorption
4	n-C_{14} solvent, no heat integration	Absorption
5	n-C_{14} solvent, with heat integration	Absorption

Table A-2 Emission rate and environmental indices of five alternative processes

	Emission rate (kg/h)						Environmental risk index					
#	CO2	CO	Ethyl acetate	SOx	NOx	Toluene	I_{GW}	I_{SF}	I_{AR}	I_{ING}	I_{INH}	I_{FT}
1	101	0.05	2.83	0.29	0.83	1.3	123	8.1	1.0	313	12.9	2.2
2	129	0.08	3.48	1.09	0.55	1.29	163	8.7	1.5	384	16.6	2.7
3	40914	10.61	13.68	322.59	42.45	0.22	15967	8.6	131.8	563	215.5	3.9
4	3096	0.80	8.19	42.45	3.21	0.09	3256	8.4	26.7	901	67.3	6.2
5	1602	0.42	7.99	0.22	1.66	0.08	1698	7.7	13.8	879	47.2	6.1

The solvent selection problem for VOC recovery was originally presented in (Chen et al., 2001). The process adopts an absorption-based technology as shown in Figure A-1. The gaseous waste stream entering the process is cooled in order to enhance the absorption. The VOCs are absorbed within the countercurrent absorption column with the solvent feeding on the top. The mixture of the solvent and the VOCs, after exchanging heat with the recycled solvent stream, is separated in the distillation column. The solvent is recycled back to the absorption column. A small stream of make-up solvent is added to compensate for emission loss from the absorption column. The distillation column top product – toluene/ethyl mixture is stored in a cone-shape fixed roof storage tank prior to recycling to the original process. The only decision variable that is allowed to change in this case study is the type of solvent. 23 different solvents were evaluated under the same operating conditions, including solvent flowrate and temperature that varied in other case studies, in order to determine the degree to which the selection of solvent influence the interested economic and environmental characteristics.

APPENDIX B MOP TEST PROBLEMS

UCMOP-1

Origin: Test function T1 in (Zitzler, et al., 2000)

$$f_1 = x_1$$
$$f_2 = p(x_2, x_3, ..., x_n)\, q(x_1, x_2, ..., x_n)$$
$$p = 1 + 9 \cdot \sum_{i=2}^{n} x_i /(n-1)$$
$$q = 1 - \sqrt{f_1 / p}$$
$$n = 30$$
$$0 \le x_i \le 1$$

UCMOP-2

Origin: Test function T2 in (Zitzler, et al., 2000)

$$f_1 = x_1$$
$$f_2 = p(x_2, x_3, ..., x_n)\, q(x_1, x_2, ..., x_n)$$
$$p = 1 + 9 \cdot \sum_{i=2}^{n} x_i /(n-1)$$
$$q = 1 - (f_1 / p)^2$$
$$n = 30$$
$$0 \le x_i \le 1$$

UCMOP-3

Origin: Test function T3 in (Zitzler, et al., 2000)

$$f_1 = x_1$$
$$f_2 = p(x_2, x_3, ..., x_n)\, q(x_1, x_2, ..., x_n)$$
$$p = 1 + 9 \cdot \sum_{i=2}^{n} x_i /(n-1)$$
$$q = 1 - \sqrt{f_1 / p} - (f_1 / g) \sin(10 \pi f_1)$$
$$n = 30$$
$$0 \le x_i \le 1$$

UCMOP-4

Origin: Test function T6 in (Zitzler, et al., 2000)

$$f_1 = 1 - \exp(-4x_1)\sin^6(6\pi x_1)$$
$$f_2 = p(x_2, x_3, ..., x_n)q(x_1, x_2, ..., x_n)$$
$$p = 1 + 9 \cdot \sum_{i=2}^{n} x_i /(n-1)$$
$$q = 1 - (f_1 / g)^2$$
$$n = 10$$
$$0 \le x_i \le 1$$

UCMOP-5

Origin: 1st function in (Schaffer, 1984)

$$f_1 = x^2$$
$$f_2 = (x-2)^2$$
$$-1000 \le x \le 1000$$

UCMOP-6

Origin: 2nd MOP in (Fonseca and Fleming, 1995b)

$$f_1 = 1 - \exp(-\sum_{i=1}^{n}(x_i - 1/\sqrt{n})^2)$$
$$f_2 = 1 - \exp(-\sum_{i=1}^{n}(x_i + 1/\sqrt{n})^2)$$
$$-4 \le x_i \le 4, i = 1,2,3$$

UCMOP-7

Origin: (Poloni et al., 2000)

$$f_1 = -[1 + (A_1 - B_1)^2 + (A_2 - B_2)^2]$$
$$f_2 = [(x_1 + 3)^2 - (x_2 + 1)^2]$$
$$A_1 = 0.5\sin 1 - 2\cos 1 + \sin 2 - 1.5\cos 2$$
$$A_2 = 1.5\sin 1 - \cos 1 + 2\sin 2 - 0.5\cos 2$$
$$B_1 = 0.5\sin x_1 - 2\cos x_1 + \sin x_2 - 1.5\cos x_2$$
$$B_2 = 1.5\sin x_1 - \cos x_1 + 2\sin x_2 - 0.5\cos x_2$$
$$-\pi \le x_1, x_2 \le \pi$$

UCMOP-8

Origin: (Kursawe, 1990)

$$f_1 = \sum_{i=1}^{n-1} (-10\, e^{(-0.2)*\sqrt{x_i^2 + x_{i+1}^2}})$$
$$f_2 = \sum_{i=1}^{n} (|x_i|^{0.8} + 5\sin(x_i)^3)$$
$$-5 \le x_i \le 5, i = 1,2,3$$

UCMOP-9

Origin: (Viennet, 1996)

$$f_1 = 0.5 \cdot (x_1^2 + x_2^2) + \sin(x_1^2 + x_2^2)$$
$$f_2 = (3x_1 - 2x_2 + 4)/8 + (x_1 - x_2 + 1)^2 / 27 + 15$$
$$f_3 = 1/(x_1^2 + x_2^2 + 1) - 1.1 \cdot e^{(-x_1^2 - x_2^2)}$$
$$-30 \le x_1, x_2 \le 30$$

SCMOP-1

Origin: (Deb, 2001)

$$f_1 = x_1$$
$$f_2 = (1 + x_2)/x_1$$
$$g_1 = x_2 + 9x_1 \ge 6$$
$$g_2 = -x_2 + 9x_1 \ge 1$$
$$0.1 \le x_1 \le 1$$
$$0 \le x_2 \le 5$$

SCMOP-2

Origin: (Chankong & Haimes, 1983) (Srinivas & Deb, 1994)

$$f_1 = 2 + (x_1 - 2)^2 + (x_2 - 1)^2$$
$$f_2 = 9x_1 - (x_2 - 1)^2$$
$$g_1 = x_1^2 + x_2^2 \le 225$$
$$g_2 = x_1 - 3x_2 + 10 \le 0$$
$$-20 \le x_1, x_2 \le 20$$

SCMOP-3

Origin: (Tanaka, 1995)

$$f_1 = x_1$$
$$f_2 = x_2$$
$$g_1 = -x_1^2 - x_2^2 + 1 + (a \cdot \cos(\ b \cdot \arctan(\ x_1 / x_2))) \leq 0$$
$$g_2 = (x_1 - 0.5)^2 + (x_2 - 0.5)^2 \leq 0.5$$
$$0 \leq x_1, x_2 \leq \pi$$

SCMOP-4

Origin: (Osyczka & Kundu, 1995)

$$f_1 = -(25(x_1 - 2)^2 + (x_2 - 2)^2 + (x_3 - 1)^2 + (x_4 - 4)^2 + (x_5 - 1)^2)$$
$$f_2 = x_1^2 + x_2^2 + x_3^2 + x_4^2 + x_5^2 + x_6^2$$
$$g_1 = x_1 - x_2 - 2 \geq 0$$
$$g_2 = 6 - x_1 - x_2 \geq 0$$
$$g_3 = 2 - x_1 - x_2 \geq 0$$
$$g_4 = 2 - x_1 - 3x_2 \geq 0$$
$$g_5 = 4 - (x_3 - 3)^2 - x_4 \geq 0$$
$$g_6 = (x_5 - 3)^2 + x_6 - 4 \geq 0$$
$$0 \leq x_1, x_2, x_6 \leq 10; \qquad 1 \leq x_3, x_5 \leq 5; \qquad 0 \leq x_4 \leq 6$$

SCMOP-5

Origin: 2nd MOP in (Binh & Korn, 1997)

$$f_1 = 4x_1^2 + 4x_2^2$$
$$f_2 = (x_1 - 5)^2 + (x_2 - 5)^2$$
$$g_1 = (x_1 - 5)^2 + x_2^2 \leq 25$$
$$g_2 = (x_1 - 8)^2 + (x_2 + 3)^2 \geq 7.7$$
$$0 \leq x_1 \leq 5, 0 \leq x_2 \leq 3$$

ECMOP-1

Revised from g11 in (Runarsson & Yao, 2000)

$$f_1 = x_1^2 + (x_2 - 1)^2$$
$$f_2 = x_1 - x_2$$
$$h_1 = x_2 - x_1^2 = 0$$
$$-1 \le x_1, x_2 \le 1$$

ECMOP-2

Revised from g13 in (Runarsson & Yao, 2000)

$$f_1 = e^{x_1 x_2 x_3 x_4 x_5}$$
$$f_2 = x_1 + x_2 + x_3 + x_4 + x_5$$
$$h_1 = x_1^2 + x_2^2 + x_3^2 + x_4^2 + x_5^2 - 10 = 0$$
$$h_2 = x_2 x_3 - 5 x_4 x_5 = 0$$
$$h_3 = x_1^3 + x_2^3 + 1 = 0$$
$$-2.3 \le x_1, x_2 \le 2.3$$
$$-3.2 \le x_3, x_4, x_5 \le 3.2$$

ECMOP-3

Revised from g05 in (Runarsson & Yao, 2000)

$$f_1 = 3x_1 + 0.000001\, x_1^3 + 2x_2 + (0.000002 / 3) x_2^3$$
$$f_2 = x_1 x_2 x_3 x_4$$
$$g_1 = -x_4 + x_3 - 0.55 \le 0$$
$$g_2 = -x_3 + x_4 - 0.55 \le 0$$
$$h_1 = 1000 \sin(-x_3 - 0.25) + 1000 \sin(-x_4 - 0.25) + 894.8 - x_1 = 0$$
$$h_2 = 1000 \sin(x_3 - 0.25) + 1000 \sin(x_3 - x_4 - 0.25) + 894.8 - x_2 = 0$$
$$h_3 = 1000 \sin(x_4 - 0.25) + 1000 \sin(x_4 - x_3 - 0.25) + 1294.8 = 0$$
$$0 \le x_1, x_2 \le 1200$$
$$-0.55 \le x_3, x_4 \le 0.55$$

ECMOP-4

Reformulated from (DiBella & Stevens, 1965)

$$f_1 = 100 * [8400(0.3x_{12} + 0.0068x_3 - 0.02x_1 - 0.03x_2 - 0.01x_4) - (0.124)(8400)$$
$$(0.3x_{12} + 0.0068x_3) - 2.22x_9 - 18000] / 180000$$

$$f_2 = x_4$$

$$h_1 = x_{10} - 0.1x_8 - x_{12} = 0$$

$$h_2 = \frac{x_3 x_8}{(x_9 - x_4 - x_{12})} - 2(2.5962 * 10^{12})(e^{-15000/x_{11}})(\frac{x_6 x_7 3000}{x_9^2}) = 0$$

$$h_3 = [(2.5962 * 10^{12})(e^{-15000/x_{11}})(x_6 x_7) - 0.5(9.6283 * 10^{15})(e^{-20000/x_{11}})(x_7 x_{10})](\frac{3000}{x_9^2})$$
$$- x_3(\frac{x_{10} - x_{12}}{x_9 - x_4 - x_{12}}) - x_{12} = 0$$

$$h_4 = x_1 - (5.9755 * 10^9)(e^{-12000/x_{11}})(x_5 x_6)(\frac{3000}{x_9^2}) - x_3(\frac{x_5}{x_9 - x_4 - x_{12}}) = 0$$

$$h_5 = x_2 - [(5.9755 * 10^9)(e^{-12000/x_{11}})(x_5 x_6) + (2.5962 * 10^{12})(e^{-15000/x_{11}})(x_6 x_7)](\frac{3000}{x_9^2})$$
$$- x_3(\frac{x_6}{x_9 - x_4 - x_{12}}) = 0$$

$$h_6 = [2(5.9755 * 10^9)(e^{-12000/x_{11}})(x_5 x_6) - 2(2.5962 * 10^{12})(e^{-15000/x_{11}})(x_6 x_7)$$
$$- (9.6283 * 10^{15})(e^{-20000/x_{11}})(x_7 x_{10})](\frac{3000}{x_9^2}) - x_3(\frac{x_7}{x_9 - x_4 - x_{12}}) = 0$$

$$h_7 = 1.5(9.6283 * 10^{15})(e^{-20000/x_{11}})(x_7 x_{10})(\frac{3000}{x_9^2}) - x_4 = 0$$

$$h_8 = x_5 + x_6 + x_7 + x_8 + x_4 + x_{10} - x_9 = 0$$

Notes: All the objective functions in the above test problems are expressed in the form of "to-be-minimized."

APPENDIX C WILLIAMS-OTTO PROCESS

C.1 Process Description

Figure C-1 illustrates a simplified Process Flow Diagram (PFD) of the so-called Williams-Otto process. The plant manufactures a chemical P at certain capacity and is operated 8400 hours (350 days) per year.

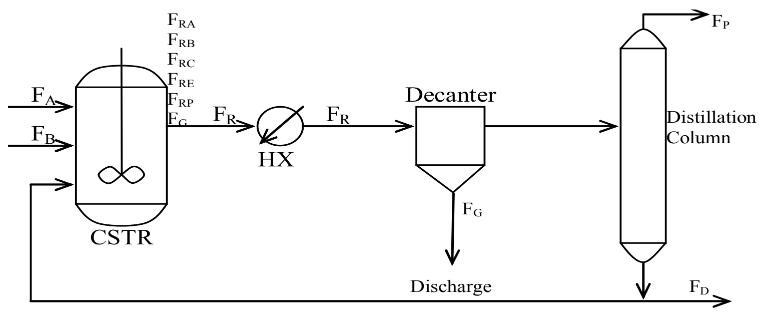

Figure C-1 Williams-Otto Process Flow Diagram

The process, in series, consists of:

1. Continueously-stirred tank reactor (CSTR) - Reactants A and B entering the reactor in pure form are converted to the desired product P in the CSTR. Three second-order irreversible reactions are involved:

$$
\begin{aligned}
A + B &\xrightarrow{K_1} C \\
C + B &\xrightarrow{K_2} P + E \\
P + C &\xrightarrow{K_3} G
\end{aligned}
$$

Intermediates C and E have no sales value but may be used as plant fuels. G is a heavy and oily byproducts that has to be disposed as a wsate material. The reaction coefficients k can be expressed in the Arrhenius form:

$$k_i = A_i \exp(-B_i / T)$$

The values of A and B are listed in Table C-1.

Table C-1 Parameters for reaction coefficients

i	A_i (hr) (weight fraction)	B_i (^oR)
1	5.9755×10^{9}	12000
2	2.5962×10^{12}	15000
3	9.6283×10^{15}	20000

2. Heat exchanger - The reator outflow is cooled to a sufficently low temperature that allows complete separation of G in the decanter.

3. Decanter - The complete separation of the byproduct G is performed.

4. Distillation column - P forms an azeotrope with E, in which P's composition at azeotropic points amounts to 10% by weight. The desired product P is obtained as the overhead product from distillation column. A portion of the column bottom product is recycled back to the CSTR, while the remainder is sent out of the process boundry.

The density of the reaction mixture ρ is taken as constant at 50lb/ft^3. The molecular weight of each pure substance is assumed as follows in Table C-2:

Table C-2 Molecular weights of pure substances

Components	Molecular weights
A	100
B	100
C	200
E	200
G	300
P	100

C.2 Single Objective Optimization in Literature

This process model was developed by the Monsanto Chemical Company and first presented in (Williams & Otto, 1960) as a generalized model basis for the comparison of different computer controls on chemical processes. DiBella and Stevens (1965) modified the model and clearly formulated into a constrained single objective optimization problem as shown below.

$$\textit{Maximize} \qquad f = 100 * [8400(0.3F_P + 0.0068F_D - 0.02F_A - 0.03F_B - 0.01F_G) - (0.124)(8400)(0.3F_P + 0.0068F_D) - 2.22F_R - 60V\rho] / 600V\rho$$

Subject to:

$$F_{RP} - 0.1F_{RE} - F_P = 0$$

$$\frac{F_D F_{RE}}{(F_R - F_G - F_P)} - (\frac{M_E}{M_B})(2.5962 * 10^{12})(e^{-15000/T})(\frac{F_{RB}F_{RC}V\rho}{F_R^2}) = 0$$

$$[(2.5962*10^{12})(e^{-15000/T})(F_{RB}F_{RC}) - (\frac{M_P}{M_E})(9.6283*10^{15})(e^{-20000/T})(F_{RC}F_{RP})](\frac{V\rho}{F_R^2}) - F_D(\frac{F_{RP}-F_P}{F_R - F_G - F_P}) - F_P = 0$$

$$F_A - (5.9755*10^9)(e^{-12000/T})(F_{RA}F_{RB})(\frac{V\rho}{F_R^2}) - F_D(\frac{F_{RA}}{F_R - F_G - F_P}) = 0$$

$$F_B - [(5.9755*10^9)(e^{-12000/T})(F_{RA}F_{RB}) + (2.5962*10^{12})(e^{-15000/T})(F_{RB}F_{RC})](\frac{V\rho}{F_R^2}) - F_D(\frac{F_{RB}}{F_R - F_G - F_P}) = 0$$

$$[(\frac{M_C}{M_B})(5.9755*10^9)(e^{-12000/T})(F_{RA}F_{RB}) - (\frac{M_C}{M_B})(2.5962*10^{12})(e^{-15000/T})(F_{RB}F_{RC}) - (9.6283*10^{15})(e^{-20000/T})(F_{RC}F_{RP})](\frac{V\rho}{F_R^2}) - F_D(\frac{F_{RC}}{F_R - F_G - F_P}) = 0$$

$$(\frac{M_G}{M_C})(9.6283*10^{15})(e^{-20000/T})(F_{RC}F_{RP})(\frac{V\rho}{F_R^2}) - F_G = 0$$

$$F_{RA} + F_{RB} + F_{RC} + F_{RE} + F_G + F_{RP} - F_R = 0$$

$$F_A + F_B - F_G - F_P - F_D = 0$$

$$580^\circ R \le T \le 680^\circ R$$

The annual rate of return on the investment (ROI) was taken as the objective function, which is calculated from the data in Table C-3. The steady state material balance essentially constitutes the equality constraints. As pointed out by several authors, the 9th equality constraint is redundant (Christensen, 1970; Jung et al., 1971).

Table C-3 Monetary data for calculation of return on investment

Income	$(0.3F_P+0.0068F_D)$/hr
Expenses	
Raw material cost	$(0.02F_A+0.03F_B)$/hr
Waste disposal cost	$0.01F_G$/hr
Utilities cost	$2.22F_R$/yr
Sales, Administration, and Research expenses	12.4% of sales
Plant fixed charge	10% of the plant investment per year
Plant investment	$600V\rho$

The Williams-Otto process, perhaps the most popular nonlinear model for chemical process optimization, has been widely studied in the settings of single objective programming (SOP) (Christensen, 1970; Jung et al., 1971; Adelman & Steven, 1972; Luus & Jaakola, 1973; Ray & Szekely, 1973; Findley, 1974; Rijckaert & Martens, 1974; Vinante & Valladares, 1985; Vasantharajan & Biegler, 1988; Biegler, 1987; Biegler et al., 1997). The popularity can be attributed to its three attributes. First, this single process model involves reaction, heat exchange, multiple separate steps, and recycle streams. This is why the WO process is widely regarded to be sufficiently close to a real typical chemical process (Ray and Szekely, 1973; Rijckaert and Marten, 1974). Second, the model's mathematical definition is explicit and somewhat simple, hence different algorithms have been applied even without thorough understanding of the chemical process itself. Third, the model is general and does not require the exact nature of the chemicals, equipment configuration, as well as detailed operating conditions. This generality allows for the considerable freedom to interpret or revise the original model in a user-specific manner.

Slightly different SOP formulations of the WO process exist in literature. The major differences lie in different handling of the product flowrate F_P and the reactor volume V, while the equality constraints keep the same. Three different formulations are demonstrated in Table C-4.

Table C-4 Different SOP formulations of the WO model

#	F_P	V	Previous work
1	≥ 0	≥ 0	(Luus & Jaakola, 1973)
2	= 4762	≥ 0	(Dibella and Stevens, 1965) (Adelman and Stevens, 1972) (Luus and Jaakola, 1973)
3	$4762 \geq F_P \geq 0$	= 60	(Jung et al., 1971) (Ray and Szekely, 1973) (Vinante and Valladares, 1985)

In literature, a range of different SOP algorithms have been applied, for instance, complex method (Adelman & Steven, 1972), geometric programming (Rijckaert & Martens, 1974), Multipliers method (Vinante & Valladares, 1985), and many more. Among those, the performance of some so-called "locally convergent" algorithms to a great extent relies upon a "good" (close to the target local optimum) initial point.

C.3 New Multi-Objective Formulation

In this study, the classical William-Otto plant model is reformulated into a multi-objective problem. This is done by changing the stream G, which is delivered to disposal in previous formulations, as being discharged to the environment. This revision introduces the second environmental objective function - minimizing environmental impact resulting from the stream G release. The original economic objective function - maximizing return on investment (ROI) is still applied, but with a different expression, as the disposal cost does not occur any more. These two objectives are optimized within the feasible region defined by 8 equality constraints, which are essentially the material balance of the process. This formulation follows (Ray & Szekely, 1973) to fix the reactor volume at 60 ft^3. All the variables are listed in Table C-5. Among them, F_P is expected to vary between 3571-4762 lb/hr, while the other variables, including 10 flowrates and reactor temperature, are allowed to vary within the -5%~+5% range around their design condition values, which is the “optimal” solution in (diBella & Stevens, 1965).

Maximize $f_1 = 100 * [8400(0.3F_P + 0.0068F_D - 0.02F_A - 0.03F_B - 0.01F_G) - (0.124)(8400)(0.3F_P + 0.0068F_D) - 2.22F_R - 18000]/180000$

Minimize $f_2 = F_G$

Subject to:

$$F_{RP} - 0.1F_{RE} - F_P = 0$$

$$\frac{F_D F_{RE}}{(F_R - F_G - F_P)} - 2(2.5962*10^{12})(e^{-15000/T})(\frac{F_{RB}F_{RC}3000}{F_R^2}) = 0$$

$$[(2.5962*10^{12})(e^{-15000/T})(F_{RB}F_{RC}) - 0.5(9.6283*10^{15})(e^{-20000/T})(F_{RC}F_{RP})](\frac{3000}{F_R^2}) - F_D(\frac{F_{RP}-F_P}{F_R - F_G - F_P}) - F_P = 0$$

$$F_A - (5.9755*10^9)(e^{-12000/T})(F_{RA}F_{RB})(\frac{3000}{F_R^2}) - F_D(\frac{F_{RA}}{F_R - F_G - F_P}) = 0$$

$$F_B - [(5.9755*10^9)(e^{-12000/T})(F_{RA}F_{RB}) + (2.5962*10^{12})(e^{-15000/T})(F_{RB}F_{RC})](\frac{3000}{F_R^2}) - F_D(\frac{F_{RB}}{F_R - F_G - F_P}) = 0$$

$$[2(5.9755*10^9)(e^{-12000/T})(F_{RA}F_{RB}) - 2(2.5962*10^{12})(e^{-15000/T})(F_{RB}F_{RC}) - (9.6283*10^{15})(e^{-20000/T})(F_{RC}F_{RP})](\frac{3000}{F_R^2}) - F_D(\frac{F_{RC}}{F_R - F_G - F_P}) = 0$$

$$1.5(9.6283*10^{15})(e^{-20000/T})(F_{RC}F_{RP})(\frac{3000}{F_R^2}) - F_G = 0$$

$$F_{RA} + F_{RB} + F_{RC} + F_{RE} + F_G + F_{RP} - F_R = 0$$

Table C-5 Variables involved in the new WO process model

Variable	x	Description
F_A	1	Flowrate of component A in reactor feed
F_B	2	Flowrate of component B in reactor feed
F_D	3	Total flowrate of distillation column bottom runoff
F_G	4	Flowrate of component G from decanter bottom
F_{RA}	5	Flowrate of component A in reactor outflow
F_{RB}	6	Flowrate of component B in reactor outflow
F_{RC}	7	Flowrate of component C in reactor outflow
F_{RE}	8	Flowrate of component E in reactor outflow
F_R	9	Total flowrate of reactor outflow
F_{RP}	10	Flowrate of component P in reactor outflow
T	11	Temperature of the reactor
F_P	12	Flowrate of component P in column overhead product
V	-	Reactor volume (fixed at 60 ft^3)

The values of the two objective and twelve decision variables at the design condition are given below. The ROI at the design condition is 89.58%, while the flowrate of the discharge waste is 3609 lb/hr, respectively.

Table C-6 Variable values under design conditions

		Design condition	Lower bound	Upper bound
F_A	(lb/hr)	13546	12869	14223
F_B	(lb/hr)	31523	29947	33099
F_D	(lb/hr)	36697	34862	38532
F_G	(lb/hr)	3609	3429	3789
F_{RA}	(lb/hr)	18187	17278	19096
F_{RB}	(lb/hr)	60915	57869	63961
F_{RC}	(lb/hr)	3331	3164	3498
F_{RE}	(lb/hr)	60542	57515	63569
F_R	(lb/hr)	157391	149522	165261
F_{RP}	(lb/hr)	10817	10276	11358
T	(^oR)	656	623	689
f_1	(%)	89.58		
f_2	(lb/hr)	3609		
Ω		250.82		

APPENDIX D FORTRAN CODE OF ORGA

```
PROGRAM main
!=================================================================
!                Ordinal Ranking-based Genetic Algorithms (version 1.0)
!                                 As of 6/10/2005
!                                  By XUN JIN
!
!
! This algorithm is a Multi-Objective Evolutioary Algorithm (MOEA), which offers the
! searching capacity when a Multiple Objective Programming (MOP) problem is solved
! with "a posteriori" preference articulation. The result obtained from using this
! algorithm is a set of evenly distributed solutions that are globally Pareto optimal within
! the feasible space of the given MOP.
!
! For details regarding this algorithm, please refer to:
! "Xun Jin, Approaching Sustainability in Engineering Design with Multiple Criteria Decision Analysis.
! Ph.D. Dissertation, December, 2005, Oklahoma State University."
!
!=================================================================

USE dfport

IMPLICIT NONE

INTEGER n, nf, ng, nh, model_n, p, i, j, gen, p_elite, r_div(pmax), r(pmax),
r_conobj(pmax)
INTEGER, PARAMETER:: nmax=200, pmax=500, fmax=10, hmax=100, gmax=100,
p_elite_max=100
REAL x(nmax,pmax), f(fmax,pmax), h(hmax,pmax), g(gmax,pmax), xu(nmax,pmax),
xl(nmax,pmax), mating_pool_x(nmax,pmax), cv(pmax), mutation_rate, crossover_rate
CHARACTER(8):: now
! n:              Number of decision variables (x1,x2,...xn)
! nf:             Number of objective functions
! ng:             Number of inequality constraints
! nh:             Number of equality constraints
! model_n:        Identification number of the problem to be solved
! p:              Number of individuals in the Population
! gen:            Number of generation
! p_elite:        Number of elites
! x(i,j):         Value of xi of the jth solution
! f(i,j):         Value of objective function i of the jth solution
! h(i,j):         Value of equality constraint I of the jth solution
! g(i,j):         Value of inequality constraint I of the jth solution
! xu(i,j):        Upper bound on xi
```

```
! xl(i,j):              Lower bound on xi
! mating_pool_x(i,j):   Value of xi of the jth solution in mating pool
! cv(i)                 Constraint violation of ith solution
! now:                  Present time
! r_div(i)              diversity rank of ith solution
! r_conobj(i):          Constrained-objective ranking of the ith solution
! r:                    Overall ranking of the ith solution

OPEN (UNIT=10, FILE="MOP_303.txt", STATUS="REPLACE",
ACTION="WRITE",POSITION="REWIND")

mutation_rate=0.1     ! set mutation rate
crossover_rate=1      ! set crossover rate
model_n=303           ! input the number of the problem to be solved
p=100                 ! set the number of population
p_elite=p/10          ! set the number of elite

WRITE ( 10, '(/)' )
WRITE ( 10, '(A,i3,A)') "SOLVING THE PROBLEM # ", model_n, " WITH ORGA"
WRITE ( 10, '(3/)' )
CALL TIME(now)      ! get the present time
WRITE (10,*) " THE PROGRAM STARTS AT ", now
! output the starting time of the program
WRITE (10,*) "* * * * * * * * * * * * * * * * * * * * * * * * * * *"
WRITE ( 10, '(2/)' )

gen=1
CALL models(model_n,n,nf,nh,ng)
! get the info of the target problem
CALL initialize (model_n,n,p,x,xu,xl)
! generate random initial population

DO
  WRITE (10,*)
  WRITE (10,'(5X,"============= ",I10.5,5X," =================")') gen
  ! output generation number
  WRITE (10,*)

  CALL objective_functions(model_n,n,nf,p,x,f)
  ! calculate objective function values
  CALL equality_constraints(model_n,n,nh,p,x,h)
  ! calculate equality constraints
  CALL inequality_constraints(model_n,n,x,ng,p,g)
  ! calculate inequality constraints
  CALL feasibility_ranking(p,h,g,nh,ng,cv,r_fea,n_fea)
  ! calculate constraint violations
```

```
  CALL diversity_ranking(nf,f,p,r_div)
  ! calcuate diversity
  CALL constrained_objective_ranking(p,cv,nf,f,r_conobj)
  ! calculate constrained-objective rank
  CALL ordinal_ranking(p,r_conobj,r_div,r,r_fea,r_obj)
  ! perform ordinal ranking on the current population
  IF (gen==1.or. REAL(gen/1000)==REAL(gen)/REAL(1000)) THEN !
     CALL output(p,nf,f,cv,r_obj,r_div,r_fea,r_conobj,r)
     ! output result to monitor the program
  END IF
IF (gen>1000) EXIT ! set stopping criterion as 1000 generation
  CALL mating_pool(p,n,x,r,mating_pool_x,gen)
  ! create mating pool by tournament selection
  CALL environmental_selection (p,p_elite,n,x,r)
  ! select elite based on individual' ordinal rank
  CALL variation(crossover_rate, mutation_rate,p,p_elite,n,x,xl,xu,mating_pool_x,gen)
  ! select parents and perform crossover and mutation to produce offsprings
  gen=gen+1   ! increase generation number by one
END DO

CALL output_x(n,p,x)  ! output x values of the final generation
CALL feasible_pareto(x,n,p,nf,f,r_conobj,r_fea)
! screen out feasible and Pareto optimal solutions and output them


CALL TIME (now)    ! get the present time
WRITE ( 10, '(2/)' )
WRITE (10,*) "+++++++++++++++++++++++++++++++++++++++++++++++”
WRITE ( 10, * ) " THE PROGRAM ENDS AT ", now
! output the ending time of the program

END PROGRAM main


!--------------------------------------------------------------------
SUBROUTINE models(model_n,n,nf,nh,ng)
! this subroutine contains the information of the problems to be solved
! 101-110: unconstrained MOP
! 201-205: side-constrained MOP
! 301-304: equality-constrained MOP
! 401:        williams-otto MOP

INTEGER model_n,n,nf,ng,nh

IF (model_n==101) THEN          ! info about unconstrained test problem 1
! ZDT 1
```

```
nf=2
n=30
nh=0
ng=0
ELSE IF (model_n==102) THEN      ! info about unconstrained test problem 2
! ZDT 2
nf=2
n=30
nh=0
ng=0
ELSE IF (model_n==103) THEN      ! info about unconstrained test problem 3
! ZDT 3
nf=2
n=30
nh=0
ng=0
ELSE IF (model_n==104) THEN      ! info about unconstrained test problem 4
! ZDT 4
nf=2
n=10
nh=0
ng=0
ELSE IF (model_n==105) THEN      ! info about unconstrained test problem 5
! ZDT 6 (F3 in Lu&Yen, 2003)
nf=2
n=10
nh=0
ng=0
ELSE IF (model_n==106) THEN      ! info about unconstrained test problem 6
! SCH
nf=2
n=1
nh=0
ng=0
ELSE IF (model_n==107) THEN      ! info about unconstrained test problem 7
! FON
nf=2
n=3
nh=0
ng=0
ELSE IF (model_n==108) THEN      ! info about unconstrained test problem 8
! POL
nf=2
n=2
nh=0
ng=0
```

```
ELSE IF (model_n==109) THEN      ! info about unconstrained test problem 9
! KUR
nf=2
n=3
nh=0
ng=0
ELSE IF (model_n==110) THEN      ! info about unconstrained test problem 10
! VNT
nf=3
n=2
nh=0
ng=0
ELSE IF(model_n==201) THEN       ! info about side-constrained test problem 1
! (Deb,2001) p.276
n=2
nf=2
ng=2
nh=0
ELSE IF (model_n==202) THEN      ! info about side-constrained test problem 2
! SRN constrained bi-objective
n=2
nf=2
ng=2
nh=0
ELSE IF (model_n==203) THEN      ! info about side-constrained test problem 3
! TNK  constrained bi-objective
n=2
nf=2
ng=2
nh=0
ELSE IF (model_n==204) THEN      ! info about side-constrained test problem 4
! OSY (Osyczka&Kundu,1995)
nf=2
n=6
nh=0
ng=6
ELSE IF (model_n==205) THEN      ! info about side-constrained test problem 5
! BNH (Binh & Korn,1997)
nf=2
n=2
nh=0
ng=2
ELSE IF (model_n==301) THEN      ! info about equality-constrained test problem 1
! revised from g11 in (Philip&Yao, 2000)
n=2
nf=2
```

```
ng=0
nh=1
ELSE IF (model_n==302) THEN      ! info about equality-constrained test problem 2
! revised from g13 in (Philip&Yao, 2000)
n=5
nf=2
ng=0
nh=3
ELSE IF (model_n==303) THEN      ! info about equality-constrained test problem 3
! revised from g05 in (Philip&Yao, 2000)
n=4
nf=2
ng=2
nh=3
ELSE IF (model_n==304) THEN      ! info about equality-constrained test problem 4
! revised from g03 in (Philip&Yao, 2000)
n=10
nf=2
ng=0
nh=1
ELSE IF (model_n==401) THEN      ! into about the williams-otto problem
! WO problem
n=12
nf=2
ng=1
nh=8
END IF

RETURN
END


!-----------------------------------------------------------------------
SUBROUTINE bounds(model_n,n,p,xu,xl)
! get all the bounds on variables in different problems

INTEGER model_n,n,p
REAL xu(n), xl(n)

IF (model_n==101.OR.model_n==102.OR.model_n==103.OR.model_n==105) THEN
xl(1:n)=0
xu(1:n)=1
ELSE IF (model_n==104) THEN
xl(1)=0
xu(1)=1
xl(2:n)=-5
```

```
xu(2:n)=5
ELSE IF (model_n==106) THEN
xl(1:n)=-1000
xu(1:n)=1000
ELSE IF (model_n==107) THEN
xl(1:n)=-4
xu(1:n)=4
ELSE IF (model_n==108) THEN
xl(1:n)=-3.1415926
xu(1:n)=3.1415926
ELSE IF (model_n==109) THEN
xl(1:n)=-5
xu(1:n)=5
ELSE IF (model_n==110) THEN
xl(1:n)=-3!0
xu(1:n)=3!0
ELSE IF (model_n==201) THEN
xl(1)=0.1
xl(2)=0
xu(1)=1
xu(2)=5
ELSE IF (model_n==202) THEN
xl(1)=-20
xu(1)=20
xl(2)=-20
xu(2)=20
ELSE IF (model_n==203) THEN
xl(1)=0
xu(1)=3.1415926
xl(2)=0
xu(2)=3.1415926
ELSE IF (model_n==204) THEN
xl(1)=0
xu(1)=10
xl(2)=0
xu(2)=10
xl(6)=0
xu(6)=10
xl(3)=1
xu(3)=5
xl(5)=1
xu(5)=5
xl(4)=0
xu(4)=6
ELSE IF (model_n==205) THEN
xl(1:2)=0
```

```
xu(1)=5
xu(2)=3
ELSE IF (model_n==301) THEN
xl(1:2)=-1
xu(1:2)=1
ELSE IF (model_n==302) THEN
xl(1:2)=-2.3
xu(1:2)=2.3
xl(3:5)=-3.2
xu(3:5)=3.2
ELSE IF (model_n==303) THEN
xl(1:2)=0
xu(1:2)=1200
xl(3:4)=-0.55
xu(3:4)=0.55
ELSE IF (model_n==304) THEN
xl(1:10)=0
xu(1:10)=1
ELSE IF (model_n==401) THEN
  xl(1)=12622.59*0.95
  xu(1)=12622.59*1.05
  xl(2)=28271.65*0.95
  xu(2)=28271.65*1.05
  xl(3)=32960.27*0.95
  xu(3)=32960.27*1.05
  xl(4)=3171.97*0.95
  xu(4)=3171.97*1.05
  xl(5)=36910.35*0.95
  xu(5)=36910.35*1.05
  xl(6)=115647.04*0.95
  xu(6)=115647.04*1.05
  xl(7)=6865.02*0.95
  xu(7)=6865.02*1.05
  xl(8)=136775.93*0.95
  xu(8)=136775.93*1.05
  xl(9)=317809.90*0.95
  xu(9)=317809.90*1.05
  xl(10)=18439.59*0.95
  xu(10)=18439.59*1.05
  xl(11)=656.36*0.95
  xu(11)=656.36*1.05
  xl(12)=4762.00
  xu(12)=3571.00
END IF

RETURN
```

```
END SUBROUTINE bounds


!-----------------------------------------------------------------------
SUBROUTINE initialize (model_n,n,p,x,xu,xl)
! create random initial population

INTEGER n,model_n,p,q
REAL x(n,p),xu(n),xl(n)
INTEGER ms(8),curr_time(1)
REAL rannum(n+1,p+1)

CALL bounds(model_n,n,p,xu,xl)

CALL DATE_AND_TIME (VALUES=ms)
q=ABS(TIME())
curr_time(1)=q/(2*ms(8))
CALL RANDOM_SEED (PUT=curr_time)
CALL RANDOM_NUMBER (rannum)
! use the current time as the seed for random number generation

DO j=1,p
  DO i=1,n
    x(i,j)=(xu(i)-xl(i))*rannum(i+1,j+1)+xl(i)
  END DO
END DO

DO j=1,p
  write (10,28) j,x(1:n,j) ! output initial population
28  FORMAT("p",i3,100f15.5)
END DO

RETURN
END


!-----------------------------------------------------------------------
SUBROUTINE objective_functions(model_n,n,nf,p,x,f)
! calculate objective function values

INTEGER model_n, nf, n,p,j,m
REAL f(nf,p), x(n,p),g(p),h(p),sigma,multiply

IF (model_n==101) THEN
  DO j=1,p
    f(1,j)=x(1,j)
```

```
      sigma=0
      DO i=2,n
        sigma=sigma+x(i,j)
      END DO
      g(j)=1+9*sigma/(n-1)
      h(j)=1-SQRT(f(1,j)/g(j))
      f(2,j)=g(j)*h(j)
  END DO
ELSE IF (model_n==102) THEN
  DO j=1,p
    f(1,j)=x(1,j)
      sigma=0
      DO i=2,n
        sigma=sigma+x(i,j)
      END DO
      g(j)=1+9*sigma/(n-1)
      h(j)=1-(f(1,j)/g(j))**2
      f(2,j)=g(j)*h(j)
  END DO
ELSE IF (model_n==103) THEN
  DO j=1,p
    f(1,j)=x(1,j)
      sigma=0
      DO i=2,n
        sigma=sigma+x(i,j)
      END DO
      g(j)=1+9*sigma/(n-1)
      h(j)=1-SQRT(f(1,j)/g(j))-(f(1,j)/g(j))*SIN(10*3.1415926*f(1,j))
      f(2,j)=g(j)*h(j)
  END DO
ELSE IF (model_n==104) THEN
  DO j=1,p
    f(1,j)=x(1,j)
      sigma=0
      DO i=2,n
        sigma=sigma+(x(i,j)**2-10*COS(4*3.1415926*x(i,j)))
      END DO
      g(j)=1+10*(n-1)+sigma
      h(j)=1-SQRT(f(1,j)/g(j))
      f(2,j)=g(j)*h(j)
      write (10,*) j, "f1=",f(1,j),"f2=", f(2,j)
  END DO
ELSE IF (model_n==105) THEN
  DO j=1,p
    f(1,j)=1-exp(-4*x(1,j))*SIN(6*3.1415926*x(1,j))**6
      sigma=0
```

```
    DO i=2,n
      sigma=sigma+x(i,j)
    END DO
    g(j)=1+9*(sigma/(n-1))**0.25
    h(j)=1-(f(1,j)/g(j))**2
    f(2,j)=g(j)*h(j)
  END DO
ELSE IF (model_n==106) THEN
  DO j=1,p
   f(1,j)=x(1,j)**2
    f(2,j)=(x(1,j)-2)**2
  END DO
ELSE IF (model_n==107) THEN
  DO j=1,p
   f(1,j)=1-EXP(-((x(1,j)-1/SQRT(3.0))**2+(x(2,j)-1/SQRT(3.0))**2+(x(3,j)-
1/SQRT(3.0))**2))
    f(2,j)=1-EXP(-
((x(1,j)+1/SQRT(3.0))**2+(x(2,j)+1/SQRT(3.0))**2+(x(3,j)+1/SQRT(3.0))**2))
  END DO
ELSE IF (model_n==108) THEN
  a1=0.5*SIN(1.0)-2*COS(1.0)+SIN(2.0)-1.5*COS(2.0)
  a2=1.5*SIN(1.0)-COS(1.0)+2*SIN(2.0)-0.5*COS(2.0)
  DO j=1,p
   b1=0.5*SIN(x(1,j))-2*COS(x(1,j))+SIN(x(2,j))-1.5*COS(x(2,j))
   b2=1.5*SIN(x(1,j))-COS(x(1,j))+2*SIN(x(2,j))-0.5*COS(x(2,j))
   f(1,j)=(1+(a1-b1)**2+(a2-b2)**2)
    f(2,j)=((x(1,j)+3)**2+(x(2,j)+1)**2)
  END DO
ELSE IF (model_n==109) THEN
  DO j=1,p
   sigma1=0
    sigma2=0
    DO i=1,n-1
      sigma1=sigma1+(-10*EXP(-0.2*SQRT(x(i,j)**2+x(i+1,j)**2)))
   END DO
    DO i=1,n
      sigma2=sigma2+(ABS(x(i,j))**0.8+5*SIN(x(i,j)**3))
    END DO
    f(1,j)=sigma1
    f(2,j)=sigma2
  END DO
ELSE IF (model_n==110) THEN
  DO j=1,p
   f(1,j)=0.5*(x(1,j)**2+x(2,j)**2)+SIN(x(1,j)**2+x(2,j)**2)
    f(2,j)=(3*x(1,j)-2*x(2,j)+4)**2/8+(x(1,j)-x(2,j)+1)**2/27+15
    f(3,j)=1/(x(1,j)**2+x(2,j)**2+1)-1.1*EXP(-x(1,j)**2-x(2,j)**2)
```

```
  END DO
ELSE IF (model_n==201) THEN
  DO j=1,p
    f(1,j)=x(1,j)
    f(2,j)=(1+x(2,j))/x(1,j)
  END DO
ELSE IF (model_n==202) THEN
  DO j=1,p
    f(1,j)=2+(x(1,j)-2)**2+(x(2,j)-1)**2
      f(2,j)=9*x(1,j)-(x(2,j)-1)**2
  END DO
ELSE IF (model_n==203) THEN
  DO j=1,p
    f(1,j)=x(1,j)
      f(2,j)=x(2,j)
  END DO
ELSE IF (model_n==204) THEN
  DO j=1,p
    f(1,j)=-(25*(x(1,j)-2)**2+(x(2,j)-2)**2+(x(3,j)-1)**2+(x(4,j)-4)**2+(x(5,j)-1)**2)
      f(2,j)=x(1,j)**2+x(2,j)**2+x(3,j)**2+x(4,j)**2+x(5,j)**2+x(6,j)**2
  END DO
ELSE IF (model_n==205) THEN
  DO j=1,p
    f(1,j)=4*x(1,j)**2+4*x(2,j)**2
      f(2,j)=(x(1,j)-5)**2+(x(2,j)-5)**2
  END DO
ELSE IF (model_n==301) THEN
  DO j=1,p
    f(1,j)=x(1,j)**2+(x(2,j)-1)**2
      f(2,j)=x(1,j)-x(2,j)
  END DO
ELSE IF (model_n==302) THEN
  DO j=1,p
    f(1,j)=exp(x(1,j)*x(2,j)*x(3,j)*x(4,j)*x(5,j))
      f(2,j)=x(1,j)+x(2,j)+x(3,j)+x(4,j)+x(5,j)
  END DO
ELSE IF (model_n==303) THEN
  DO j=1,p
    f(1,j)=3*x(1,j)+0.000001*x(1,j)**3+2*x(2,j)+(0.000002/3)*x(2,j)**3
      f(2,j)=x(1,j)*x(3,j)+x(2,j)*x(4,j)
  END DO
ELSE IF (model_n==304) THEN
  DO j=1,p
    f(1,j)=-
SQRT(REAL(n))**n*(x(1,j)*x(2,j)*x(3,j)*x(4,j)*x(5,j)*x(6,j)*x(7,j)*x(8,j)*x(9,j)*x(10,j
))
```

```
    f(2,j)=x(1,j)*x(3,j)*x(5,j)*x(7,j)*x(9,j)
  END DO
ELSE IF (model_n==401) THEN
  DO j=1,p
   f(1,j)=-100*(8400*(0.3*x(12,j)+0.0068*x(3,j)-0.02*x(1,j)-0.03*x(2,j))-2.22*x(9,j)-
0.124*8400*(0.3*x(12,j)+0.0068*x(3,j))-3000*60)/(30000*60)
   f(2,j)=x(4,j)
  END DO
END IF

RETURN
END SUBROUTINE objective_functions


!----------------------------------------------------------------------
SUBROUTINE equality_constraints(model_n,n,nh,p,x,h)
! calculate equality constraints

INTEGER model_n,nh,n,p
REAL h(nh,p), x(n,p)

IF (model_n==301) THEN
  DO j=1,p
   h(1,j)=x(2,j)-x(1,j)**2
  END DO
ELSE IF (model_n==302) THEN
  DO j=1,p
   h(1,j)=x(1,j)**2+x(2,j)**2+x(3,j)**2+x(4,j)**2+x(5,j)**2-10
    h(2,j)=x(2,j)*x(3,j)-5*x(4,j)*x(5,j)
    h(3,j)=x(1,j)**3+x(2,j)**3+1
  END DO
ELSE IF (model_n==303) THEN
  DO j=1,p
   h(1,j)=1000*SIN(-x(3,j)-0.25)+1000*SIN(-x(4,j)-0.25)+894.8-x(1,j)
    h(2,j)=1000*SIN(x(3,j)-0.25)+1000*SIN(x(3,j)-x(4,j)-0.25)+894.8-x(2,j)
    h(3,j)=1000*SIN(x(4,j)-0.25)+1000*SIN(x(4,j)-x(3,j)-0.25)+1294.8
  END DO
ELSE IF (model_n==304) THEN
  DO j=1,p

h(1,j)=(x(1,j)**2+x(2,j)**2+x(3,j)**2+x(4,j)**2+x(5,j)**2+x(6,j)**2+x(7,j)**2+x(8,j)*
*2+x(9,j)**2+x(10,j)**2)-1
  END DO
ELSE IF (model_n==401) THEN
  DO j=1,p
   h(1,j)=x(10,j)-0.1*x(8,j)-x(12,j)
```

```
   h(2,j)=x(3,j)*x(8,j)/(x(9,j)-x(4,j)-x(12,j))-2*(2.5962e12)*exp(-
15000/x(11,j))*x(6,j)*x(7,j)*50*60/(x(9,j)*x(9,j))
   h(3,j)=2.5962e12*exp(-15000/x(11,j))*x(6,j)*x(7,j)*50*60/(x(9,j)*x(9,j))-
0.5*9.6283e15*exp(-20000/x(11,j))*x(7,j)*x(10,j)*50&
   *60/(x(9,j)*x(9,j))-(x(10,j)-x(12,j))*x(3,j)/(x(9,j)-x(4,j)-x(12,j))-x(12,j)
   h(4,j)=x(1,j)-5.9755e9*exp(-12000/x(11,j))*x(5,j)*x(6,j)*50*60/(x(9,j)*x(9,j))-
x(5,j)*x(3,j)/(x(9,j)-x(4,j)-x(12,j))
   h(5,j)=x(2,j)-5.9755e9*exp(-12000/x(11,j))*x(5,j)*x(6,j)*50*60/(x(9,j)*x(9,j))-
2.5962e12*exp(-15000/x(11,j))*x(6,j)*x(7,j)*50*60&
   /(x(9,j)*x(9,j))-x(6,j)*x(3,j)/(x(9,j)-x(4,j)-x(12,j))
   h(6,j)=2*(5.9755e9*exp(-12000/x(11,j))*x(5,j)*x(6,j)*50*60/(x(9,j)*x(9,j))-
2.5962e12*exp(-15000/x(11,j))*x(6,j)*x(7,j)*50*60&
   /(x(9,j)*x(9,j)))-9.6283e15*exp(-20000/x(11,j))*x(7,j)*x(10,j)*50*60/(x(9,j)*x(9,j))-
x(7,j)*x(3,j)/(x(9,j)-x(4,j)-x(12,j))
   h(7,j)=1.5*9.6283e15*exp(-20000/x(11,j))*x(7,j)*x(10,j)*50*60/(x(9,j)*x(9,j))-x(4,j)
   h(8,j)=x(9,j)-x(5,j)-x(6,j)-x(7,j)-x(8,j)-x(10,j)-x(4,j)
  END DO
END IF

RETURN
END SUBROUTINE equality_constraints


!----------------------------------------------------------------------
SUBROUTINE inequality_constraints(model_n,n,x,ng,p,g)
! calculate inequality constraints
! all equality constraints are of the "g(x)<=0" type

INTEGER model_n, n, ng,p,j
REAL x(n,p), g(ng,p)

IF (model_n==201) THEN
  DO j=1,p
   g(1,j)=6-x(2,j)-9*x(1,j)
     g(2,j)=1+x(2,j)-9*x(1,j)
  END DO
ELSE IF (model_n==202) THEN
  DO j=1,p
   g(1,j)=x(1,j)**2+x(2,j)**2-225
     g(2,j)=x(1,j)-3*x(2,j)+10
  END DO
ELSE IF (model_n==203) THEN
  tanaka=1
  IF (tanaka==1) THEN
   a=0.1
     b=16
```

```
  ELSE IF (tanaka==2) THEN
    a=0.1
      b=32
  ELSE IF (tanaka==3) THEN
    a=0.1
      b=32
  ELSE IF (tanaka==4) THEN
    a=0.1
      b=32
  END IF
  DO j=1,p
    g(1,j)=-(x(1,j)**2+x(2,j)**2-1-a*COS(b*ATAN(x(2,j)/x(1,j))))
      g(2,j)=(x(1,j)-0.5)**2+(x(2,j)-0.5)**2-0.5
  END DO
ELSE IF (model_n==204) THEN
  DO j=1,p
    g(1,j)=-(x(1,j)+x(2,j)-2)
      g(2,j)=-(6-x(1,j)-x(2,j))
      g(3,j)=-(2-x(2,j)+x(1,j))
      g(4,j)=-(2-x(1,j)+3*x(2,j))
      g(5,j)=-(4-(x(3,j)-3)**2-x(4,j))
      g(6,j)=-((x(5,j)-3)**2+x(6,j)-4)
  END DO
ELSE IF (model_n==205) THEN
  DO i=1,p
    g(1,j)=(x(1,j)-5)**2+x(2,j)**2-25
      g(2,j)=-((x(1,j)-8)**2+(x(2,j)-3)**2-7.7)
  END DO
ELSE IF (model_n==303) THEN
  DO i=1,p
    g(1,j)=-x(4,j)+x(3,j)-0.55
      g(2,j)=-x(3,j)+x(4,j)-0.55
  END DO
ELSE IF (model_n==401) THEN
  DO j=1,p
    g(1,j)=-(8400*(0.3*x(12,j)+0.0068*x(3,j)-0.02*x(1,j)-0.03*x(2,j))-2.22*x(9,j)-
0.124*8400*(0.3*x(12,j)+0.0068*x(3,j))-3000*60)
  END DO
END IF

RETURN
END SUBROUTINE inequality_constraints


!-----------------------------------------------------------------------
SUBROUTINE feasibility_ranking(p,h,g,nh,ng,cv,r_fea,n_fea)
```

```
! calculate feasibility measures for the current population

INTEGER p,ng,nh,nc,counter, r_fea(p),n_fea
REAL h(nh,p),g(ng,p),c(nh+ng,p),cv(p), h_threshold(nh)
REAL max_c(ng+nh), min_c(ng+nh), norm_c(nh+ng,p)

nc=nh+ng  ! nc is total number of equality and inequality constraints
h_threshold(1:nh)=0.01 ! set threshold value for equality constraints

DO j=1,p
  DO i=1,nh
    c(i,j)=MAX(ABS(h(i,j))-h_threshold(i),0.0)
      ! calculate constraint violation for equality constraints
  END DO
  DO i=1,ng
    c(nh+i,j)=MAX(0.0,g(i,j))
      ! calculate constraint violation for ineqaulity constraints
  END DO
END DO

cv=SUM(c,DIM=1) ! feasibility measure uses the total violation
n_fea=0

DO j=1,p
  IF (cv(j)==0) THEN
    r_fea(j)=0
      n_fea=n_fea+1
  ELSE
    r_fea(j)=1
  END IF
END DO

DO i=1,p-1
  DO j=i+1,p
    IF (cv(i)/=0 .AND.cv(j)/=0) THEN
        IF (cv(i)>cv(j)) THEN
          r_fea(i)=r_fea(i)+1
        ELSE IF (cv(i)<cv(j)) THEN
          r_fea(j)=r_fea(j)+1
        END IF
    END IF
  END DO
END DO

RETURN
END
```

```
!---------------------------------------------------------------------
SUBROUTINE distance_check(n_dimension,point,p,distance)
! calculate the distance between each pair of individuals

INTEGER n_dimension,p
REAL point(n_dimension,p), normalized_point(n_dimension,p),distance(p,p),
delta_point(n_dimension),squaresum_delta_point
REAL max_point(n_dimension),min_point(n_dimension)

max_point(1:n_dimension)=-1000000000
min_point(1:n_dimension)=1000000000

DO i=1,n_dimension
  DO j=1,p
    IF (point(i,j)>max_point(i)) THEN
        max_point(i)=point(i,j)
        ! identify the highest valued point in each dimension
      END IF
      IF (point(i,j)<min_point(i)) THEN
        min_point(i)=point(i,j)
        ! identify the lowest valued point in each dimension
      END IF
  END DO
END DO

DO i=1,n_dimension
  DO j=1,p
    normalized_point(i,j)=(point(i,j)-min_point(i))/(max_point(i)-min_point(i))
      ! normalize the individuals in each dimension before distance calculation
  END DO
END DO

DO j=1,p-1
  DO k=j+1,p
    squaresum_delta_point=0
      DO i=1,n_dimension
        delta_point(i)=normalized_point(i,j)-normalized_point(i,k)
        squaresum_delta_point=squaresum_delta_point+delta_point(i)**2
      END DO
      distance(j,k)=SQRT(squaresum_delta_point)
      ! the distance from j to k is the square root of the sum of their differences in each
dimension
  END DO
END DO
```

```
DO j=p,2,-1
  DO k=j-1,1,-1
    distance(j,k)=distance(k,j)
      ! the distanace from j to k equals the distance from k to j
  END DO
END DO

DO j=1,p
  distance(j,j)=0
  ! the distance from an individual to itself is zero
END DO

RETURN
END


!------------------------------------------------------------------------
SUBROUTINE diversity_ranking(n_dimension,point,p,r_div)
! calculate diversity measures for the current population

INTEGER p,  n_dimension,distance_rank(p,p),kth,average_k_distance_rank(p),r_div(p)
REAL point(n_dimension), distance(p,p), ranked_distance(p,p)
REAL k_distance_sum,average_k_distance(p)

CALL distance_check(n_dimension,point,p,distance)
! calculate the distance between each pair of individuals

DO i=1,p
  distance_rank(i,1:p)=1
  DO j=1,p-1
    DO k=j+1,p
      IF (distance(i,j)<distance(i,k)) THEN
          distance_rank(i,k)=distance_rank(i,k)+1
        ELSE IF (distance(i,j)>distance(i,k)) THEN
        distance_rank(i,j)=distance_rank(i,j)+1
        END IF
      END DO
  END DO
END DO
! For each individual, rank the entire population based on the distance to it.

DO i=1,p
  DO j=1,p
    ranked_distance(i,distance_rank(i,j))=distance(i,j)
  END DO
```

```
END DO

kth=INT(SQRT(REAL(p)))
! k equals the square root of the number of the individuals in the population

DO i=1,p
  k_distance_sum=0
  DO j=1,kth
    k_distance_sum=k_distance_sum+ranked_distance(i,j)
  END DO
  average_k_distance(i)=k_distance_sum/kth
END DO
! for each individual, calculate the average distance to its kth nearest neighbor

r_div(1:p)=1
DO j=1,p-1
  DO k=j+1,p
    IF (average_k_distance(j)>average_k_distance(k)) THEN
      r_div(k)=r_div(k)+1
    ELSE IF(average_k_distance(j)<average_k_distance(k)) THEN
      r_div(j)=r_div(j)+1
    END IF
  END DO
END DO
! the diversity measure of an individual equals its average distance to its kth nearest
neighbors

RETURN
END


!----------------------------------------------------------------------
SUBROUTINE
twop_weak_dominance(point1,point2,p,n_vector,vector,counter_point1,counter_point2)
! check weak dominance relation between two points

INTEGER counter_point1,counter_point2,n_vector, point1,point2
REAL vector(n_vector,p)
counter_point1=0
counter_point2=0

DO i=1,n_vector
  IF (vector(i,point1)-vector(i,point2)<0) THEN
    counter_point1=counter_point1+1
  ELSE IF (vector(i,point1)-vector(i,point2)==0) THEN
    counter_point1=counter_point1+1
```

```
    counter_point2=counter_point2+1
  ELSE IF (vector(i,point1)-vector(i,point2)>0) THEN
    counter_point2=counter_point2+1
END IF
END DO

RETURN
END


!----------------------------------------------------------------------
SUBROUTINE constrained_objective_ranking(p,cv,nf,f,r_conobj)
! perform a so-called constrained-objective ranking on the current population
! using constrain dominance in (Deb, 2001)

INTEGER i,j,nf,p,binary_cv(p,p), binary_f(p,p), binary(p,p), r_conobj(p)
INTEGER counter_point1, counter_point2
REAL cv(p), f(nf,p)

r_conobj(1:p)=0

DO i=1,p-1
  DO j=i+1,p
      binary_cv(i,j)=0
      binary_f(i,j)=0
      binary(i,j)=0

      IF (cv(i)<cv(j)) THEN
      binary_cv(i,j)=1
    ELSE IF (cv(i)>cv(j)) THEN
        binary_cv(i,j)=-1
      END IF
      ! compare the individials i and j in terms of their constraint violation

      CALL  twop_weak_dominance(i,j,p,nf,f,counter_point1,counter_point2)
      IF (counter_point1==nf .and. counter_point2<nf) THEN
      binary_f(i,j)=1
    ELSE IF ((counter_point2==nf .and. counter_point1<nf)) THEN
        binary_f(i,j)=-1
      END IF
      ! perform dominance check between the individual i and j in terms of their vector
objective function values

      ! below is the definition of constrain-dominance
      IF (cv(i)>0.AND.cv(j)>0) THEN
        binary(i,j)=binary_cv(i,j)
```

```
    ! if both infeasible, the one with less constraint violation is better
    ELSE IF (cv(i)==0.AND.cv(j)==0) THEN
    binary(i,j)=binary_f(i,j)
    ! if both feasible, look at the dominance check results
   ELSE IF (cv(i)==0.AND.cv(j)>0) THEN
     binary(i,j)=1
    ELSE IF (cv(i)>0.AND.cv(j)==0) THEN
     binary(i,j)=-1
    ! if one is feasible and the other is not, then feasible one is better
    END IF

    IF (binary(i,j)==1) THEN
    r_conobj(j)=r_conobj(j)+1
   ELSE IF (binary(i,j)==-1) THEN
    r_conobj(i)=r_conobj(i)+1
   END IF
   ! one's the constrained-objective rank equals the number of individuals that constrain-
dominate it
  END DO
END DO

RETURN
END


!-----------------------------------------------------------------------
SUBROUTINE ordinal_ranking(p,r_conobj,r_div,r)
! perform ordinal ranking on the current population

INTEGER i,j
INTEGER p,r_conobj(p),r_div(p), r(p)

r(1:p)=1

DO i=1,p-1
  DO j=i+1,p
   IF (r_conobj(i)>r_conobj(j)) THEN
     r(i)=r(i)+1
    ELSE IF (r_conobj(i)<r_conobj(j)) THEN
     r(j)=r(j)+1
   ELSE
    IF (r_div(i)<r_div(j)) THEN
     r(j)=r(j)+1
    ELSE IF (r_div(j)<r_div(i)) THEN
     r(i)=r(i)+1
    END IF
```

```
    END IF
  END DO
END DO

RETURN
END


!-----------------------------------------------------------------------
SUBROUTINE output(p,nf,f,cv,r_obj,r_div,r_fea,r_conobj,r)
! this subroutine output the objective function values, constraint violation values
! and various ranks in the desired format

INTEGER nf,p,r_obj(p),r_fea(p),r_div(p),r(p),r_conobj(p)
REAL f(nf,p),cv(p)

write (10,*)
write (10,*) "    "," ------cv------ "," -------------f------------- ", " r_fea ", "r_conobj ", "
r_div "," r "
DO j=1,p
  write (10,26) j,cv(j),f(1:nf,j),r_fea(j),r_conobj(j),r_div(j),r(j)
END DO
26 FORMAT (i3,e10.3,6x,2f10.3,12x,i4,3x,i4,3x,i4,3x,i4)

RETURN
END


!-----------------------------------------------------------------------
SUBROUTINE output_x(n,p,x)
! this subroutine output x values in the desire format

INTEGER n,p
REAL x(n,p)

  write (10,*)
  DO j=1,p
     write (10,33) j,x(1:n,j)
33  FORMAT("p",i3,100f12.3)
  END DO
  write (10,*)

RETURN
END
```

```
!-----------------------------------------------------------------------
SUBROUTINE mating_pool(p,n,x,r,mating_pool_x,gen)
! perform tournament selection on the current population until the mating pool is created

INTEGER, PARAMETER:: tournament_size=5
INTEGER n,p, ms(8),q,curr_time(1),athlete(tournament_size),r(p),lowest_r,champ,gen
REAL x(n,p),rannum1(tournament_size,p), mating_pool_x(n,p)

! use random number generator
CALL DATE_AND_TIME (VALUES=ms)
q=ABS(TIME())
curr_time(1)=q+(8*ms(8))+gen
CALL RANDOM_SEED (PUT=curr_time)
CALL RANDOM_NUMBER (rannum1)

DO j=1,p
  DO i=1,tournament_size
    athlete(i)=1+INT(p*rannum1(i,j))
      ! randomly select tournament_size individuals from the population
  END DO
  lowest_r=1000000
  DO i=1, tournament_size
    IF (r(athlete(i))<=lowest_r) THEN
         lowest_r=r(athlete(i))
      END IF
  END DO
  ! rank selected individuals in terms of their ordinal rank

  DO i=1, tournament_size
    IF (r(athlete(i))==lowest_r) THEN
       champ=athlete(i)
      END IF
  END DO
  ! lowest ranked individual wins the tournament

  DO i=1,n
       mating_pool_x(i,j)=x(i,champ)
  END DO
  ! copy the winner the send it to the mating pool
END DO

RETURN
END


!-----------------------------------------------------------------------
```

```
SUBROUTINE environmental_selection (p,p_elite,n,x,r)
! select the first p_elite ranked individuals and save them as elites
! elites in this case is always preseved in the last p_elite seats of the population

INTEGER p,p_elite,n,r(p)
REAL  ascent_r_x(n,p),x(n,p)

DO j=1,p
  DO i=1,n
    ascent_r_x(i,r(j))=x(i,j)
  END DO
END DO

DO j=1,p_elite
  DO i=1,n
    x(i,p-j+1)=ascent_r_x(i,j)
  END DO
END DO

RETURN
END


!----------------------------------------------------------------------
SUBROUTINE variation(crossover_rate,
mutation_rate,p,p_elite,n,x,xl,xu,mating_pool_x,gen)
! perform genetic operations to update the current population

INTEGER n,p,p_elite, ms(8), o,curr_time(1), identity, identity1,identity2,gen
REAL crossover_rate, mutation_rate, x(n,p), parent1(n),
parent2(n),offspring1(n),offspring2(n)
REAL rannum2(2,p), rannum3(2,n,p), rannum4(2,p),
rannum5(2,p),rannum6(2,p),rannum7(n,p),rannum8(n,p),rannum9(n,p)
REAL xl(n),xu(n),cmin(n),cmax(n),q(n),l(n),u(n),alfa,temp,mating_pool_x(n,p)

k=1 ! replacement counter

! generate the required random numbers
CALL DATE_AND_TIME (VALUES=ms)
o=ABS(TIME())
curr_time(1)=o-(2*ms(8))+gen
CALL RANDOM_SEED (PUT=curr_time)
CALL RANDOM_NUMBER (rannum2)
CALL RANDOM_NUMBER (rannum3)
CALL RANDOM_NUMBER (rannum4)
CALL RANDOM_NUMBER (rannum5)
```

```
CALL RANDOM_NUMBER (rannum6)
CALL RANDOM_NUMBER (rannum7)
CALL RANDOM_NUMBER (rannum8)
CALL RANDOM_NUMBER (rannum9)

DO
  n1=1+INT((p-1)*rannum2(1,k))
  n2=1+INT((p-1)*rannum2(2,k+1))
  DO i=1,n
    parent1(i)=mating_pool_x(i,n1)
    parent2(i)=mating_pool_x(i,n2)
  END DO
  ! select two random individuals from the mating pool as the parents

  DO i=1,n
  offspring1(i)=parent1(i)
  offspring2(i)=parent2(i)
  END DO
  ! copy both parents as two offsprings

  identity=0
  DO i=1,n
    IF (offspring1(i)==offspring2(i)) THEN
      identity=identity+1
    END IF
  END DO

  IF (identity==n) THEN
    DO i=1,n
        offspring2(i)=(xu(i)-xl(i))*rannum7(i,k)+xl(i)
      END DO
  ! if the two offsprings happen to be the same, change the second offspring to a new
random value
  END IF

  IF (rannum4(1,k)<crossover_rate) THEN
  ! if crossover is activated (by a given possibility)
  ! perform BLX-alfa crossover
    alfa=0.5 ! set the parameter alfa
    DO i=1,n
      cmax(i)=max(offspring1(i),offspring2(i))
      cmin(i)=min(offspring1(i),offspring2(i))
      q(i)=cmax(i)-cmin(i)
      l(i)=max(cmin(i)-q(i)*alfa,xl(i))
      u(i)=min(cmax(i)+q(i)*alfa,xu(i))
      offspring1(i)=(u(i)-l(i))*rannum3(1,i,k)+l(i)
```

```
    offspring2(i)=(u(i)-l(i))*rannum3(2,i,k)+l(i)
   END DO
 END IF

 100 CONTINUE

 IF (rannum4(2,k)<mutation_rate) THEN
 ! if mutation is activated (by a given possiblity)
 ! perform random mutation
   offspring1(INT((n-1)*rannum5(1,k)+1))=(xu(INT((n-1)*rannum5(1,k)+1))-xl(INT((n-1)*rannum5(1,k)+1)))*rannum6(1,k)+xl(INT((n-1)*rannum5(1,k)+1))
   offspring2(INT((n-1)*rannum5(2,k)+1))=(xu(INT((n-1)*rannum5(2,k)+1))-xl(INT((n-1)*rannum5(2,k)+1)))*rannum6(2,k)+xl(INT((n-1)*rannum5(2,k)+1))
 END IF

 DO j=p-p_elite+2-k,p
   identity1=0
     DO i=1,n
       IF (offspring1(i)==x(i,j)) THEN
         identity1=identity1+1
       END IF
     END DO
   IF (identity1==n) THEN
       WRITE (10,*) "find a clone! --1, same as ", j, "th individual"
     END IF
     GO TO 131
 END DO

131 CONTINUE

 DO j=p-p_elite+2-k,p
   identity2=0
     DO i=1,n
       IF (offspring2(i)==x(i,j)) THEN
         identity2=identity2+1
       END IF
     END DO
   IF (identity2==n) THEN
       WRITE (10,*) "find a clone! --2,same as ", j, "th individual"
     END IF
     GO TO 141
 END DO

141 CONTINUE

 IF (identity1==n) THEN
```

```
    DO i=1,n
      offspring1(i)=(xu(i)-xl(i))*rannum8(i,k)+xl(i)
    END DO
    write (10,*) "clone 1 mutated!"
  END IF
  IF (identity2==n) THEN
    DO i=1,n
     offspring2(i)=(xu(i)-xl(i))*rannum9(i,k)+xl(i)
    END DO
    write (10,*) "clone 2 mutated!"
  END IF

  DO i=1,n
    x(i,k)=offspring1(i)
  END DO
  IF (k<p-p_elite) THEN
    DO i=1,n
     x(i,k+1)=offspring2(i)
    END DO
     k=k+1
  END IF
  ! update the current population until all the non-elite (first p-p_elite individuals)
  ! are replaced by newly produced individuals
IF (k>=p-p_elite) EXIT
k=k+1
END DO

RETURN
END


!----------------------------------------------------------------------
SUBROUTINE feasible_pareto(x,n,p,nf,f,r_conobj,r_fea)
! this subroutine identify the feasible and Pareto optimal solutions in the population

INTEGER n,p,nf,r_conobj(p),k,r_fea(p)
REAL x(n,p),f(nf,p),feasible_pareto_x(n,p),feasible_pareto_f(nf,p)

k=0
DO j=1,p
  IF (r_conobj(j)==0.and.r_fea(j)==0) THEN
    k=k+1
     DO i=1,n
      feasible_pareto_x(i,k)=x(i,j)
     END DO
     DO i=1,nf
```

```
      feasible_pareto_f(i,k)=f(i,j)
    END DO
  END IF
END DO
! if a solution is feasible and Pareto optimal, send it to the designated set

DO i=1,n
  WRITE (10,*) "feasible_pareto_x",i,"="
  DO j=1,k
    WRITE (10,*) feasible_pareto_x(i,j)
  END DO
END DO

DO i=1,nf
  WRITE (10,*) "feasible_pareto_f",i,"="
  DO j=1,k
    WRITE (10,*) feasible_pareto_f(i,j)
  END DO
END DO
! output these feasible and Pareto optimal solutions
RETURN
END
```

VITA

XUN JIN

Candidate for the Degree of

Doctor of Philosophy

Thesis: APPROACHING SUSTAINABILITY IN ENGINEERING DESIGN WITH MUTLIPLE CRITERIA DECISION ANALYSIS

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Title of Study: APPROACHING SUSTAINABILITY IN ENGINEERING DESIGN WITH MULTIPLE CRITERIA DECISION ANALYSIS

Pages in Study: 236 Candidate for the Degree of Doctor of Philosophy

Major Field: Chemical Engineering

Scope and Method of Study: This research aimed to the establishment of a general methodological framework, via which the "fuzzy" and "debatable" goal of sustainability can be practically achieved in engineering design. In-depth literature review on the sustainability concept was first conducted in an attempt to grasp its philosophical essence from various interpretations and distinct implementations. The application of the proposed framework was addressed by developing or identifying specific building block techniques, each of which accomplish a different task, such as criteria-attribute mapping, preference modeling, and search. The proposed building block techniques were selected based on systematic comparisons among a wide range of alternative methods and tested by case studies or test problems.

Findings and Conclusions: Sustainability is a multiplex property of an integrated system. The key to make a reality of sustainability in engineering design is to properly handle its complex nature and deeply rooted conflicts. In this work, Multiple Criteria Decision Analysis (MCDA) was proven ideal for filling the vacuum of a general operational framework. To implement this framework, a four-step procedure needs to be first performed to formulate a sustainability-oriented design into a "standard" Multiple Criteria Decision Making (MCDM) problem. The proposed attribute hierarchy "Stressor-Status-Effect-Integrality-Well-being" and the 4-class metric classification scheme could help engineers to accomplish such a task in the environmental dimension. The achievement of the final "sustainable" design relies on making appropriate decisions. A MAVT-based technique developed in this study provides a rational and informed way of solving the decision problems with a discrete set of explicitly known alternatives. For Multi-Objective Programming (MOP) problems featuring an infinite and implicitly characterized alternative space, the proposed Ordinal Ranking-based Genetic Algorithm (ORGA) offers a desired searching tool by generating uniformly sampled solutions that are feasible and globally Pareto optimal.

ADVISER'S APPROVAL: Dr. Karen A. High