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Fuzzy Hierarchical Model for Risk Assessment

Principles, Concepts, and Practical Applications

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Chapter 1
Introduction

1.1 Multi-Criteria Decision-Making Problems and Risk Assessment

Making decisions is part of human life. Nevertheless, making a good decision is not always easy. This is mainly because there are many contributing factors (i.e. we have multiple criteria) in a problem. Even worse, many of them involve multiple objectives (i.e. multiple input, multiple output). That means the objectives of the problems in question may be conflicting with each other. On the one hand, solving such problems can entertain multiple dimensionalities. If the factors involved in such decision-making process are all quantitative in nature, the best solution can be obtained by evaluating a multi-attribute utility function as follows (Chan and Chan 2004):

$$U_i(x_1, x_2, \ldots, x_m) = k_1 u_{i1}(x_1) + k_2 u_{i2}(x_2) + \ldots + k_m u_{im}(x_m), \quad i = 1, 2, \ldots, n \tag{1.1}$$

where $U_i(x_1, x_2, \ldots, x_m)$ is the utility function of m attributes (i.e. inputs) of the ith alternative,

x_i are attributes under consideration,
k_j is weighing of jth attribute such that summation of k_j is equal to 1 and
u_{ij} is the effect of ith alternative related to jth attribute, that is, x_j.

Therefore, the solution to such problems is the feasible solution with the maximum or minimum value of the utility function. Subject to such setting, the quality of the solutions of such problems can be maintained relatively easily. The only concern would be to determine the scientific way to measure each input (i.e. x_i) and its effect (i.e. u_{ij}). Of course, finding a right balance between the set of weightings is also crucial as this may involve subjective judgement on the relative importance of one effect to the other effects.

On the other hand, many of the real-life problems are unfortunately not that easy to solve. This is mainly because most of them involve qualitative factors. That means they cannot be modelled mathematically as in Eq. (1.1), regardless of

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the aforementioned shortcomings. Therefore, how to quantify such qualitative variables is always the controversial topic, if not impossible, when solving such multiple-criteria decision-making (MCDM) problems. The controversy mainly comes from the subjective judgement of the qualitative factors, which always rely on experts' opinion, and is not consistently reliable. Such judgement inevitably affects the quality of the solution obtained. This is analogous in many cases to assign the weightings in Eq. (1.1). However, the latter is relatively consistent as the importance can be deduced through a more rigours and scientific way.

Luckily, Saaty (1978, 1980) developed a ground-breaking tool to handle such MCDM problems. This is called analytic hierarchy process (AHP). The basic idea is to represent such MCDM problems by a hierarchical structure with different criteria and their sub-criteria (which can be further extended to include more layers of sub-criteria). Those criteria or sub-criteria can be qualitative or quantitative in nature. Then, pairwise comparisons among those criteria are performed so that the weightings of the criteria (or priority in some applications) with respect to the problem can then be estimated. Although experts' judgement is also required in this procedure, at least there is a way to ensure that the judgement is consistent by examining the consistency ratio (to be discussed in Chap. 3). In addition, this approach can be used to select the best alternative based on these weightings and their relative importance to each criterion. Details of the theory and an illustrative example are presented in Chap. 3.

There has been much research in the literature on the uncertainty and risk assessment with the increasing emphasis on risk management across various industry sectors. Risk management is a typical MCDM problem and is always a practical subject in the research and industrial community (Gómez-Limón et al. 2003; Wang et al. 2010; Krohling and De Souza 2012). The most basic objective of risk management is to prevent things going wrong due to reliability issues, system failure and so on. Owing to its multi-criteria nature, researchers or practitioners are hindered to approach the solutions of many of these problems. This is particularly obvious if the problem involved many entities like in supply chains (Wieland and Wallenburg 2012). As an important element of risk management, many risk assessment methods and tools have been proposed and applied in practice over the last few decades. One common characteristic of different risk assessment studies is that both qualitative and quantitative elements are present that makes the problems even more unattainable. In this connection, a hierarchical approach like AHP is a logical tool to address risk assessment applications or problems. As a consequence, qualitative and quantitative information can be used in the risk assessment process.

Nevertheless, risks are highly random in nature, which means different forms of uncertainty exist which further hamper the development of solutions, if any. For instance, demand is well known to be uncertain in supply chain systems, but lead time could also be uncertain due to interruption in supply, breakdown of machinery in production and so on (Chan and Chan 2010). Probabilistic approach is one of many methods to model uncertainty for risk assessment (Khadam and Kaluarachchi 2003; Zafra-Cabeza et al. 2007). Even the aforementioned AHP is not able to take those factors into consideration. In this connection, fuzzy logic, which can handle vague information (Zadeh 1965), is incorporated into the model so that a final risk index can be calculated. Such application is not uncommon in the literature (e.g. Chen and Chen 2003; Nieto-Morote and Ruz-Vila 2011; Wang et al. 2012).

In this book, a variety of cases, namely supplier management, eco-design of electronic products, food supply chain and implementation of green supply chain strategies will be used to illustrate how the proposed fuzzy hierarchical model can be employed in real-life applications.

1.2 Organisation of this Book

The rest of this book contains eight chapters. Chapters 2 and 3 provide the basic knowledge of the topics covered in this book, including risk assessment and hierarchical models for MCDM problems. Then, applications of five different models in five different cases are presented. The organisation of this book is outlined as follows:

- Chapter 2 provides a review of the risk assessment in the manufacturing and supply chain domain. The chapter is divided into two parts. First, different risk assessment methods including quantitative methods, qualitative methods and fuzzy risk assessment are discussed. The benefits and disadvantages of each method are outlined. The second part of the chapter reviews the implementations of different risk assessment methods across a wide range of application areas including supply chain risk management, environmental risk assessment, food safety risk assessment and project risk assessment. In addition to highlighting the development of risk assessment in those areas, it also finds that using MCDM approach and fuzzy set theory in the risk assessment gives structure to the decision-making process and allows users to model the uncertainty mathematically.
- Chapter 3 discusses various fuzzy hierarchical models available in the literature. The chapter first introduces the basic of AHP. It is followed by an illustrative numerical example of using AHP. The case is in fact a preliminary case of a study in a later chapter. Then, four main fuzzy AHP approaches are briefly discussed. They are standard fuzzy AHP, fuzzy extent analysis, fuzzy TOPSIS and fuzzy analytic network process (ANP). The basic operations and some applications of the approaches are briefly reviewed. These sections pave the way for the subsequent chapters.
- Chapter 4 first introduces a simply hybrid model that incorporates fuzzy logic and AHP. A two-step approach is proposed such that the pairwise comparisons of standard AHP are first carried out. The objective is to determine the weightings of different criteria as in standard AHP operations, like the one in Chap. 3. Then, fuzzy logic is incorporated to calculate the aggregated risk index of the problem under study. The idea is to quantify the risk of individual criteria

as a measure of the vulnerability of system in question. The proposed approach is easy to use compared to other fuzzy-based AHP approaches presented in subsequent chapters. This approach is applied in the supplier management problems. A case study of a stainless steel parts manufacturer is presented. The main products of the company are of course stainless steel products, and the major customers are for final production of telecommunication equipment. An aggregative supplier risk index is developed for supplier risk assessment.

- Chapter 5 presents the most basic fuzzy AHP formulation (e.g. Buckley 1985). In such approach, pairwise comparisons are carried out using linguistic variables such that the elements in the AHP reciprocal matrix (to explain in Chap. 3) are represented by fuzzy membership functions (triangular membership functions in this chapter). The matrix is then defuzzified using the most commonly employed centre-of-area approach. This operation is of vital importance because a non-fuzzy matrix will then form for standard AHP operations in order to determine the weightings of each criterion and so on. The approach is applied in the selection of eco-design options for electronic products, subject to different environmental risk assessments. From those weightings, the importance of different criteria with respect to different environmental assessment can be determined so that the risk to comply with good eco-design practices can be minimised.
- One problem of the fuzzy AHP used in Chap. 5 is its lengthy comparisons. Chapter 6 thus makes use of a relatively sophisticated approach, but with less computational effort, to tackle this problem. The fuzzy extent analysis proposed by Chang (1996) for AHP is employed. This can reduce the number of comparisons (and hence computational effort) as in fuzzy AHP. One core step in the approach is to calculate the fuzzy extent value of each criterion with respect to each goal or alternative, depending on the problem formulation. In Chap. 6, an application of the food supply chain risk management using this method is presented. A noticeable contribution of the application is that an aggregative food safety risk indicator (AFSRI) which provides a single value representing the risk rating is proposed. Alternative with the lowest risk can then be determined.
- A competitor to the fuzzy extent analysis is fuzzy technique for order preference by similarity to ideal solution (TOPSIS). The latter can also be used together with AHP so that a fuzzy TOPSIS for AHP is applied in another case study in Chap. 7. The principle of TOPSIS is to evaluate the performance of alternatives through the similarity with the ideal solution (Hwang and Yoon 1981). Detailed discussions of the operations can be found in Chap. 7, where an application of green supply chain implementation on risk assessment is also presented.
- One of the drawbacks of the above methods is that independency among criteria and sub-criteria of the hierarchical structure is not considered. That may lead to inaccurate, or even wrong, decisions. Therefore, Saaty (1986) also developed an ANP to address this issue. As a matter of fact, this approach can also be supplemented by fuzzy logic, so vague information can be taken into account in the model. The procedure of the ANP is of course more complicated than the AHP

counterpart. Development of a supermatrix is required during the decision-making process. More information will be presented in Chap. 8. In that chapter, the method is applied to environmental risk assessment of product design case used in Chap. 5. The major objective is to allow readers to compare and contrast the standard fuzzy AHP and this fuzzy ANP approach.

- Chapter 9 will conclude this book by summarising the methods and cases that appear in various chapters. In addition, future research directions are suggested.

References

Buckley, J. (1985). Fuzzy hierarchical analysis. *Fuzzy Sets and Systems, 17*, 233–247.

Chan, F. T. S., & Chan, H. K. (2004). A comprehensive survey and future trend of simulation study on FMS scheduling. *Journal of Intelligent Manufacturing, 15*(1), 87–102.

Chan, H. K., & Chan, F. T. S. (2010). Comparative study of adaptability and flexibility in distributed manufacturing supply chains. *Decision Support Systems, 48*(2), 331–341.

Chang, D. Y. (1996). Applications of the extent analysis method on fuzzy AHP. *European Journal of Operational Research, 95*(3), 649–655.

Chen, S. J., & Chen, S. M. (2003). Fuzzy risk analysis based on similarity measures of generalized fuzzy numbers. *IEEE Transactions on Fuzzy Systems, 11*(1), 45–56.

Gómez-Limón, J. A., Arriaza, M., & Riesgo, L. (2003). An MCDM analysis of agricultural risk aversion. *European Journal of Operational Research, 151*(3), 569–585.

Hwang, C. L., & Yoon, K. (1981). *Multiple attributes decision making methods and applications*. Berlin: Springer.

Khadam, I. M., & Kaluarachchi, J. J. (2003). Multi-criteria decision analysis with probabilistic risk assessment for the management of contaminated ground water. *Environmental Impact Assessment Review, 23*(6), 683–721.

Krohling, R. A., & De Souza, T. T. M. (2012). Combining prospect theory and fuzzy numbers to multi-criteria decision making. *Expert Systems with Applications, 39*(13), 11487–11493.

Nieto-Morote, A., & Ruz-Vila, F. (2011). A fuzzy approach to construction project risk assessment. *International Journal of Project Management, 29*(2), 220–231.

Saaty, T. L. (1978). Modeling unstructured decision problems—the theory of analytical hierarchies. *Mathematics and Computers in Simulation, 20*(3), 147–158.

Saaty, T. L. (1980). *The analytic hierarchy process*. New York: McGraw-Hill.

Saaty, T. L., & Takizawa, M. (1986). Dependence and independence: From linear hierarchies to nonlinear networks. *European Journal of Operational Research, 26*, 229–237.

Wang, X., Chan, H. K., Yee, R. W. Y., & Diaz-Rainey, I. (2012). A two-stage fuzzy-AHP model for risk assessment of implementing green initiatives in the fashion supply chain. *International Journal of Production Economics, 135*(2), 595–606.

Wang, X., Li, D., O'Brien, C., & Li, Y. (2010). A production planning model to reduce risk and improve operations management. *International Journal of Production Economics, 124*(2), 463–474.

Wieland, A., & Wallenburg, C. M. (2012). Dealing with supply chain risks: Linking risk management practices and strategies to performance. *International Journal of Physical Distribution and Logistics Management, 42*(10), 887–905.

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control, 8*(3), 338–353.

Zafra-Cabeza, A., Ridao, M. A., Camacho, E. F., Kempf, K. G., & Rivera, D. E. (2007). Managing risk in semiconductor manufacturing: A stochastic predictive control approach. *Control Engineering Practice, 15*(8), 969–984.

Chapter 2
Risk Assessment

2.1 Introduction

Risk is defined by ISO 31000 (2009) as the effect of uncertainty on objectives. Generally, risks may result from different circumstances such as uncertainty in financial markets, supply chain disruptions, project failures, security breaches, quality and safety incidents, environmental causes and disasters as well as deliberate attack from an adversary or unpredictable root cause. It is therefore important to identify and assess risks in order to enable them to be understood clearly and managed effectively. According to Flanagan and Norman (1993), risk management is a process which aims to identify and quantify all risks to which the business is exposed, so that a conscious decision can be made to manage the risks. Norman and Jansson (2004) considered risk management as understanding the risks and minimising their impact by addressing, for example, probability and direct impact. Depending on whether the risk management is assessed under the context of supply chain management, engineering, financial portfolios, information technology, project management, or public health and safety, the definitions and methods for risk management can vary widely. Risk management often includes risk identification, risk assessment, risk prioritisation and risk mitigation strategies as displayed in Fig. 2.1.

Among them, risk identification is a fundamental phase which is to recognise the potential uncertainties and enables a decision maker or a group of decision makers to become conscious about the event that cause uncertainty (Hallikas et al. 2004). There are many methods available for risk identification such as risk mapping and event tree analysis. Risk assessment determines the quantitative or qualitative value of risk relating to a concrete situation, which is required to be able to choose suitable management actions for the identified risk factors according to the situation. Risk assessment and prioritisation gave a more specific indication on where the risk management actions should be focused on. It is followed with risk mitigation strategies, which include risk transfer, risk taking, risk elimination, risk reduction and further analysis of individual risks (Hallikas et al. 2004).

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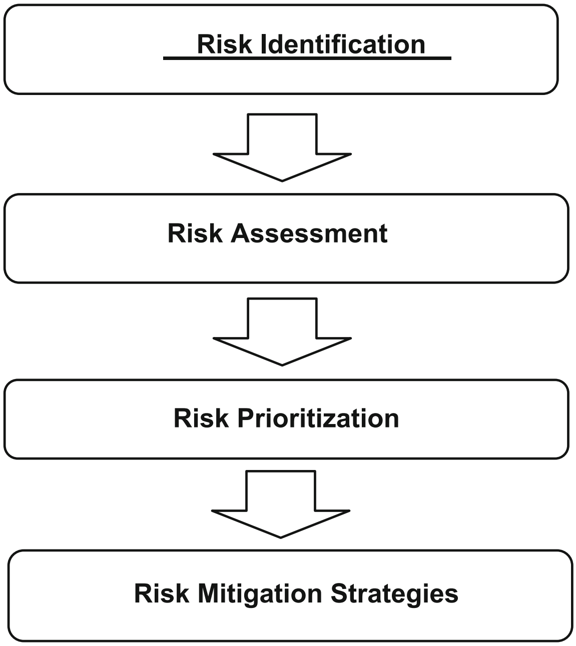
Fig. 2.1 Steps in risk management



Risk management is an expanding field, growing beyond the rich work done in finance and insurance field (Wu and Olson 2009). The application of risk management in recent years has drawn wide attention from both academics and practitioners. Power (2004) stated that the explosion of risk management practices as a social phenomenon and equates it as "the risk management of everything". Furthermore, risk management can be used as a tool for greater rewards and not just to control against loss (Wu and Olson 2008). This book concentrates on the risk assessment element of risk management. In the following sections, different risk assessment methods including both quantitative and qualitative methods are discussed. In addition, applications of risk assessment in various business areas are illustrated.

2.2 Risk Assessment

According to the Royal Society (1992), "risk is the chance, in quantitative terms, of a defined hazard occurring. It therefore combines a probabilistic measure of the occurrence of the primary event(s) with a measure of the consequences of that/those event(s)". Hence, risk reflects both the range of possible outcomes and the distribution of respective probabilities for each of the outcomes. This quantitative definition could be expresses as:

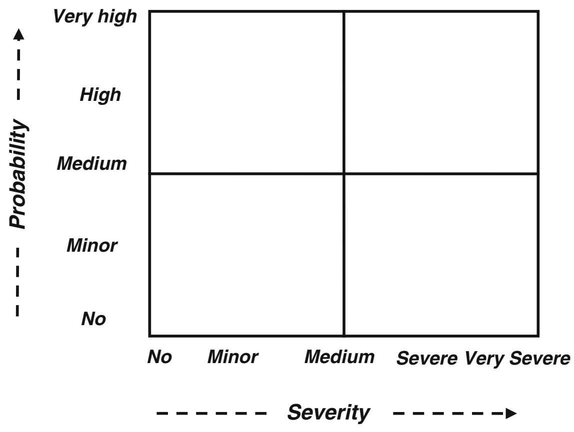


Fig. 2.2 Risk assessment matrix

$$R = P \times S \tag{2.1}$$

where R is the risk associated with a hazardous event, P represents the probability (or likelihood) of the occurrence of the hazardous event, S represents the severity or consequence of the event. This definition can also be illustrated in a risk matrix shown in Fig. 2.2 and has been applied to risk assessment in many applications such as software development (Lee 1996), environment modelling (Sadiq and Husain 2005), process plant modelling (Khan et al. 2002; Khan and Haddara 2003; Krishnasamy and Haddara 2005), water pipe deterioration analysis (Kleiner et al. 2006) and supply chain risk assessment (Wang et al. 2012a). By positioning various risks on the risk assessment matrix, it gives an overall view upon all risks and makes the most important risks requiring the most attention visible. In addition, it indicates whether the risks can be mitigated by decreasing their probability or the severity of their consequences. Risk assessment methods tend to be analytical and data-driven techniques. These methods can be either qualitative or quantitative depending on the information available and the level of detail that is required. When the data for historical events are available for the assessment, this could be quite a straightforward and quantitative task, but in practice this could be a subjective process relying on specialists' judgements. Here, different risk assessment methods including quantitative, qualitative and fuzzy risk assessment are illustrated.

2.2.1 Quantitative Risk Assessment

Quantitative risk assessment often involves a systematic and comprehensive methodology to evaluate risks. It requires quantifying the probability of the occurrence of a particular adverse event and the magnitude of the associated consequence of its outcome. Many risk assessment methods that are widely discussed in the literature are quantitative in nature and require high-quality data. In addition, quantitative techniques rely heavily on statistical approaches, which include Monte Carlo simulation (White 1995), event tree analysis (ETA) and fault tree analysis (FTA) (White 1995; Bennett et al. 1996; Ahmed et al. 2007), sensitivity analysis (White 1995; Ahmed et al. 2007), annual loss expectancy (Rainer et al. 1991; Mercuri 2003), risk exposure (Boehm 1989), probability and impact grids (Ahmed et al. 2007), failure mode and effects analysis (White 1995; Ahmed et al. 2007) and so on.

2.2.2 *Qualitative Risk Assessment*

However, the successful implementation of a comprehensive quantitative risk assessment requires the availability of good quality data and essential knowledge and skills of the assessment team. Obviously, if there are no data available, a quantitative risk assessment would not be possible. Constraints in data quality, time, expertise or resources may not permit a full quantitative risk assessment. To overcome these challenges, many organisations conduct the risk assessment qualitatively or semi-quantitatively. For example, in situations where knowledge about risk generation is limited, point estimate approaches (Huss et al. 2000; Tuominen et al. 2003) have often been employed to evaluate the risk due to their simplicity. Although this is a reasonable justification for its use in the early stages of risk assessment, it conveys a false sense of certainty when risk is estimated as a numerical value. Nevertheless, qualitative risk assessment can assist a risk manager in priority setting, policy decision making, such as decisions to allocate resources to sampling or risk reduction actions (Coleman and Marks 1999).

2.2.3 *Fuzzy Risk Assessment*

In fact, most risk assessment problems contain a mixture of quantitative and qualitative data. Using quantitative or qualitative risk assessment techniques alone is inadequate for prioritising risks. Baloi and Price (2003) argued that as most of the risk analysis tools are founded on statistical decision theory, organisations rarely use them in practice. In addition, substantial uncertainties and subjectivities in the risk assessment process have hampered the applicability of many risk assessment methods discussed earlier.

Nonetheless, the application of “Fuzzy Set Theory” (Zadeh 1965) in the risk assessment enables qualitative risk assessment descriptions to be modelled mathematically. Linguistic terms such as high probability, minor impact or low risk cannot be defined meaningfully with a precise single value. Fuzzy set theory provides a means by which these terms may be formally defined in mathematical logic (Carr and Tah 2001). For instance, Wirba et al. (1996) apply linguistic variables and fuzzy logic to quantify the likelihood of a risk event occurring, the level of dependence between risk and the severity of a risk event. It is an effective way to deal with complicated problems in an uncertain decision-making environment. It enables assessors to quantify imprecise information and incorporate vagueness in the assessment.

There have been growing attempts to exploit fuzzy logic in the risk assessment domain. The use of fuzzy methods in risk assessment has covered a range of applications: earthquake risks (Huang 1996), environmental risk (Stansbury et al. 1999; Sadiq and Husain 2005; Li et al. 2007; Chen et al. 2010), software development (Lee 1996; Bennett et al. 1996; Chen 2001; Lee et al. 2003), project risk assessment (Carr and Tah 2001; Dikmen and Birgonul 2006; Dikmen et al. 2007; Nieto-Morote and Ruz-Vila 2011), food safety risk assessment (Davidson et al. 2006; Iliey et al. 2006; Wang et al. 2012b), e-commerce development risks (Ngai and Wat 2005; Khokhar et al. 2006) and supply chain risk assessment (Chan and Kumar 2007; Wang et al. 2012a).

Some fuzzy risk assessment approaches have been inspired in the classical risk assessment methods, such as ETA and FTA. For example, Chun and Ahn (1992) proposed the use of fuzzy set theory to quantify the imprecision and judgmental uncertainties of accident progression event trees; Durkin (1994) used fuzzy set theory for the mathematical representation of fault trees and event trees were used in risk assessment problems; Huang et al. (2001) proposed a fuzzy formal procedure in order to integrate both human error and hardware failure events into a ETA methodology; Cho et al. (2002) developed a fuzzy ETA methodology characterised by the use of new forms of fuzzy membership curves.

In addition to using fuzzy concepts into conventional risk assessment frameworks, new methods have also been proposed. Carr and Tah (2001) proposed a hierarchical risk breakdown structure to represent a formal model for qualitative risk assessment and defined risk descriptions and their consequences using descriptive linguistics variables. Wang and Elhag (2007) developed a risk assessment methodology which allows experts to evaluate risk factors, in terms of likelihood and consequences, using linguistic terms and aggregate the assessments of multiple risk factors. Zeng et al. (2007) combined fuzzy reasoning and analytic hierarchy process (AHP) approach to develop a risk assessment model, in which a modified analytical hierarchy process is used to structure and prioritise risks considering three fundamental risk parameters: risk likelihood, risk severity and factor index. Nieto-Morote and Ruz-Vila (2011) presented a new methodology based trapezoidal fuzzy number and AHP for construction project risk analysis in order to deal with risks associated with the construction projects in the complicated situations in which the information to assess risks is unquantifiable, incomplete or non-obtainable. All these proposed fuzzy risk assessment methods have a common procedure: definition and measurement of risk factors, definition of fuzzy inference and defuzzification into an exact numerical value.

2.3 Risk Assessment Applications

In the financial market, risk techniques determine adequate capital requirements in proportion to the amount of risk taken, suggesting that banks should reserve more capital for higher-risk businesses and carry less capital for less risky ventures (Mikes 2009). In recent years, the applications of risk assessment techniques have gone beyond the financial and insurance field, for example, managing supply chain risk, food safety and health risk to the general public, environmental risk and project risk management. In this section, the applications of risk assessment methods in these areas will be discussed in detail.

2.3.1 Supply Chain Risk Management

Supply chains are networks of suppliers, manufacturers, distributors and retailers that are connected by transportation, information and financial infrastructure (Sahin and Robinson 2002). Managing a supply chain effectively to fulfil customer needs is a difficult task. Various sources of uncertainty and complex interrelationships between different entities make the supply chain even harder to manage. Globalisation has added further complexity to supply chains which are usually slow to respond to changes and more vulnerable to business disruptions. For instance, the global supply chains have experienced severe disruption after the earthquake and tsunami in Japan and flooding in Thailand in 2011. The ongoing piracy in the India Ocean has affected international shipping lines for many years. The Arab Spring in the Middle East has also caused ambiguity of global oil supply which leads to more volatility of the oil market.

In a supply chain, uncertainty is a major factor that can influence the effectiveness of supply chain coordination. With the increasing trend of collaboration with international supply partners and expended supply networks, it also brings uncertainties that significantly threaten normal business operations of the organisations in the supply chain. The sources of uncertainty are often classified into three categories: supply, process and demand (Lee and Billinton 1993; Childerhouse and Towill 2002; Ho et al. 2005; Tang and Tomlin 2008). Supply uncertainty is often caused by the variability brought by the suppliers such as the faults or delays in delivery. A long logistics cycle affects product availability and increases the risk of inventory obsolescence. Demand uncertainty is often presented as volatility in the demand of goods or services. Inaccurate demand forecasting may lead to either excessive product inventory or loss of opportunities. Process uncertainty also known as manufacturing uncertainty is a result of unreliable production processes. While process uncertainty has often been discussed in the literature of production and manufacturing studies, demand uncertainty and supply uncertainty are two of the most common cause of supply chain risks that have been widely studied in the literature (Handfield et al. 2009).

Supply chain risk has emerged as a key challenge to supply chain management. Supply chain risk management is a field of escalating importance and is aimed at developing approaches to the identification, assessment, analysis and treatment of areas of risk in supply chains (Neiger et al. 2009). Supply Chain Council (2010) provides a similar definition of supply chain risk management which is the systematic identification, assessment and mitigation of potential disruptions in logistics networks with the objective to reduce their negative impact on the logistics network's performances. When assessing supply chain risk, the causes, probability and consequences for each potential risk have to be collected and documented.

There has emerged a growing body of research into risk from a number of different perspectives such as economics, finance and international management (Juettner 2005). Researchers in the supply chain management field tend to focus on risks related to supply and demand coordination and uncertainty (Nagurney et al. 2005; Cigolini and Rossi 2006; Chan and Kumar 2007; Tang and Tomlin 2008; Yang et al. 2009; Oehmen et al. 2009; Xia and Chen 2011; Wang et al. 2012a, b) and disruption risks that are caused by such events as natural disaster, terrorism and labour strike (Kleindorfer and Saad 2005; Tang 2006; Knemeyer et al. 2009; Trkam and McCormack 2009). The incorporation of risk constructs and management response within supply chain management reflects both theoretical imperatives and practitioner requirements (Ritchie and Brindely 2007).

2.3.2 Environmental Risk Assessment

Over the last several decades, environmental risk assessment has become increasingly more sophisticated, information intensive and complex, including such approaches as expert judgment, cost–benefit analysis and toxicological risk assessment (Linkov et al. 2006). Pavlou and Stansbury (1998) used a formal analysis of the trade-off between environmental risk reduction and cost to contaminated sediment disposal applications. Stansbury et al. (1999) employed fuzzy set theory and composite programming to conduct risk-cost trade-off analysis. Wu and Wang (2007) proposed a systematic approach for establishment of an analytical risk assessment model to evaluate the risk index for soil erosion by water. In addition to the environmental risk assessment in the science field, there is growing number of studies of environmental risk assessment in the business and management field. This book mainly focuses on the applications of environmental risk assessment for business and management purpose.

Because of the increasing public awareness of the need to protect the environment and the regulatory pressures coming from governments and organisations, businesses are under more pressure to introduce and promote practices that help to ease negative impacts on the environment (Zhu and Sarkis 2003). Businesses are more sensitive on the decisions of what items are purchased for use in various processes, the effects of manufacturing process, how products are packaged and delivered, and the recycle (or reuse) policies. Environmental consequences are considered strategically essential for business operations with the aim to reduce costs and develop quality products (Kleindorfer et al. 2005; Atasu et al. 2008; Wong et al. 2012). Nevertheless, it is a challenging task to balance environmental issues and sound business practices in the dynamic, complex and uncertain surroundings.

One of the main recent developments of environmental risk assessment is the environmental impact assessment. It is defined by Kaya and Kahraman (2011) as the assessment of the possible impact that a proposed plan or project may have on the environment. Together with the social and economic aspects, environmental impact assessment has drawn much attention among both academics and practitioners. Environmental impact assessment examines the potential and actual environmental effects from the use of materials and energy. Spengler et al. (1998) developed a multiple criteria-based decision support system for environmental assessment of recycling measures in the iron and steel making industry. Seppala et al. (2001) provided an overview of the commonly used multiple criteria decision-making methods and discuss life cycle impact assessment in relation to them. Payraudeau and van der Werf (2005) provided an analysis of six main types of methodologies (environmental risk mapping, environmental impact assessment, life cycle analysis, agro-environmental indicators, multi-agent system and linear programming and) to illustrate the variety of methods used in environmental impact assessment. Wang and Chan (2011) proposed an innovative approach to performing structured environmental assessment by using the concepts of life cycle assessment and fuzzy AHP. This is also reflected in the recently adopted directive by the European Council (2005) on so-called energy using products (EuPs). According to this mandate, preventive actions should be taken as early as possible during the design phase of EuPs, and the environmental impacts of their whole product life cycle should be considered.

2.3.3 Food Safety Risk Assessment

Food risk is defined as a function of the probability of an adverse health effect and the severity of that effect, consequential to a hazard (European Commission 2002a). The application of risk assessment methods to food safety have been reported extensively in the literature. Risk assessment is one of three parts of the greater process of food risk analysis that includes risk management and risk communication. It is a scientific evaluation of known or potential adverse health effects resulting from exposure to biological, chemical or physical factors in food (CAC 2002). The ultimate goal of a food safety risk assessment process is to estimate the probability of occurrence, and this may be based on qualitative and/or quantitative information (Davidson et al. 2006).

A food safety risk assessment process consists of four steps: hazard identification, hazard characterisation, exposure assessment and risk characterisation.

Hazard identification is a qualitative approach of systematically identifying the potential adverse health effects. This related to the identification of biological, chemical and physical agents capable of causing adverse health effects and which may be present in a particular food or group of foods (CAC 1999). Hazard characterisation is the qualitative and/or quantitative evaluation of the nature of the adverse health effects associated with biological, chemical and physical agents, which may be present in food (CAC 1999). It is the process of obtaining quantitative information (dose–response assessment) on the magnitude of adverse effects on human health following exposure to a hazardous entity. Exposure assessment is defined as the qualitative and/or quantitative evaluation of the likely intake of biological, chemical and physical agents via food as well as exposures to other sources if relevant (CAC 1999). Risk characterisation is the qualitative and/or quantitative estimation, including attendant uncertainties, of the probability of occurrence and severity of known or potential adverse health effects in a given population based on hazard identification, hazard characterisation and exposure assessment (CAC 1999).

Various risk assessment methodologies and approaches (Serra et al. 1999; Hoomstra and Notemans 2001; Parsons et al. 2005) have been developed and are increasingly being used to quantitatively assess risks to human health imposed by the food chain. Sperber (2001) indicated that food safety risk assessment is a quantitative, global process in which a numerical degree of risk can be calculated for any particular hazard. Quantitative risk assessment, in particular when using stochastic models, is a specialised task that requires mathematical and statistical skills in addition to microbiological and technological knowledge (European Commission 2002b). As a consequence, it involves collaboration between regulatory, public health, academic and industrial organisations.

Traditionally, food safety risk assessment has mainly focused on assessing the risk of the end product on consumers' health and making decisions about food safety objectives that comply with regulatory and customer requirements (Hoomstra et al. 2001; European Commission 2002b). End point testing is not a good way of ensuring food safety (Walker et al. 2003). By the time the results are obtained, the food has been served and consumed and it is hard to trace or recall. The question of application level is related to the reason for conducing risk assessment, that is, to provide information sufficient to make risk management decisions. There is a need to provide an additional focus of risk assessment application from production perspective and more procedures must be taken during the processing. For example, "Pre-screening" of the risk by simpler methods can aid decisions about the value of investing resources in fully quantitative risk assessment (Ross and Sumner 2002). From a company's perspective, by using elements of quantitative risk assessment, the Hazard Analysis of Critical Control Points (HACCP) system can be transformed into a more meaningful managerial tool. In reality, many companies, particularly in small- and medium-sized enterprises (SMEs), struggle with their practical applications, because of a lack of expertise, training, time, motivation, commitment and ability to implement a systematic and quantitative risk assessment.

2.3.4 Project Risk Assessment

Every project has a different degree of risk. There is vast literature devoted to risk in a project, and there are several ways of understand it (Kelly 1961; Tavares 1999; Kuchta 2001; Cooper and Champan 1987; Mark et al. 2004; Cooper et al. 2005; Ahmed et al. 2007; Mojtahedi et al. 2010). The definitions of project risk in the literature include "the exposure to the possibility of economic or financial loss or gain, physical damage or injury, or delay, as a consequence of the uncertainty associated with pursuing a particular course of action" (Chapman and Ward 1997), "the probability of losses in a project" (Jaffari 2001; Kartam and Kartam 2001), "the likelihood of a detrimental event occurring to the project" (Baloi and Price 2003), "the potential for complications and problems with respect to the completion of a project task and the achievement of a project goal" (Mark et al. 2004). Although risk has been defined in various ways, there are some common characteristics (Chia 2006):

- A risk is a future event that may or may not occur.
- A risk must also be an uncertain event or condition that, if it occurs, has an effect on, at least, one of the project objectives, such as scope, schedule, cost or quality.
- The probability of the future event occurring must be greater than 0 % and less than 100 %. Future events that have a zero or 100 % chance of occurrence are not risks.
- The impact or consequence of the future event must be unexpected or unplanned for.

Commonly, risks involved in projects have been assessed in order for decision makers to decide whether the project should go ahead considering potential profit and the degree risk. High levels of risk are considered to be a significant obstacle for project success (Zwikael and Sadeh 2007). In addition, complicated projects are often constituted by many activities or tasks. Each activity or task also carries certain level of risk. It is essential for project managers to understand the level of risk involved in each task. Therefore, a proper monitoring system can be put in place, and more attention could be paid to these high-risk activities. The purpose of risk assessment in project management is to measure the impact of identified risks on a project (Mojtahedi et al. 2010). Cooper et al. (2005) stated that there are several objectives for risk assessment in managing large projects:

- It provides an overview of the general level and pattern of risk facing the project.
- It focuses management attention on the high-risk items in the list.
- It helps to decide where action is needed immediately and where action plans should be developed for future activities.
- It facilitates the allocation of resources to support management's action decisions.

The key attributes of project risk are probability (or likelihood) and severity. The risk assessment process requires an assessment of the probability or likelihood of the risk and the impact on the project. Risk probability assessment investigates the likelihood that individual risk will occur and risk impact assessment investigates the potential effect on a project objective such as time and cost including both negative effect of threats and positive effect for opportunities (Mojtahedi et al. 2010). Similar to other risk assessment applications, depending on the available data, project risk assessment can be performed qualitatively or quantitatively.

Quantitative project risk assessment methods have been developed with sophisticated statistical techniques. Organisations often find them difficult to adapt due to limited technical ability. Therefore, more applications of qualitative risk assessment have been developed recently in the literature including methods for prioritising the identified risks for further actions. Among them, the most widely used assessment method is multi-attribute risk rating where a set of attributes/risk factors are defined and their magnitude are determined by using simple multi-attribute rating technique such as AHP or variations of these methods. Hastak and Shaked (2001) provide a structured approach for evaluating risk indicators involved in an international construction operation. It is designed to estimate the risk level of a specific project in a foreign country. Han et al. (2004) proposed a multi-criteria decision-making framework for financial portfolio risk management to integrate risk hierarchies at the project and corporate levels. Tuysuz and Kahraman (2006) developed a risk management framework using fuzzy AHP and apply it in information technology project. Dikmen and Birgonul (2006) also developed a methodology for the quantification of risks and opportunities associated with international projects using AHP, so that the decision makers may compare attractiveness of alternative project options. Dey (2010) introduced a hierarchical framework for risk analysis, in which risks are identified using brainstorming sessions, while probability is obtained using AHP, and the risk impact is determined using risk maps in project, work package and activity level separately. Mojtahedi et al. (2010) developed a new methodology for identifying and assessing project risks with applying multi-attribute group decision-making technique. Nieto-Morote and Ruz-Vila (2011) combined AHP and fuzzy set theory to develop a new methodology for construction project risk analysis in order to deal with risks associated with the construction projects in the complicated situations. Dey (2012a, 2012b) also proposed an integrated analytical framework for effective management of project risk using a case study of Indian oil refinery.

2.4 Summary

In this chapter, we reviewed different risk assessment methods and their implementations across a wide range of application areas particularly in supply chain risk management, environmental risk assessment, food safety risk assessment and project risk assessment. With the increasing emphasis on risk management across various industries, effective risk assessment tools for understanding and analysing risks are now attracting much attention. Many approaches including both quantitative and qualitative methods have been suggested in the literature for assessing risks by researchers from the physical sciences and the social sciences. However, risk assessment is a complex subject involving vagueness and uncertainty in the decision-making process. While comprehensive quantitative risk assessment methods are constrained by data quality, time, expert and resources, qualitative methods are often criticised due to its simplicity and false sense of certainty. Nonetheless, fuzzy set theory enables qualitative risk assessment descriptions to be modelled mathematically and incorporates uncertainty and vagueness into the assessment. Furthermore, using multi-criteria decision analysis and fuzzy set theory in the risk assessment gives structure to the decision-making process and allows users to conveniently describe uncertainty. In following chapters, the benefits of applying fuzzy set theory and multiple criteria decision analysis in the risk assessment will be further investigated.

References

Ahmed, A., Kayis, B., & Amornsawadwatana, S. (2007). A review of techniques for risk management in projects. *Benchmarking, 14*, 22–36.

Atasu, A., Sarvary, M., & Wassenhove, L. N. V. (2008). Remanufacturing as a marketing strategy. *Management Science, 54*(10), 1731–1746.

Baloi, D., & Price, A. D. F. (2003). Modelling global risk factors affecting construction cost performance. *International Journal of Project Management, 21*, 261–269.

Bennett, J. C., Bohoris, G. A., Aspinwall, E. M., & Hall, R. C. (1996). Risk analysis techniques and their application to software development. *European Journal of Operational Research, 95*, 467–475.

Boehm, B. W. (1989). Software risk management. *IEEE Computer*. Washington: Society Press.

Carr, V., & Tah, J. H. M. (2001). A fuzzy approach to construction project risk assessment and analysis: construction project risk management system. *Advances in Engineering Software, 32*, 847–857.

Chan, F. T. S., & Kumar, N. (2007). Global supplier development considering risk factors using fuzzy extended AHP-based approach. *Omega-International Journal of Management Science, 35*, 417–431.

Chapman, C. B. & Ward, S. C. (1997). Project risk management: processes, techniques and insights. NY: Wiley.

Chen, S.-M. (2001). Fuzzy group decision making for evaluating the rate of aggregative risk in software development. *Fuzzy Sets and Systems, 118*(1), 75–78.

Chen, Z., Zhao, L., & Lee, K. (2010). Environmental risk assessment of offshore produced water discharges using a hybrid fuzzy-stochastic modelling approach. *Environmental Modelling and Software, 25*(6), 782–792.

Chia, S. E. (2006). Risk assessment framework for project management. *IEEE*, (pp. 376–379).

Childerhouse, P., & Towill, D. R. (2002). Analysis of the factors affecting real-world value stream performance. *International Journal of Production Research, 40*(15), 3499–3518.

Cho, H. M., Choia, H. H., & Kimb, Y. K. (2002). A risk assessment methodology for incorporating uncertainties using fuzzy concepts. *Reliability Engineering and System Safety, 78*, 173–183.

Chun, M., & Ahn, K. (1992). Assessment of the potential application of fuzzy set theory to accident progression event trees with phenomenological uncertainties. *Reliability Engineering and System Safety, 37*(3), 237–252.

Cigolini, R., & Rossi, T. (2006). A note on supply risk and inventory outsourcing. *Production Planning and Control, 17*(4), 424–437.

Codex Alimentarius Commission (CAC) (1999). Principles and guidelines for the conduct of a microbiological risk assessment, in C.A. Commission (Ed.) FAO, Rome, CAC/GL30.

Codex Alimentarius Commission (CAC) (2002) Food hygiene basic texts, 2nd edn, the Codex Alimentarius Commission and the FAO/WHO Food Standard Programme.

Coleman, M. E., & Marks, H. M. (1999). Qualitative and quantitative risk assessment. *Food Control, 10*, 289–297.

Cooper, D. F., & Champan, C. B. (1987). *Risk Analysis for Large Project*. Chichester: Wiley.

Cooper, D., Grey, S., Raymond, G., & Walker, P. (2005). *Managing risks in large projects and complex procurements*. England: Wiley.

Davidson, V. J., Ryks, J., & Fazil, A. (2006). Fuzzy risk assessment tool for microbial hazards in food system. *Fuzzy Sets and Systems, 157*, 1201–1210.

Dey, P. K. (2010). Managing project risk using combined analytic hierarchy process and risk map. *Applied Soft Computing*, *10*(4), 990–1000.

Dey, P. K. (2012a). Managing project risk using combined analytic hierarchy process and risk map. *Applied Soft Computing, 10*(4), 990–1000.

Dey, P. K. (2012b). Project risk management using multiple criteria decision-making technique and decision tree analysis: a case of study of Indian oil refinery. *Production Planning and Control, 23*(12), 903–921.

Dikmen, I., & Birgonul, M. T. (2006). An AHP based model for risk and opportunity assessment of international construction projects. *Canadian Journal of Civil Engineering, 33*(1), 58–68.

Dikmen, I., Birgonul, M. T., & Han, S. (2007). Using fuzzy risk assessment to rate cost overrun risk in international construction projects. *International Journal of Project Management, 25*, 494–505.

DurKin, J. (1994). *Expert Systems: design and development*. New York: Prentice Hall.

European Commission (2002a) European commission regulation No 178/of the European parliament and the council of 28 official *Journal of the European Communities*.

European Commission (2002b) Risk assessment of food borne bacterial pathogens: Quantitative methodology relevant for human exposure assessment, European Commission Preliminary Report.

European Council (2005). Directive 2005/32/EC of the European parliament of the council of 6 July 2005 establishing a framework for the settings of ecodesign requirements for energy-using products and amending council directive 92/42/EEC and directive 96/57/EC and 2000/55/EC of the European parliament and of the council. *Official Journal of the European Union, L191*(48), 29058.

Flanagan, R., & Norman, G. (1993). *Risk management and construction*. Victoria: Blackwell Science Pty. Ltd.

Hallikas, J., Karvonen, I., Pulkkinen, U., Virolainen, V.-M., & Tuominen, M. (2004). Risk management processes in supplier networks. *International Journal of Production Economics, 90*, 47–58.

Han, S. H., Diekmann, J. E., Lee, Y., & Ock, J. H. (2004). Multicriteria financial portfolio risk management for international projects. *Journal of Construction Engineering Management, 130*(3), 346–356.

Handfield, R., Warsing, D., & Wu, X. (2009). (Q, r) Inventory policies in a fuzzy uncertain supply chain environment. *European Journal of Operational Research, 197*, 609–619.

Hastak, M., & Shaked, A. (2001). ICRAM-1: model for international construction risk assessment. *Journal of Management in Engineering, 16*(1), 59–69.

Ho, C. F., Chi, Y. P., & Tai, Y. M. (2005). A structural approach to measuring uncertainty in supply chains. *International Journal of Electronic Commerce, 9*(3), 91–114.

Hoornstra, E., Northolt, M. D., Notermans, S., & Barendsz, A. W. (2001). The use of quantitative risk assessment in HACCP. *Food Control, 12*, 229–234.

Hoornstra, E., & Notermans, S. (2001). Quantitative microbiological risk assessment. *International Journal of Food Microbiology, 66*, 21–29.

Huang, C. (1996). Fuzzy risk assessment of urban natural hazards. *Fuzzy Sets and Systems, 83*(2), 271–282.

Huang, D., Chen, T., & Wang, M. J. J. (2001). A fuzzy set approach for event tree analysis. *Fuzzy Sets and Systems, 118*, 153–165.

Huss, H., Reilly, A., & Embarek, P. (2000). Prevention and control of hazards in seafood. *Food Control, 11*, 149–156.

Iliey, B., Lindquist, M., Robertsson, L., & Wide, P. (2006). A fuzzy technique for food and water quality assessment with an electronic tongue. *Fuzzy Sets and Systems, 157*(9), 1155–1168.

ISO/DIS 31000 (2009). Risk management—principles and guidelines on implementation, International Organisation for Standardization.

Jaafari, A. (2001). Management of risk, uncertainties and opportunities on projects: time for a fundamental shift. *International Journal of Project Management, 19*, 89–101.

Juettner, U. (2005). Supply chain risk management: understanding the business requirements from a practitioner perspective. *The International Journal of Logistics Management, 16*(1), 120–141.

Kartam, N. A., & Kartam, S. A. (2001). Risk and its management in the Kuwaiti construction industry: a contactors' perspective. *International Journal of Project Management, 19*, 325–335.

Kelly, J. E. (1961). Critical path planning and scheduling mathematical bases. *Operations Research, 9*, 246–320.

Khan, F. I., Sadiq, R., & Husain, T. (2002). Risk-based process safety assessment and control measures design for offshore process facilities. *Journal of Hazardous Materials, 94*, 1–32.

Khan, F. I., & Haddara, M. M. (2003). Risk-based maintenance: a quantitative approach for maintenance/inspection scheduling and planning. *Journal of Loss Prevention in the Process Industries, 16*, 561–573.

Khokhar, R. H., Bell, D. A., Cuan, J., & Wu, Q. (2006). Risk assessment of e-commerce projects using evidential reasoning. *Lecture Notes in Computer Science, 4223*(2006), 621–630.

Kleindorfer, P. P., Singhal, K., & van Wassenhove, L. N. (2005). Sustainable operations management. *Production and Operations Management, 14*(4), 482–492.

Kleiner, Y., Sadiq, R., & Rajani, B. (2006). Failure risk management of buried infrastructure using fuzzy-based. *Journal of Water Supply Research and Technology: aquaculture, 55*, 81–94.

Kleindorfer, P., & Saad, G. (2005). Managing disruption risks in supply chains. *Production and Operations Management, 14*(1), 53–68.

Knemeyer, M. A., Zinn, W., & Eroglu, C. (2009). Proactive planning for catastrophic events in supply chains. *Journal of Operations Management, 27*(2), 141–153.

Krishnasamy, K., & Haddara, M. (2005). Development of a risk-based maintenance (RBM) strategy for a power-generation plant. *Journal of Loss Prevention in the Process Industries, 18*, 69–81.

Kuchta, D. (2001). Use of fuzzy numbers in project (criticality) assessment. *International Journal of Project Management, 19*, 305–310.

Lee, H. L., & Billington, C. (1993). Material management in decentralized supply chains. *Operations Research, 41*(5), 835–847.

Lee, H.-M., Lee, S.-Y., Lee, T.-Y., & Chen, J.-J. (2003) A new algorithm for applying fuzzy set theory to evaluate the rate of aggregative risk in software development. *Information Sciences, 153*, 177–197.

Li, J., Huang, G. H., Zeng, G., Maqsood, I., & Huang, Y. (2007) An integrated fuzzy-stochastic modeling approach for risk assessment of groundwater contamination. *Journal of Environmental Management, 82*(2), 173–188.

Lee, H. M. (1996). Applying fuzzy set theory to evaluate the rate of aggregative risk in software development. *Fuzzy Sets and Systems, 79*, 323–336.

Linkov, I., Satterstrom, F. K., Kiker, G., Batchelor, C., Bridges, T., & Ferguson, E. (2006). From comparative risk assessment to multi-criteria decision analysis and adaptive management: recent developments and applications. *Environment International, 32*, 1072–1093.

Mark, W., Cohen, P. E. & Glen, R. P., (2004). Project risk identification and management. *AACE International Transaction*, INT.01.1-5.

Mercuri, R. T. (2003). Security watch: Analyzing security costs. *Communications of the ACM, 46*(6), 15–18.

Mikes, A. (2009). Risk management and calculative cultures. *Management Accounting Research, 20*, 18–40.

Mojtahedi, S. M. H., Mousavi, S. M., & Makui, A. (2010). Project risk identification and assessment simultaneously using multi-attribute group decision making technique. *Safety Science, 48*, 499–507.

Nagurney, A., Cruz, J., Dong, J., & Zhang, D. (2005). Supply chain networks, electronic commerce, and supply side and demand side risk. *European Journal of Operational Research, 164*(1), 120–142.

Neiger, D., Botaru, K., & Churilov, L. (2009). Supply chain risk identification with value-focused process engineering. *Journal of Operations Management, 27*(2), 154–168.

Ngai, E. W. T., & Wat, F. K. T. (2005). Fuzzy decision support system for risk analysis in ecommerce development. *Decision Support Systems, 40*(2), 235–255.

Nieto-Morote, A., & Ruz-Vila, F. (2011). A fuzzy approach to construction project risk assessment. *International Journal of Project Management, 29*, 220–231.

Norrman, A., & Jansson, U. (2004). Ericsson's proactive supply chain risk management approach after a serious sub-supplier accident. *International Journal of Physical Distribution and Logistics Management, 34*(5), 434–456.

Oehmen, J., Ziegenbein, A., Alard, R., & Schöbskebeb, P. (2009). System-oriented supply chain risk management. *Production Planning and Control, 20*(4), 343–361.

Parsons, D. J., Orton, T. G., Souza, J. D., Moore, A., Jones, R. & Dodd, C. E. R. (2005). A comparison of three modelling approaches for quantitative risk assessment using the case study of Salmonella spp. In poultry meat, *International Journal of Food Microbiology*, 98, 35–51.

Pavlou, S. P., & Stansbury, J. S. (1998). Risk-cost trade off considerations for contaminated sediment disposal. *Human Ecological Risk Assessment: An International Journal, 4*(4), 991–1002.

Payraudeau, S., & van der Werf, H. M. G. (2005). Environmental impact assessment for a farming region: A review of methods. *Agriculture, Ecosystems and Environment, 107*, 1–19.

Power, M. K. (2004). *The risk management of everything*. London: Demos.

Rainer, R. K. J. R., Snyder, C. A., & Carr, H. H. (1991). Risk analysis for information technology. *Journal of Management Information Systems, 8*(1), 129–147.

Ritchie, B., & Brindley, C. (2007). Supply chain risk management and performance: A guiding framework for future development. *International Journal of Operations and Production Management, 27*(3), 303–322.

Ross, T., & Sumner, J. (2002). A simple, spread-sheet based, food safety risk assessment tool. *Journal of Food Microbiology, 77*, 39–53.

Sadiq, R., & Husain, T. (2005). A fuzzy-based methodology for an aggregative environmental risk assessment: a case study of drilling waste. *Environmental Modelling and Software, 20*, 33–46.

Sahin, F., & Robinson, E. P. (2002). Flow coordination and information sharing in supply chains: Review, implications, and directions for future research. *Decision Sciences, 33*(4), 505–536.

Seppala, J., Basson, L., & Norris, G. A. (2001). Decision analysis frameworks for lifecycle impact assessment. *Journal of Industrial Ecology, 5*(4), 45–68.

Serra, J. A., Domenech, E., Escrche, I., & Martorell, S. (1999). Risk assessment and critical control points from the production perspective. *International Journal of Food Microbiology, 66*, 9–26.

Sperber, W. H. (2001). Hazard identification: From a quantitative to a qualitative approach. *Food Control, 12*, 223–228.

Spengler, T., Geldermann, J., Hahre, S., Sieverdingbeck, A., & Rentz, O. (1998). Development of a multiple criteria based decision support system for LCA. Case study: Tinplate production. *Journal of Cleaner Production, 6*, 37–52.

Stansbury, J., Member, P. E., Bogardi, I., & Stakhiv, E. Z. (1999). Risk-cost optimization under uncertainty for dredged material disposal. *Journal of Water Resource Planning Management, 125*(6), 342–351.

Supply Chain council (2010). Supply chain operation reference model (SCOR) Version 10.0 Overview. URL: http://www. supply-chain.org, accessed 2010-12-10.

Tang, C. S. (2006). Robust strategies for mitigating supply chain disruptions, International Journal of Logistics: Research and Applications, 9(1), 33–45Lee, H.L., and Billington, C. (1993). Material management in decentralized supply chains. *Operations Research, 41*(5), 835–847.

Tang, C., & Tomlin, B. (2008). The power of flexibility for mitigating supply chain risks. *International Journal of Production Economics, 116*, 12–27.

Tavares, T. L. (1999). *Advanced models for project management*. Dordrecht: Kluwer Academic Publishers.

The Royal Society. (1992). *Analysis*. The Royal Society: Perception and Management.

Tolga Kaya, T., & Kahraman, C. (2011). An integrated fuzzy AHP–ELECTRE methodology for environmental impact assessment. *Expert Systems with Applications, 38*, 8553–8562.

Tuominen, P., Hielm, S., Aarnisalo, K., Raaska, L., & Maijala, R. (2003). Trapping the food safety performance of a small or medium-size food company using a risk-based model: The HYGRAM system. *Food Control, 14*, 573–578.

Trkam, P., & McCormack, K. (2009). Supply chain risk in turbulent environments—a conceptual model for managing supply chain network risk. *International Journal of Production Economics, 119*(2), 247–258.

Tuysuz, F., & Kahraman, C. (2006). Project Risk management in oil and gas construction projects in Vietnam. *International Journal of Intelligent System, 21*(6), 559–584.

Walker, E., Pritchard, C., & Forsythe, S. (2003). Hazard analysis critical control point and prerequisite programme implementation in small and medium size food business. *Food Control, 14*, 169–174.

Wang, Y. M., & Elhag, T. M.-S. (2007). A fuzzy group decision making approach for bridge risk assessment. *Computers and Industrial Engineering, 53*, 137–148.

Wang, X & Chan, H. K. (2011). Fuzzy-AHP approach for evaluation of green product design, 21st *International Conference of Production Research,* Stuttgart, Germany.

Wang, X., Chan, H. K., Yee, W. Y., & Diaz-Rainey, I. (2012a). A two-stage Fuzzy-AHP model for risk assessment of implementing green initiatives in the fashion supply chain. *International Journal of Production Economics, 135*(2), 595–606.

Wang, X., Li, D., & Shi, X. (2012b). A fuzzy enabled model for aggregative food safety risk assessment in food supply chains. *Production Planning and Control, 23*(5), 377–395.

White, D. (1995). Application of systems thinking to risk management: A review of the literature. *Management Decision, 3*(10), 35–45.

Wirba, E. N., Tah, J. H. M., & Howes, R. (1996). Risk interdependencies and natural language computations. *Engineering Construction and Architectural Management, 3*(4), 251–269.

Wong, C. W. Y., Lai, K.-H., Shang, K.-C., Lu, C.-S., & Leung, T. K. P. (2012). Green operations and the moderating role of environmental management capability of suppliers on manufacturing firm performance. *International Journal of Production Economics, 140*, 283–294.

Wu, Q., & Wang, M. (2007). A framework for risk assessment on soil erosion by water using an integrated and systematic approach. *Journal of Hydrology, 337*, 11–21.

Wu, D. D., & Olson, D. L. (2008). Supply risk, simulation and vendor selection. *International Journal of Production Economics, 114*(2), 646–655.

Wu, D. D., & Olson, D. L. (2009). Risk issues in operations: methods and tools. *Production Planning Control, 20*(4), 293–294.

Xia, D., & Chen, B. (2011). A comprehensive decision-making model for risk management of supply chain. *Expert Systems with Applications, 28*, 4957–4966.

Yang, D., Xiao, T., & Shen, H. (2009). Pricing, service level and lot size decisions of a supply chain with risk-adverse retailers: implications to practitioners. *Production Planning and Control, 20*(4), 320–331.

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control, 8*(3), 338–353.

Zeng, J., An, M., & Smith, N. J. (2007). Application of a fuzzy based decision making methodology to construction project risk assessment. *International Journal of Project Management, 27*, 589–600.

Zhu, Q., & Sarkis, J. (2003). Relationships between operational practices and performance among early adopters of green supply chain management practices in Chinese manufacturing enterprises. *Journal of Operations Management, 22*(3), 265–289.

Zwikael, O., & Sadeh, A. (2007). Planning effort as an effective risk management tool. *Journal of Operations Management, 25*, 755–767.

Chapter 3
Hierarchical Model in Decision Making

3.1 Introduction

Decision-making problems normally involve multiple criteria. This is already not an easy problem to address. The problems are even more difficult to tackle if some of the criteria are qualitative in nature. How to quantify such qualitative variables is always the controversial topic when solving such multiple criterion decision-making (MCDM) problems. In the 1970s and 1980s, Saaty (1978, 1980) developed a ground-breaking tool to handle such MCDM problems. This is called analytic hierarchy process (AHP). The basic idea is to represent such MCDM problems by a hierarchical structure with different criteria and sub-criteria. Then, pairwise comparisons between those criteria are performed, so that the weightings of the criteria (or priority in some applications) with respect to the problem can then be estimated. In addition, this approach can be employed to select the best alternative based on these weightings and their relative importance to each criterion. Details of the theory and an illustrative example are presented in this chapter.

3.2 Brief Review of AHP

Since there are different factors that can affect decision involving multiple judging criteria, trade-offs can always be found between different factors (Tan 2005). The analysis will usually involve multiple objectives or criteria. AHP is a useful approach for evaluating such complex multiple criteria alternatives (Chan et al. 2006; Chan and Chan 2010; Wu et al. 2012). AHP is one of the widely used approaches to prioritise multiple factors (Saaty and Peniwati 2008). In order to evaluate or select an alternative, a design concept or a solution, weighted rating methods are generally used. It is a combinatorial decision analysis of quantitative and qualitative methods. The basic idea of AHP is to establish an orderly hierarchical system (Satty 1980) by analysing elements of complex systems and their mutual relations. Proposed by Saaty (1980), AHP has been employed to aid in many MCDM problems, particularly when qualitative criteria are involved. AHP

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is a useful approach for evaluating two or more competing alternatives along multiple criteria. AHP requires a decision maker to determine the relative importance of each criterion/factor by means of pairwise comparisons between the relevant criteria/factors included in the analysis.

After the development of AHP, it has been employed to solve MCDM problems. AHP analyses an MCDM problem by setting up a hierarchy of criteria and sub-criteria, which could be either quantitative or qualitative in nature. This can be done by introducing pairwise comparison between those criteria, which are assessed by professionals or experts in the corresponding area. Applications of AHP have been reported in many MCDM studies. For example, AHP approaches have been utilised to investigate issues such as assessing the environmental impacts of different stages of a supply chain life cycle (Sarkis 2003), evaluating the eco-efficiency of a product (Chang and Chen 2004), supplier development based on environmental criteria (Lu et al. 2007), matching of product characteristics with supplier characteristics to select potential vendors (Chen and Huang 2007), supplier development based on environmental criteria (Lu et al. 2007), selection of preferred partners and final product concept (Yan et al. 2008), evaluation of a product's impact and influence on the environment for early product planning and development (Yang et al. 2010), selection and evaluation of innovative designs (Li 2010), identifying improvement areas when implementing green initiatives (Sarmiento and Thomas 2010) and risk analysis of implementing different green initiatives (Wang et al. 2012a).

Although AHP is a useful method for MCDM problems particularly when qualitative assessments are needed, it is unable to process ambiguous variables (Wang et al. 2008). In many cases, the uncertainty inherent to some situations and problems cannot be expressed simply by using crisp values of nine scales or the concept of probability. For example, in certain contexts, conducting a full life cycle assessment (LCA) for eco-design may not be possible because of the uncertainty associated with the problem or because of the lack of scientific data. Please refer to Appendix 1 for an introduction of LCA. To address this limitation of AHP, some scholars have made use of fuzzy logic, which can be employed to deal with uncertain parameters and information. The major benefit introduced by fuzzy AHP is that it enables a more accurate description of the decision-making process that takes place in real applications where uncertainties are not uncommon (Huang et al. 2008). The next section first illustrates the brief mathematical derivation of AHP. Then, this is followed by a section to demonstrate how AHP can be applied in a real-life example. Section 3.5 will present the basics of fuzzy logic and the variations of fuzzy-based AHP models.

3.3 Formulation of AHP

The mathematical formulation of the AHP has been well presented by Saaty (1978). In the section, the key mathematical derivation is reproduced with respect to the seminal work of Saaty (1978, 1990). The basic assumption is that any

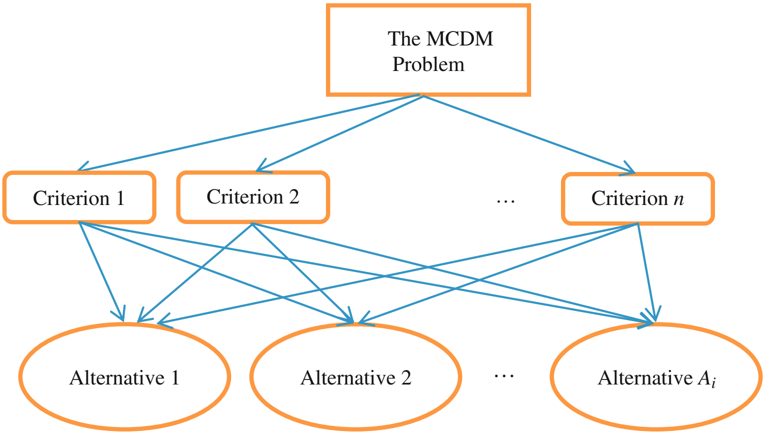

Fig. 3.1 Basic hierarchical structure

MCDM can be structured using a hierarchical method with different qualitative or quantitative judging criteria. The simplest one is that we need to select different alternative subjects to a single layer of judging criteria. This is illustrated in Fig. 3.1.

Figure 3.1 shows that there are i alternatives of the problem, namely $A_1, A_2, \ldots, A_i$. In addition, there are n judging criteria $C_1, C_2, \ldots, C_n$. One important step in AHP analysis is to conduct pairwise comparisons between the criteria. Assume w_{ij} is such relative weighting of Criterion i over Criterion j, and that no interdependency exists among the criteria, the relative weighting of Criterion j over Criterion i would then be $1/w_{ij}$. Therefore, we can construct a reciprocal matrix in the following form to show the relationship of different relative weightings.

$$A = \begin{bmatrix} 1 & w_{12} & \cdots & w_{1n} \\ 1/w_{12} & 1 & & w_{2n} \\ \vdots & & \ddots & \vdots \\ 1/w_{1n} & 1/w_{2n} & \cdots & 1 \end{bmatrix} \tag{3.1}$$

The above matrix can be rewritten in the following form:

$$A = \begin{bmatrix} w_1/w_1 & w_1/w_2 & \cdots & w_1/w_n \\ w_2/w_1 & w_2/w_2 & & w_2/w_n \\ \vdots & & \ddots & \vdots \\ w_n/w_1 & w_n/w_2 & \cdots & w_n/w_n \end{bmatrix} \tag{3.2}$$

where w_i are the actual weightings of each criterion.

A matrix of this form is also consistent because $w_{jk} = w_{ik}/w_{ij}$ for all $i, j, k = 1, \ldots, n$ (Saaty 1980). If we multiply the matrix by its weighting vector $w = [w_1, \ldots w_n]^{\mathrm{T}}$, then we will obtain the following linear equation:

$$A = \begin{bmatrix} {}^{w_1}\!/_{w_1} & {}^{w_1}\!/_{w_2} & \cdots & {}^{w_1}\!/_{w_n} \\ {}^{w_2}\!/_{w_1} & {}^{w_2}\!/_{w_2} & & {}^{w_2}\!/_{w_n} \\ \vdots & & \ddots & \vdots \\ {}^{w_n}\!/_{w_1} & {}^{w_n}\!/_{w_2} & \cdots & {}^{w_n}\!/_{w_n} \end{bmatrix} \begin{bmatrix} w_1 \\ \vdots \\ w_n \end{bmatrix} = n \begin{bmatrix} w_1 \\ \vdots \\ w_n \end{bmatrix} \tag{3.3}$$

Or $(\mathrm{A}-n\mathrm{I})w = 0$. In this format, we can find a non-trivial solution on w if n is an eigenvalue of A. Since the rank of A is 1 as all rows are multiplied by any one of the rows, there is only 1 eigenvalue. The sum of all eigenvalues of A equals to its trace which is n; therefore, n is an eigenvalue of A. Therefore, the elements of the weights vector can also be expressed as follows:

$$w_i = \frac{1}{n}\sum_{j=1}^{n} w_{ij} w_j \tag{3.4}$$

In reality, the relative weightings (w_{ij}) are estimated values only; otherwise, we do not need to calculate (or estimate to be precise) the weights vector. The question is whether or not such estimation is reliable. This can be done normally by a set of expert panel and a final consensus can be reached. Delphi study is also possible. However, an easier approach is that a pre-defined scale is employed to aid the judgement. It is not uncommon in the literature to use a scale of 1 to 9 (or just the odd numbers) to represent the importance of Criterion i over Criterion j. In other words, the reverse scale (1/9, …, 1) is employed to show the negative relationship. This poses a problem on the accuracy of the pairwise comparison as only discrete values are used.

To tackle above problem, Saaty (1980) introduced the concept of consistency ratio. The concept is very straightforward. If there is any error due to inconsistency, the following value would be non-zero:

$$\lambda_{\max} - n = -\sum_{i=1}^{n} \lambda_i \tag{3.5}$$

where $\lambda_{\max} = \lambda_1,\ \lambda_i, i = 1, \ldots, n$ are the eigenvalues of A.

Since $\lambda_{\max} = n$ represents the ideal case, Saaty (1980) suggested that as long as the consistency ratio (CR) is less than 0.1 (or 10 % in other words), the comparisons are performed consistently:

$$\mathrm{CR} = (\lambda_{\max} - n)/(n - 1) \tag{3.6}$$

In other words, CR is a measure of the deviation of $\lambda_{\max}$ from n. Based on the above, it can also be noted that there are $(n^2-n)/2$ comparisons need to be made in order to construct the matrix. Above discussion is a brief introduction to one level of hierarchical structure. The analysis can be extended to a full hierarchy of many levels. Of course, the more levels of the hierarchical model are involved, the more comparisons are needed.

3.4 An Illustrative Case Study Using AHP

This section illustrates how an AHP enabled novel approach to perform structured analysis of LCA (please refer to Appendix 1 for more details). LCA is a comprehensive technique that can be used to analyse the environmental impact of a product design. This can be reflected by numerous studies in this area (Bhander et al. 2003; Hur et al. 2005; Finnveden et al. 2009; Huntzinger and Eatmon 2009; Sobotka and Rolak 2009; Yung et al. 2011, 2012). Facing shorter product life cycle (Chiang et al. 2011) firms, however, do not normally have the leisure time to conduct LCA for each new product alternative. Despite this restriction, we should take the whole life cycle of the product into consideration while developing a green design (Lin et al. 2009). Therefore, a simplified, easy to use approach is desired for quick assessment and initial screening of new product development from environmental conscious perspective.

Before conducting an LCA, information has to be collected. This includes bill of materials and information on the corresponding materials; the way the product is manufactured, including what kind of machines are used, delivery methods, information on usage like electricity consumption and so on. If a part or module is purchased from the supplier, information from the supplier or a visit is needed in order to collect the material phase information. Therefore, conducting a full LCA is time consuming.

According to the energy-using product (EuP) directive, a product life cycle is divided into six main phases, namely material (selection) phase, manufacturing phase, packaging, transportation and distribution phase, installation and maintenance phase, use phase and end-of-life phase (European Council 2005, p. 27). Since the focus of this study is on consumer electronic products, the installation and maintenance phase is omitted. However, the same philosophy can be applied equally well to other products including this phase. The model is then divided into sub-criteria under each phase (i.e. the main criteria of the AHP model) and then each criterion and its sub-criteria. They all will affect the environmental assessment attributes that monitor subject to the requirements of the EuP directive. The main purpose of this case is to illustrate how AHP can be employed. A generic AHP model is thus developed based on the LCA approach for this type of product. This is illustrated in Table 3.1.

In this model, most of the elements are grouped into categories as it is very rare that one single component would be dominant in a design, despite some distinctive items like printed circuit board (PCB) or user manual which has been identified in the model. In other words, once we have a LCA as a reference, pairwise comparisons of criteria and sub-criteria, to be discussed below, can be assessed quite easily.

The model is analysed using the software package Expert Choice, which is a commercially available package for modelling AHP (Expert Choice 1995). Pairwise comparisons, one of the key steps in AHP, are conducted with the expertise gained from the aforementioned case studies. For example, Table 3.2 below illustrates an example of the pairwise comparison on the Criterion LC_1.

Table 3.1 Hierarchical structure for LCA-based green design selection in the case study

Life cycle phases	Criteria	Environmental assessment attributes
LC_1. Material (selection)	LC_{11}. Plastic: general (ABS, PE, etc.) LC_{12}. Plastic: special (rubber, high impact, etc.) LC_{13}. Metal LC_{14}. Electronic component (resistors, capacitors, LCD, etc.) LC_{15}. Printed circuit board (PCB)	EA_1. Consumption of material, energy and other resources
LC_2. Manufacturing	LC_{21}. Surface mount LC_{22}. Die bonding LC_{23}. General assembly LC_{24}. Metal processing (stamping, etc.) LC_{25}. Plastic processing (injection, etc.)	EA_2. Emission to air, water or soil
LC_3. Packaging, transportation and distribution	LC_{31} Packaging: product level LC_{32}. Packaging: carton level LC_{33}. Manual	EA_3. Anticipated pollution
LC_4. Usage	LC_{41}. Operating LC_{42}. Standby	EA_4. Generation of waste material
LC_5. End-of-life	LC_{51}. Extend of recyclability LC_{52}. Extend of reuse LC_{53}. Extend of recovery	EA_5. Possibility of re-use, recycling, and recovery of materials and/or energy

As discussed before, CR of the comparisons should be checked, which is found to be 0.07 in this case. The value is less than the threshold 0.1, so this is deemed consistent. Table 3.3 shows another example with respect to the Criterion LC_3. Again, the CR is checked, which is at 0.04, so the comparisons are found satisfactory. The full pairwise comparisons of other criteria and sub-criteria are listed in Appendix 2.

Following the same procedures, all the inconsistency ratios have been recorded and checked to ensure that they are all below the widely recommended threshold

Table 3.2 Pairwise comparisons of the sub-criteria of LC_1

	LC_{11}	LC_{12}	LC_{13}	LC_{14}	LC_{15}
LC_{11}	1	1/5	1/3	2	1/7
LC_{12}	5	1	5	7	1/3
LC_{13}	3	1/5	1	5	1/5
LC_{14}	1/2	1/7	1/5	1	1/9
LC_{15}	7	3	5	9	1

Table 3.3 Pairwise comparisons of the sub-criteria of LC_3

	LC_{31}	LC_{32}	LC_{33}
LC_{31}	1	1/3	1/5
LC_{32}	3	1	1/3
LC_{33}	5	3	1

value of 0.1. Then, weightings for individual criterion and environmental assessment attributes are calculated and listed in Table 3.4. In addition to that, Figs. 3.2 and 3.3 summarise the overall weightings of different life cycle phases and environmental assessments, respectively. These figures serve to exemplify the results.

Referring to Table 3.4 and Fig. 3.2, it can be concluded that LC_1 (the material selection phase) contributes most to the environmental assessments followed by LC_2 (the manufacturing phase). To probe further, LC_{15} (PCB) and LC_{12} (special types of plastic) are the two most important criteria under LC_1. The former contributes more than 50 % of that phase (LC_1), whereas the second one contributes almost 30 % of that phase. Another important life cycle phase is LC_2 (the manufacturing phase). Among the criteria under this phase, LC_{25} (plastic processing) and LC_{24} (metal processing) ranked at the top which contributes over 50 and 20 % of the environmental assessments, respectively. Apart from the above, other phases should not be overlooked, of course. It is very obvious that LC_{33} (manual), LC_{41} (operating) and LC_{52} (extend of reuse) are the core factors of their respective life cycle phase (all over 50 % with respect to their life cycle phase). In other words, improvement options should be proposed pinpointing these phases and the corresponding criteria. The most straightforward design options are then to reduce the size of PCB, and usage of special types of plastic should be reduced, which can also help to reduce the impact created by plastic processing.

In addition, size of user manual (for example, changing from a multi-language manual to a single-language manual or a graphic, which is also a kind of commonly known language, dominated manual) and usage of electricity in the operating mode should also be taken into consideration. The former in fact affects the packaging design and hence also contributes to the environmental impacts generated in the packaging, transportation and distribution phase as the larger the packaging, the bigger the volume of the overall product size. For the latter, it is also a matter of environmental consciousness: whether the software and hardware designers have taken this into consideration or not.

3.5 Fuzzy AHP and Related Models

As mentioned earlier, MCDM problems are not always easy to solve. With the aid of AHP, such problems can be modelled systematically. More importantly, both quantitative and qualitative factors can be taken into account. Having said that,

Table 3.4 Weightings of the AHP model (obtained from the expert choice software)

Level 1	Level 2	Level 3	Level 1	Level 2	Level 3
$LC_1 = 0.512$	$LC_{11} = 0.028$	$EA_1 < 0.001$	$LC_3 = 0.039$	$LC_{31} = 0.004$	$EA_1 = 0.001$
		$EA_2 = 0.004$			$EA_2 < 0.001$
		$EA_3 = 0.011$			$EA_3 < 0.001$
		$EA_4 = 0.002$			$EA_4 < 0.001$
		$EA_5 = 0.010$			$EA_5 = 0.002$
	$LC_{12} = 0.150$	$EA_1 = 0.004$		$LC_{32} = 0.010$	$EA_1 = 0.004$
		$EA_2 = 0.025$			$EA_2 = 0.002$
		$EA_3 = 0.075$			$EA_3 < 0.001$
		$EA_4 = 0.013$			$EA_4 < 0.001$
		$EA_5 = 0.033$			$EA_5 = 0.004$
	$LC_{13} = 0.059$	$EA_1 = 0.015$		$LC_{33} = 0.025$	$EA_1 = 0.013$
		$EA_2 = 0.008$			$EA_2 = 0.004$
		$EA_3 = 0.004$			$EA_3 = 0.006$
		$EA_4 = 0.002$			$EA_4 = 0.002$
		$EA_5 = 0.030$			$EA_5 < 0.001$
	$LC_{14} = 0.018$	$EA_1 = 0.001$	$LC_4 = 0.127$	$LC_{41} = 0.111$	$EA_1 = 0.070$
		$EA_2 = 0.005$			$EA_2 = 0.015$
		$EA_3 = 0.003$			$EA_3 = 0.015$
		$EA_4 = 0.008$			$EA_4 = 0.006$
		$EA_5 < 0.001$			$EA_5 = 0.004$
	$LC_{15} = 0.257$	$EA_1 = 0.014$		$LC_{42} = 0.016$	$EA_1 = 0.010$
		$EA_2 = 0.028$			$EA_2 = 0.002$
		$EA_3 = 0.055$			$EA_3 = 0.002$
		$EA_4 = 0.152$			$EA_4 < 0.001$
		$EA_5 = 0.008$			$EA_5 < 0.001$
$LC_2 = 0.293$	$LC_{21} = 0.013$	$EA_1 = 0.007$	$LC_5 = 0.029$	$LC_{51} = 0.003$	$EA_1 = 0.001$
		$EA_2 = 0.001$			$EA_2 < 0.001$
		$EA_3 = 0.001$			$EA_3 < 0.001$
		$EA_4 = 0.004$			$EA_4 < 0.001$
		$EA_5 < 0.001$			$EA_5 = 0.001$
	$LC_{22} = 0.009$	$EA_1 = 0.005$		$LC_{52} = 0.018$	$EA_1 = 0.008$
		$EA_2 < 0.001$			$EA_2 = 0.002$
		$EA_3 < 0.001$			$EA_3 = 0.002$
		$EA_4 = 0.002$			$EA_4 < 0.001$
		$EA_5 < 0.001$			$EA_5 = 0.007$
	$LC_{23} = 0.036$	$EA_1 = 0.003$		$LC_{53} = 0.007$	$EA_1 = 0.003$
		$EA_2 = 0.014$			$EA_2 < 0.001$
		$EA_3 = 0.014$			$EA_3 < 0.001$
		$EA_4 = 0.004$			$EA_4 < 0.001$
		$EA_5 = 0.001$			$EA_5 = 0.003$
	$LC_{24} = 0.067$	$EA_1 = 0.037$			
		$EA_2 = 0.005$			
		$EA_3 = 0.005$			

(continued)

Table 3.4 (continued)

Level 1	Level 2	Level 3	Level 1	Level 2	Level 3
		$EA_4 = 0.013$			
		$EA_5 = 0.006$			
	$LC_{25} = 0.168$	$EA_1 = 0.083$			
		$EA_2 = 0.014$			
		$EA_3 = 0.014$			
		$EA_4 = 0.038$			
		$EA_5 = 0.019$			

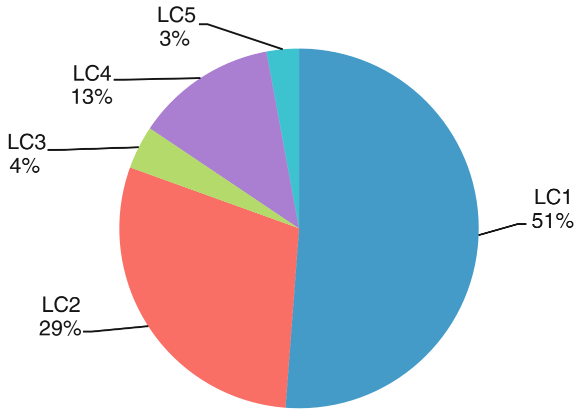

Fig. 3.2 Overall weightings of different life cycle phases

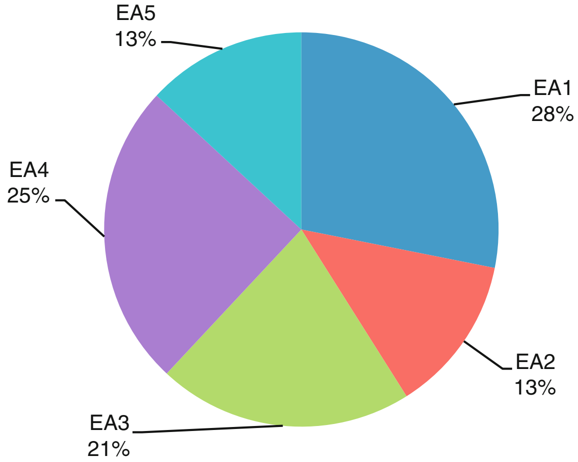

Fig. 3.3 Overall weightings of different environmental assessments

AHP has its shortcomings. The major pitfall is that the tool cannot handle uncertain parameters. Although the model can incorporate imprecise judgement using, for example, the nine-point scale in the assessment process, the scale is still not well defined. This is of course not a flaw but the limitation is that this is unable to capture imprecise information. This section aims to review several key AHP-based models that utilise fuzzy logic to tackle the aforementioned problem. Fuzzy set theory has been proven advantageous within vague, imprecise and uncertain contexts. Fuzzy logic resembles human reasoning in its use of approximate information and uncertainty to support decision making (Zadeh 1965).

3.5.1 Fuzzy AHP

Although the discrete scale of AHP has the advantage of simplicity and ease of use for pairwise comparison of different alternatives, it has been generally criticised because it cannot handle the uncertainty and ambiguity present in deciding the ratings of different attributes (Chan and Kumar 2007). In addition, it is often difficult to compare different factors due to a lack of adequate information. In this connection, another stream of research focuses on FAHP.

The basic operations of FAHP are not difficult to understand. Instead of assigning deterministic values in the pairwise comparisons process, the judgements are made using linguistic parameters (e.g. more important, very important) which are characterised by fuzzy membership functions. If there is more than one expert involved in the judging process, different matrices are combined together to form one synthetic pairwise comparison matrix. The fuzzy geometric mean approach is the most popular approach to construct the matrix. After that, the matrix [which is analogous to Eq. (3.1)] needs to be defuzzified (i.e. turn the fuzzy values into crisp values). There are many approaches to handle this process, but the centre of area approach is the most commonly employed. The remaining procedures are just standard AHP operations. This way, uncertain judgement can be coped with by fuzzy logic. Chapter 5 includes an application which can illustrate how the FAHP operates.

Since Van Laarhoven and Pedrycz (1983) and Buckley (1985) presented their preliminary work in FAHP, many studies using FAHP have been proposed in different problem environments (Weck et al. 1997; Arshinder et al. 2007; Chan and Kumar 2007; Huang et al. 2008; Abdi 2009; Faez et al. 2009; Güngör et al. 2009; Wang et al. 2012). The reason behind adopting fuzzy AHP is due to the uncertain nature of a problem. FAHP can be used to rank how well the relevant selection criteria of one design feature performs over another. For example, Kang and Li (2010) presented a FAHP method for “green rationality evaluation” of degradable packaging with respect to LCA. Zheng et al. (2011) applied an FAHP assessment model to evaluate energy conservation in the building sector. In both studies, hierarchical models were developed based on the AHP concept, and then the weightings of the evaluation factors were determined following the AHP procedures. In addition, fuzzy membership degrees were only employed in the lowest hierarchy to measure each criterion. Therefore, such approach is not full FAHP and cannot address the aforementioned shortcoming. Wang and Chan (2011) proposed an innovative approach to perform structured LCA in conjunction with the concept of fuzzy AHP. Although it is an effective approach to prioritise alternatives and select new design options for design improvement, the method does not consider the interaction between criteria. In fact, the above-mentioned studies that employed FAHP only consider one-way hierarchical relationships between the factors. This is a simplistic assumption that does not consider many possible relationships (Wu et al. 2009). This issue can be addressed by using a network approach, which will be discussed later in this chapter.

3.5.2 Fuzzy Extent Analysis

Fuzzy extent analysis is first analysis proposed by Chang (1996) to help formulate the fuzzy decision-making process, which is multi-tier in nature. Like in FAHP, the fuzzy judgement matrix is first constructed. Then, the synthetic degree value is calculated (instead of defuzzifying the matrix). These values are also fuzzy numbers, and because of this analysis, the method is called extent analysis. The operations are further discussed in Chap. 6. By applying the principle of the comparison of fuzzy numbers, the priority vectors for the AHP can be calculated. The merit of this method is that the computational effort is reduced, especially for large problem.

Since the development of this method by Chang (1996), it has been applied in many applications. For example, Kahraman et al. (2003) applied this method for supplier selection problem using three main criteria, namely supplier criteria, product performance criteria and service performance criteria in the hierarchical model. Chan and Kumar (2007) applied a similar approach with five main criteria to investigate the risk associated with various options for global supplier selection. Lee et al. (2009) employed a similar approach to analyse the green supplier selection problem in the hi-tech industry. Some environmental-related factors like green product development, environmental management and so on are added in the hierarchical model. The fuzzy extent analysis has also attracted applications in the service industry. For example, Vahidnia et al. (2009) applied the fuzzy extent analysis in choosing hospital location. They also compared the method with other fuzzy approaches and concluded that fuzzy extent analysis is simpler to use. Chan et al. (2012) employed the same fuzzy approach for green product design evaluation.

Some researchers attempted to merge the merits of fuzzy extent analysis with other methods. For instance, Ertuğrul and Karakaşoğlu (2008) combined the fuzzy extent analysis and fuzzy TOPSIS method (to be discussed in Sect. 3.5.3) as a two-step approach on a performance evaluation problem in the cement market. The former is utilised for determining the weights of the criteria in the AHP, and then the latter is used for determining the ranking of different firms. Büyüközkan et al. (2008) used the same method to select strategic alliance partner in the logistics industry. Gumus (2009) also applied a similar two-step approach to study the performance of different transportation firms in terms of their transportation of hazardous waste. Similar approach was also used by Mahmoodzadeh et al. (2007) to evaluate different investment decision of different industrial projects. In the service sector, Seçme et al. (2009) used the same approach to evaluate the performance of different banks. Apart from the above two-step approach, Zeydan et al. (2011) added a further step to use data envelopment analysis to analyse the crisp outputs of the above approach for supplier selection problems. In fact, Ertuğrul and Karakaşoğlu (2008) compared the fuzzy extent analysis and the fuzzy TOPSIS on the same problem, which is factory location selection, and found that the ranking results are the same. Of course, the observation is on one problem and cannot be generalised. They also concluded that the former is more preferable for widely spread hierarchies, whereas the latter is more suitable for single-tier problems.

Like many other models, fuzzy extent analysis also has its problems despite its usefulness and numerous applications found in the literature. Wang et al. (2008) argued that under certain circumstances, the method could lead to wrong decision. The main reasons are that the method could not make full use of all the fuzzy comparison matrices information, and might assign an irrational zero weight to some useful decision criteria.

3.5.3 Fuzzy TOPSIS

Apart from AHP, several MCDM approaches have been developed to solve such type of real-world problems. One of these techniques is known as Technique for Order Performance by Similarity to Ideal Solution (TOPSIS), which is a technique to evaluate the performance of alternatives through the similarity with the ideal solution proposed by Hwang and Yoon (1981). The main concept of TOPSIS is to define the positive ideal solution and negative ideal solution. The positive ideal solution is the one that maximises the benefit criteria and minimises the cost criteria. The negative ideal solution maximises the cost criteria and minimises the benefit criteria. The most preferred alternative should have the shortest distance from the positive ideal solution and the longest distance from the negative ideal solution.

Despite its popularity and simplicity in concept, TOPSIS, similarly to AHP, is often criticised because of its inability to deal adequately with uncertainty and imprecision inherent in the process of mapping the perceptions of decision makers (Krohling and Campanharo 2011). In fact, the decisions on implementing different alternatives contain considerable amount of uncertainty causing elements, which may confuse the decision maker to reach the targeted performance. Uncertainty arises from both internal and external multiple sources including technical, operational and commercial issues. To address this limitation of TOPSIS, some scholars have made use of fuzzy logic, which can be employed to deal with uncertain parameters and information as discussed in preceding sections. TOPSIS has been expanded to MCDM to deal with an uncertain decision matrix resulting in fuzzy TOPSIS, which has successfully been applied to solve various MCDM problems such as plant location selection (Yong 2006; Ertuğrul and Karakaşoğlu 2008), customer evaluation (Chamodrakas et al. 2009), supplier selection and evaluation (Chen et al. 2005; Bottani and Rizzi 2006; Boran et al. 2009; Roghanian et al. 2010; Büyüközkan and Çifçi 2012a), bridge risk assessment (Wang and Elhag 2006), evaluation of new product design (Kahraman et al. 2007; Gao et al. 2010; Ng and Chuah 2010) and personnel selection (Kelemenis and Askounis 2010; Kelemenis et al. 2011). Gao et al. (2010) proposed an MCDM model utilising fuzzy TOPSIS for selecting different design schemes and applied the model in a case study. Ng and Chuah (2010) applied fuzzy AHP for evaluating different eco-design alternatives also employing TOPSIS as the fuzzy decision-making tool. Their research raised concerns about the cost and time of performing conventional LCA and outlined the advantages of fuzzy AHP. Both of the aforementioned studies employed fuzzy TOPSIS for making the decision.

Although classical TOPSIS method and its extended fuzzy TOPSIS have demonstrated their effectiveness in addressing the MCDM and easiness of implementation, there are some limitations. First of all, the TOPSIS method does not consider a hierarchical structure between main criteria and sub-criteria as it is in the additive weighting and weighted product methods (Kahraman et al. 2007). There is also a lack of comparative analysis of different criteria, and the approach separates qualitative and quantitative variables (Ertuğrul and Karakaşoğlu 2008). These characteristics make fuzzy TOPSIS more applicable to one-tier decision problem, rather than multi-tier decision problem (Bottani and Rizzi 2006). Meanwhile, the well known and widely used MCDM methods, AHP, consider a hierarchical model which gives the ability of taking into consideration more information and provide superiority to solve such complex decision problems. Any complex problem can be decomposed into several sub-problems using AHP in terms of hierarchical levels where each level represents a set of criteria or attributes relative to each sub-problem. Some studies (Kahraman et al. 2009; Wang et al. 2009; Bao et al. 2012) make use of the benefits of AHP by proposing a hierarchical fuzzy TOPSIS approach. Such an approach can benefit from both the superiority of the hierarchical structure of AHP and easiness of implementation of TOPSIS in a fuzzy environment. This concept is illustrated in an application in Chap. 7.

3.5.4 Fuzzy Analytic Network Process

One limitation of AHP is the assumption of independence among various factors. AHP does not explicitly consider the interactions within various factors/clusters. Unfortunately, the criteria considered are usually not independent because of the dynamic nature of the problems. To overcome the disadvantages of the previously proposed AHP models, analytic network process (ANP) is often used to solve the problem of dependence among alternatives or criteria. Comparing to AHP method, ANP is more accurate for many complicated models in which many criteria feedback and interrelations between criteria are used. It evaluates all relationships systematically by adding potential interdependences, interactions and feedbacks in the decision-making system.

There are many applications of ANP. For example, Sarkis (2002) presented a systemic ANP model to evaluate environmental practices and programs in analysing various projects, technological or business decision alternatives. To address the interrelated attributes of a manufacturing system, Yurdakul (2003) employed the ANP approach and developed a performance measurement model. Chung et al. (2005) proposed an approach that adopts ANP to deal with integrated factors for the selection of product mix for efficient manufacturing in a semiconductor fabricator. Bayazit and Karpak (2007) developed an ANP-based framework to identify the level of impact of different factors on total quality management (TQM) implementation and to assess the readiness of the Turkish manufacturing industry to adopt TQM practices. Because of the dependency among the measurement, Karpak and Topcu (2010) employed ANP to develop a multiple criteria framework for prioritise the measures of success and the antecedents for small- and medium-sized enterprises (SMEs) in Turkey.

Nevertheless, ANP does not allow for any uncertainty among factors. Thereby, fuzzy logic, which can be employed to deal with uncertain parameters and information, is introduced in the pairwise comparison of ANP to make up for this deficiency in the conventional ANP. In order to address the limitation of ANP, many researchers combine fuzzy set theory and ANP and have applied fuzzy ANP to several research fields (e.g. Mikhailov and Madan 2003; Mohanty et al. 2005; Tuzkaya and Onut 2008; Tuzkaya et al. 2009; Liu and Lai 2009; Dağdeviren and Yüksel 2010; Luo et al. 2010; Liu and Wang 2010; Büyüközkan and Çifçi 2012a, b; Vinodh et al. 2011).

More specifically, Liu and Lai (2009) proposed an integrated decision support framework for the environmental impact assessment of construction project. Tuzkaya et al. (2009) combined fuzzy ANP and Fuzzy Preference Ranking Organisation Method for Enrichment Evaluations (PROMETHEE) methodology to evaluate the suppliers' performance. Büyüközkan and Çifçi (2012b) proposed an analytic approach based on the fuzzy ANP methodology to assist in green supply chain management (GSCM) strategic decisions. They also combined the ANP, the fuzzy Decision-Making Trial and Evaluation Laboratory Model (DEMATEL) and TOPSIS and developed a novel hybrid fuzzy multiple criteria decision-making model for green supplier evaluation in Ford Otosan (Büyüközkan and Çifçi 2012a). In the aforementioned studies, on the one hand, fuzzy ANP is used to manage the dependences among environmental factors. On the other hand, the application of fuzzy ANP also encompasses and solves the ambiguity and imprecision of the pairwise comparison process substantially. Chapter 8 presents an application using fuzzy ANP, and the model will also be discussed in that chapter in more detail.

3.6 Conclusions

This chapter provides the basic review of the AHP and a number of its variations using fuzzy logic. Section 3.5 provides high-level description of the fuzzy-based models as they will be discussed in more detail in the subsequent chapters. The major aim of this chapter is to bring out the basic understanding of the AHP model and various fuzzy-based variants. In addition, readers should be able to spot the usefulness of the AHP and the corresponding variations. To supplement this, various applications using the aforementioned fuzzy models are discussed in the following chapters.

References

Abdi, M. R. (2009). Fuzzy multi-criteria decision model for evaluating reconfigurable machines. *International Journal of Production Economics, 117*(1), 1–15.

Arshinder, K. A., & Deshmukh, S. G. (2007). Coordination in supply chains: An evaluation using fuzzy logic. *Production Planning and Control, 18*(5), 420–435.

Bao, Q., Ruan, D., Shen, Y., Hermans, E., & Janssens, D. (2012). Improved hierarchical fuzzy TOPSIS for road safety performance evaluation. *Knowledge-Based Systems, 32*, 84–98.

Bayazit, O., & Karpak, B. (2007). An analytical network process-based framework for successful total quality management (TQM): An assessment of Turkish manufacturing industry readiness. *International Journal of Production Economics, 105*, 79–96.

Bhander, G. S., Hauschild, M., & McAloone, T. (2003). Implementing life cycle assessment in product development. *Environmental Progress, 22*(4), 255–267.

Boran, F. E., Genc, S., Kurt, M., & Akay, D. (2009). A multi-criteria intuitionistic fuzzy group decision making for selection of supplier with TOPSIS method. *Expert System with Applications, 36*(8), 11363–11368.

Bottani, E., & Rizzi, A. (2006). A fuzzy TOPSIS methodology to support outsourcing of logistics services. *Supply Chain Management: An International Journal, 11*(4), 294–308.

Buckley, J. (1985). Fuzzy hierarchical analysis. *Fuzzy Sets and Systems, 17*, 233–247.

Büyüközkan, G., & Çifçi, G. (2012a). A novel hybrid MCDM approach based on fuzzy DEMATEL, fuzzy ANP and fuzzy TOPSIS to evaluate green suppliers. *Expert Systems with Applications, 39*, 3000–3011.

Büyüközkan, G., & Çifçi, G. (2012b). Evaluation of the green supply chain management practices: A fuzzy ANP approach. *Production Planning and Control, 23*(6), 405–418.

Büyüközkan, G., Feyzioğlu, O., & Nebol, E. (2008). Selection of the strategic alliance partner in logistics value chain. *International Journal of Production Economics, 113*(1), 148–158.

Chamodrakas, I., Alexopoulou, N., & Martakos, D. (2009). Customer evaluation for order acceptance using a novel class of fuzzy methods based on TOPSIS. *Expert Systems with Applications, 36*(4), 7409–7415.

Chan, F. T. S., & Chan, H. K. (2010). An AHP model for selection of suppliers in the fast changing fashion market. *International Journal of Advanced Manufacturing Technology, 51*(9–12), 1195–1207.

Chan, F. T. S., & Kumar, N. (2007). Global supplier development considering risk factors using fuzzy extended AHP-based approach. *Omega, 35*(4), 417–431.

Chan, F. T. S., Chan, H. K., Lau, H. C. W., & Ip, R. W. L. (2006). Benchmarking logistics performance of the postal industry: A double AHP approach. *Benchmarking: An International Journal*, *13*(6), 636–661.

Chan, H. K., Wang, X., White, G., & Nick, Y. (2012). An extended fuzzy AHP approach for the evaluation of green product designs. *IEEE Transactions on Engineering Management*, (99), 1–13.

Chang, D. Y. (1996). Applications of the extent analysis method on fuzzy AHP. *European Journal of Operational Research, 95*, 649–655.

Chang, H.-T., & Chen, J. L. (2004). The conflict-problem-solving CAD software integrating TRIZ into eco-innovation. *Advances in Engineering Software, 35*(8–9), 553–566.

Chen, Y. M., & Huang, P.-N. (2007). Bi-negotiation integrated AHP in suppliers selection. *International Journal of Operations and Production Management, 27*(11), 1254–1274.

Chen, C. T., Lin, C. T., & Huang, S. F. (2005). A fuzzy approach for supplier evaluation and selection in supply chain management. *International Journal of Production Economics, 102*(2), 289–301.

Chiang, S.-Y., Wei, C.-C., Chiang, T.-H., & Chen, W.-L. (2011). How can electronics industries become green manufacturers in Taiwan and Japan. *Clean Technologies and Environmental Policy, 13*(1), 37–47.

Choice, Expert. (1995). *Decision Support Software*. PA: Pittsburgh.

Chung, S. H., Lee, A. H. I., & Pearn, W. L. (2005). Analytic network process (ANP) approach for product mix planning in semiconductor fabricator. *International Journal of Production Economics, 96*, 15–36.

Council, European. (2005). Directive 2005/32/EC of the European Parliament of the council of 6 July 2005 establishing a framework for the settings of ecodesign requirements for energy-using products and amending Council Directive 92/42/EEC and Directive 96/57/EC and 2000/55/EC of the European Parliament and of the Council. *Official Journal of the European Union, L191*(48), 29058.

Dağdeviren, M., & Yüksel, İ. (2010). A fuzzy analytic network process (ANP) model for measurement of the sectoral competition level. *Expert System with Application, 37*, 1005–1014.

Ertuğrul, İ., & Karakaşoğlu, N. (2008). Comparison of fuzzy AHP and fuzzy TOPSIS methods for facility location selection. *International Journal of Advanced Manufacturing Technology, 39*(7–8), 783–795.

Faez, F., Ghodsypour, S. H., & O'Brien, C. (2009). Vendor selection and order allocation using an integrated fuzzy case-based reasoning and mathematical programming model. *International Journal of Production Economics, 121*(2), 395–408.

Finnveden, G., Hauschild, M. Z., Ekvall, T., Guinee, J., Heijungs, R., Hellweg, S., et al. (2009). Recent developments in Life Cycle Assessment. *Journal of Environmental Management, 91*(1), 1–21.

Gao, Y., Liu, Z., Hu, D., Zhang, L., & Gu, G. (2010). Selection of green product design scheme based on multi-attribute decision-making method. *International Journal of Sustainable Engineering, 3*(4), 277–291.

Gumus, A. T. (2009). Evaluation of hazardous waste transportation firms by using a two step fuzzy-AHP and TOPSIS methodology. *Expert Systems with Applications, 36*(2), 4067–4074.

Güngör, Z., Serhadlıoğlu, G., & Kesen, E. (2009). A fuzzy AHP approach to personnel selection problem. *Applied Soft Computing, 9*(2), 641–646.

Huang, C., Chu, P., & Chiang, Y. (2008). A fuzzy AHP application in government-sponsored R&D project selection. *Omega, 36*, 1038–1052.

Huntzinger, D. N., & Eatmon, T. D. (2009). A life-cycle assessment of Portland cement manufacturing: Comparing the traditional process with alternative technologies. *Journal of Cleaner Production, 17*(7), 668–675.

Hur, T., Lee, J., Ryu, J., & Kwon, E. (2005). Simplified LCA and matrix methods in indentifying the environmental aspects of a product system. *Journal of Environmental Management, 75*(3), 229–237.

Hwang, C. L., & Yoon, K. (1981). *Multiple attributes decision making methods and applications*. Berlin: Springer.

Kahraman, C., Cebeci, U., & Ulukan, Z. (2003). Multi criteria supplier selection using fuzzy AHP. *Logistics Information Management, 16*(6), 382–394.

Kahraman, C., Büyüközkan, G., & Ateş, N. Y. (2007). A two phase multi-attribute decision-making approach for new product introduction. *Information Sciences, 177*, 1567–1582.

Kahraman, C., Engin, O., Kabak, Ö., & Kaya, I. (2009). Information systems outsourcing decisions using a group decision-making approach. *Engineering Applications of Artificial Intelligence, 22*(6), 832–841.

Kang, Y., & Li, J. (2010). *Green rationality evaluation of degradable packaging based on LCA and fuzzy AHP*: *Proceedings of the IEEE 17th International Conference on Industrial Engineering and Engineering Management (IE&EM)*, 329–332.

Karpak, B., & Topcu, I. (2010). Small medium manufacturing enterprises in Turkey: An analytic network process framework for prioritizing factors affecting success. *International Journal of Production Economics, 125*, 60–70.

Kelemenis, A., & Askounis, D. (2010). A new TOPSIS-based multi-criteria approach to personnel selection. *Expert Systems with Applications, 37*(7), 4999–5008.

Kelemenis, A., Eragzakis, A., & Askounis, D. (2011). Support managers' selection using an extension of fuzzy TOPSIS. *Expert Systems with Applications, 38*(3), 2774–2782.

Krohling, R. A., & Campanharo, V. C. (2011). Fuzzy TOPSIS for group decision making: A case study for accidents with oil spill in the sea. *Expert System with Applications, 38*(4), 4190–4197.

Lee, A. H. I., Kang, H. Y., Hsu, C. F., & Hung, H. C. (2009). A green supplier selection model for high-tech industry. *Expert Systems with Applications, 36*(4), 7917–7927.

Li, T. (2010). Applying TRIZ and AHP to develop innovative design for automated assembly systems. *International Journal of Advanced Manufacturing Technology, 46*, 301–313.

Lin, S.-S., Juang, Y.-S., Chen, M.-Y., & Yu, C.-J. (2009). *Analysis of green design criteria and alternative evaluation processes for 3C products. Proceedings of the Asia Pacific Industrial Engineering & Management Systems Conference (APIEMS),* Dec 14–16, (pp. 2675–2685), Japan: Kitakyushu.

Liu, K. F. R., & Lai, J. H. (2009). Decision-support for environmental impact assessment: A hybrid approach using fuzzy logic and fuzzy analytic network process. *Expert Systems with Applications, 36*, 5119–5136.

Liu, H. T., & Wang, C. H. (2010). An advanced quality function deployment model using fuzzy analytic network process. *Applied Mathematical Modelling, 34*(11), 3333–3351.

Lu, L. Y. Y., Wu, C. H., & Kuo, T.-C. (2007). Environmental principles applicable to green supplier evaluation by using multi-objective decision analysis. *International Journal of Production Research, 45*(18–19), 4317–4331.

Luo, Z. M., Zhou, J. Z., Zheng, L. P., Mo, L., & He, Y. Y. (2010). A TFN–ANP based approach to evaluate Virtual Research Center comprehensive performance. *Expert Systems with Applications, 37*(12), 8379–8386.

Mahmoodzadeh, S., Shahrabi, J., Pariazar, M., & Zaeri, M. S. (2007). Project selection by using fuzzy AHP and TOPSIS technique. *International Journal of Human and Social Sciences, 2*(7), 397–402.

Mikhailov, L., & Madan, G. (2003). Fuzzy analytic network process and its application to the development of decision support system. *IEEE Transactions on Systems, Man, and Cybernetics-Part C: Application and Reviews, 33*(1), 33–41.

Mohanty, R. P., Agarwal, R., Choudhury, A. K., & Tiwari, M. K. (2005). A fuzzy ANP based approach to R&D project selection: A case study. *International Journal of Production Research, 43*, 5199–5216.

Ng, C. Y., & Chuah, K. B. (2010). Evaluation of eco design alternatives using fuzzy AHP methodology. *Design Principles and Practices: An International Journal, 4*(1), 1–14.

Roghanian, E., Rahimi, J., & Ansari, A. (2010). Comparison of first aggregation and last aggregation in fuzzy group TOPSIS. *Applied Mathematical Modelling, 34*(12), 3754–3766.

Saaty, (1978). Modeling unstructured decision problems: The theory of analytical hierarchies. *Mathematics and Computers in Simulation, 20*(3), 147–158.

Saaty, T. L. (1980). *The analytic hierarchy process*. New York: McGraw-Hill.

Saaty, T. L. (1990). How to make a decision: The analytic hierarchical process. *European Journal of Operational Research, 48*(1), 9–26.

Saaty, T. L., & Peniwati, K. (2008). *Group decision making: Drawing out and reconciling differences*. Pittsburgh: RWS Publications.

Sarkis, J. (2002). Quantitative models for performance measurement systems-alternate considerations. *International Journal of Production Economics, 86*, 81–90.

Sarkis, J. (2003). A strategic decision framework for green supply chain management. *Journal of Cleaner Production, 11*(4), 397–409.

Sarminento, R., & Thomas, A. (2010). Identifying improvement areas when implementing green initiatives using a multitier AHP approach. *Benchmarking: An International Journal*, 17(3), 452–463.

Seçme, N. Y., Bayrakdaroğlu, A., & Kahraman, C. (2009). Fuzzy performance evaluation in Turkish Banking Sector using Analytic Hierarchy Process and TOPSIS. *Expert Systems with Applications, 36*(9), 11699–11709.

Sobotka, A., & Rolak, Z. (2009). Multi-attribute analysis for the eco-energetic assessment of the building life cycle. *Technological and Economic Development of Economy, 15*(4), 593–611.

Tan, R. R. (2005). Application of symmetric fuzzy linear programming in life cycle assessment. *Environmental Modelling and Software, 20*, 1343–1346.

Tuzkaya, U. R., & Onut, S. (2008). A fuzzy analytic network process based approach to transportation-mode selection between Turkey and Germany: A case study. *Information Sciences, 178*, 3133–3146.

Tuzkaya, G., Ozgen, A., Ozgen, D., & Tuzkaya, U. R. (2009). Environmental performance evaluation of suppliers: A hybrid fuzzy multi-criteria decision approach. *International Journal of Environmental Science and Technology, 6*, 477–490.

Vahidnia, M. H., Alesheikh, A. A., & Alimohammadi, A. (2009). Hospital site selection using fuzzy AHP and its derivatives. *Journal of Environmental Management, 90*(10), 3048–3056.

Van Laarhoven, P. J. M., & Pedrycz, W. (1983). A fuzzy extension of Saaty's priority theory. *Fuzzy Sets and Systems, 11*, 229–241.

Vinodh, S., Ramiya, R. A., & Gautham, S. G. (2011). Application of fuzzy analytic network process for supplier selection in a manufacturing organisation. *Expert Systems with Applications, 38*(1), 272–280.

Wang, X., & Chan, H. K. (2011). *Fuzzy-AHP approach for evaluation of green product design*. *Proceedings of the 21st International Conference of Production Research*, 31 July–4 Aug, Germany: Stuttgart.

Wang, Y. M., & Elhag, T. M. S. (2006). Fuzzy TOPSIS method based on alpha level sets with an application to bridge risk assessment. *Expert Systems with Applications, 31*(2), 309–319.

Wang, Y., Luo, M. Y., & Hua, Z. (2008). On the extent analysis method for fuzzy AHP and its applications. *European Journal of Operational Research, 186*(2), 735–747.

Wang, J.-W., Cheng, C.-H., & Huang, K.-C. (2009). Fuzzy hierarchical TOPSIS for supplier selection. *Applied Soft Computing, 9*, 377–386.

Wang, X., Chan, H. K., Yee, W. Y., & Diaz-Rainey, I. (2012a). A two-stage Fuzzy-AHP model for risk assessment of implementing green initiatives in the fashion supply chain. *International Journal of Production Economics, 135*(2), 595–606.

Wang, X., Li, D., & Shi, X. (2012b). A fuzzy enabled model for aggregative food safety risk assessment in food supply chains. *Production Planning and Control, 23*(5), 377–395.

Weck, M., Klocke, F., Schell, H., & Ruenauver, E. (1997). Evaluating alternative production cycles using the extended fuzzy AHP method. *European Journal of Operational Research, 100*(2), 351–366.

Wu, C., Barnes, D., Rosenberg, D., & Luo, X. (2009). An analytic network process-mixed integer multi-objective programming model for partner selection in agile supply chains. *Production Planning and Control, 20*(3), 254–275.

Wu, W., Kou, G., Peng, Y., & Ergu, D. (2012). Improved AHP-group decision making for investment strategy selection. *Technological and Economic Development of Economy, 18*(2), 299–316.

Yan, W., Chen, C.-H., Huang, Y., & Mi, W. (2008). An integration of bidding-oriented product conceptualization and supply chain formation. *Computers in Industry, 59*(2–3), 128–144.

Yang, C., Liu, T., Kao, C., & Wang, H. (2010). Integrating AHP and DELPHI methods to construct a green product assessment hierarchy for early stage of product design and development. *International Journal of Operations Research, 7*(3), 35–43.

Yong, D. (2006). Plant location selection based on fuzzy TOPSIS. *International Journal of Advanced Manufacturing Technology, 28*, 839–844.

Yung, K. C., Chan, H. K., So, H. T., Wong, W. C., Choi, C. K., & Yue, T. M. (2011). A life-cycle assessment for eco-redesign of a consumer electronic product. *Journal of Engineering Design, 22*(2), 69–85.

Yung, W. K. C., Chan, H. K., So, J. H. T., Wong, D. C. W., Choi, A. C. K., & Yue, T. M. (2012). Environmental impact of two electrical products with reference to the energy-using products directive. *International Journal of Sustainable Engineering, 5*(2), 86–90.

Yurdakul, M. (2003). Measuring long-term performance of a manufacturing firm using the analytic network process (ANP) approach. *International Journal of Production Research, 41*(11), 2501–2529.

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control, 8*(3), 338–353.

Zeydan, M., Çolpan, C., & Çobanoğlu, C. (2011). A combined methodology for supplier selection and performance evaluation. *Expert Systems with Applications, 38*(3), 2741–2751.

Zheng, G., Jing, Y., Huang, H., & Gao, Y. (2011). Applying LCA and fuzzy AHP to evaluate building energy conservation. *Civil Engineering and Environmental Systems, 28*(2), 123–141.

Chapter 4
An Integrated Fuzzy Approach for Aggregative Supplier Risk Assessment

4.1 Introduction

Managing supply chain risk has become a key challenge to many organisations. Among the studies on supply chain risk, supplier risk is one important area (Xiao et al. 2012). Supply uncertainty triggered by supplier performance variability and inconsistency often leads to delayed, deficient or defective deliveries (Davis 1993). It is brought by machine breakdowns, downtimes during manufacturing, quality and yield problems, order-entry errors, forecast inaccuracies or logistical malfunctions (Fynes et al. 2004). In order to manage the dynamics of marketplaces and associated risks, there is a need to develop an effective risk assessment approach for sustainable supplier evaluation and selection purpose. As Perona and Miragliotta (2004) stated, an effective supplier assessment and selection process are essential for improving the performance of a focal company and its supply chains. A number of studies in the literature have also pointed out that the one important aspect of supply chain management is the selection of suppliers (Park and Krishnan 2001; McCollum 2001; Chan et al. 2007). For these reasons, the aim of the chapter is to propose an aggregative risk assessment framework for the measurement of supplier risk to improve supply chain performance.

This study integrates analytic hierarchy process (AHP) and fuzzy set theory for conducting aggregative supplier risk assessment and solving the supplier selection problem. A decision model coupled AHP with fuzzy logic is developed for aggregative supplier risk assessment. This method not only incorporates various criteria-associated supplier selection process, but also considers uncertainties in the decision-making process. This is also the major difference between previous chapter and this chapter (indeed and also subsequent chapters). A case study of supplier selection considering aggregative risk is employed to demonstrate the effectiveness of the proposed method.

H. K. Chan and X. Wang, *Fuzzy Hierarchical Model for Risk Assessment*,
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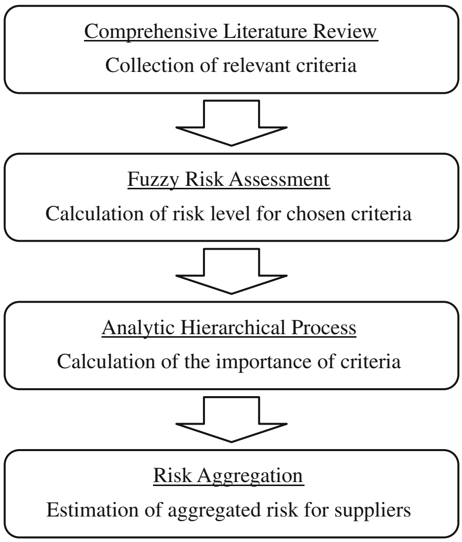
4.2 An Aggregative Risk Assessment Model for Supplier Selection

The proposed methodology consists of a systematic literature review, fuzzy risk assessment and AHP technique. The procedure of aggregative supplier risk assessment is displayed in Fig. 4.1. With a comprehensive review of literature, the critical aspects for achieving the goal of sustainable supplier management are first defined, and the criteria under each aspect are collected. Then, a hierarchical decision model is then developed for aggregative supplier risk assessment. After that, fuzzy set theory is applied to assess the risk level of individual criteria within the hierarchical model. Through AHP, the priority weights are calculated. Finally, the aggregative supplier risk indicator (ASRI) is obtained for alternative suppliers, and the supplier with the lowest ASRI should be selected. The detailed descriptions of the main steps are elaborated in each of the following sections.

4.2.1 Comprehensive Literature Review

Many researchers have studied the factors associated with supply risk assessment and supplier selection in a variety of settings. As a consequence, these diversified studies have adopted different perspectives and have thus come up with different sets of evaluation criteria. Ho et al. (2010) conducted a literature review on multi-criteria decision-making approaches for supplier evaluation and selection. Through analysing relevant articles appearing in the international journals from 2000 to 2008, they found that quality, delivery, price/cost, manufacturing capacity and

Fig. 4.1 Framework for risk assessment–based supplier evaluation



service are the most popular five criteria among the hundreds of criteria that were proposed for evaluating and selecting the most appropriate suppliers. Therefore, in this chapter, quality, delivery, cost, manufacturing capacity and service are adopted as the five main risk categories. Based on the five categories, focusing on the relevant literature since 2000, a comprehensive literature review was carried out to identify detailed risk items for the supplier selection purpose. The review results are displayed in Table 4.1, and the identified assessment criteria are incorporated in the hierarchy model shown in Fig. 4.2. The risk assessment categories and their associated assessment criteria are described in the subsequent paragraphs.

4.2.1.1 Quality

Quality has been established as a primary concern in the supplier evaluation and selection process for decades (Chan and Chan 2004). This is also confirmed by the study of Ho et al. (2010), in which quality is the most popular criterion for evaluating and selecting appropriate supplier, and various quality-related attributes have been found in the literature. In this chapter, the quality category is assessed in terms of suppliers' ability to conform the quality speciality, which provides reliable and durable products, inspection and control, quality management practices and systems, quality management improvement programmes, quality award and certificate and finally, shipment quality.

4.2.1.2 Delivery

Delivery is the second most popular criterion found in the study of Ho et al. (2010). Here, the delivery factor is assessed on the basis of the importance and risk level of the following criteria in the supplier selection process: geography location, delivery reliability/dependability, delivery lead time, on-time delivery, delivery delays and delivery mistakes.

4.2.1.3 Cost

Although the cost factor is no longer the single criterion in contemporary supply management, as expected, it is still an important factor in supplier evaluation and selection process. Here, the assessment criteria in the cost category include competitive pricing, ordering cost, manufacturing cost, logistics cost, fluctuation on cost and cost reduction capabilities.

Table 4.1 Categories of supply risk sources

Risk categories	Assessment criteria	References
Quality	Conformance quality	Choy et al. (2002), Chan and Chan (2004), Chen et al. (2006), Perçin (2006), Chen and Huang (2007), Wang and Li (2012)
	Product durability	Kwong et al. (2002), Chan and Chan (2004), Lau et al. (2006), Wang and Li (2012)
	Product reliability	Kwong et al. (2002), Chan and Chan (2004)
	Inspection and control	Sevkli et al. (2007), Ho et al. (2010)
	Quality management improvement programmes	Akarte et al. (2001), Florez-Lopez (2007), Ha and Krishnan (2008), Ho et al. (2010), Wang et al. (2012)
	Quality reward and certificate	Bevilacqua et al. (2006), Gencer and Güpinar (2007), Chan and Chan (2010), Wang et al. (2012)
	Quality management practices and systems	Forker and Mendez (2001), Kwong et al. (2002), Kahraman et al. (2003), Choy et al. (2003), Talluri and Narasimhan (2004), Sarkar and Mohapatra (2006), Ha and Krishnan (2008)
	Shipment quality	Choy et al. (2003), Choy and Lee (2003), Sevkli et al. (2007)
Delivery	Geography location	Chan and Chan (2004), Bevilacqua et al. (2006), Perçin (2006), Hou and Su (2007), Gencer and Güpinar (2007), Ng (2008), Wang et al. (2012)
	Delivery reliability/ dependability	Karpak et al. (2001), Ghodspour and O'brien (2001), Narasimhan et al. (2001), Chan and Chan (2004), Wang et al. (2004), Perçin (2006), Chan et al. (2007)
	Delivery lead time	Bayazit (2006), Sarkar and Mohapatra (2006), Chen and Huang (2007)
	On-time delivery	Choy et al. (2002), Choy et al. (2003), Ding et al. (2005), Bayazit (2006), Xia and Wu (2007), Ha and Krishnan (2008), Demirtas and Üstün (2008), Wang et al. (2012)
	Delivery delays	Florez-Lopez (2007)
	Delivery mistakes	Çebi and Bayraktar (2003), Florez-Lopez (2007)
Cost	Competitive pricing	Choy and Lee (2002), Choy et al. (2003), Chan and Chan (2004), Lau et al. (2006), Gemcer amd Gürpinar (2007), Xia and Wu (2007), Chan and Kumar (2007), Wang et al. (2012)
	Ordering cost	Ghodspour and O'brien (2001), Ho et al. (2010)
	Cost reduction capabilities	Narasimhan et al. (2001), Talluri and Narasimhan (2004), Talluri and Narasimhan (2005), Florez-Lopez (2007), Chan et al. (2007), Micheli et al. (2009)
	Fluctuation on cost	Florez-Lopez (2007), Chan et al. (2007)
	Manufacturing cost	Garfamy (2006), Ramanathan (2007), Demirtas and Üstün (2008)
	Logistics cost	Chen and Huang (2007), Chan and Chan (2010), Wang et al. (2012)

(continued)

Table 4.1 (continued)

Risk categories	Assessment criteria	References
Manufacturing capacity	Volume and mix flexibility	Chan and Chan (2004), Choy et al. (2005), Wu et al. (2006), Chen and Huang (2007), Micheli et al. (2009)
	Process control capabilities	Forker and Mendez (2001), Braglia and Petroni (2002), Talluri and Narasimhan (2004), Talluri and Narasimhan (2005), Bayazit (2006), Gencer and Güpinar (2007), Demirtas and Üstün (2008), Micheli et al. (2009)
	Technological capabilities	Chan and Chan (2004), Liu and Hai (2005), Chen et al. (2006), Sarkar and Mohapatra (2006), Perçin (2006), Yan and Chen (2006), Gencer and Güpinar (2007), Sevkli et al. (2007), Chan et al. 2007), Chou and Chang 2008), Micheli et al. 2009
	Production facilities and capacity	Braglia and Petroni (2002), Wu et al. 2006), Gencer and Gürpinar 2007), Chan and Kumar (2007), Micheli et al. (2009)
	Product development capability	Forker and Mendez (2001), Choy and Lee (2002), Narasimhan et al. (2001), Choy et al. (2003), Talluri and Narasimhan (2004), Sevkli et al. (2007)
Service	Handing of complaints	Chan and Chan (2004), Perçin (2006), Demirtas and Üstün (2008)
	Information sharing	Chan and Chan (2004), Perçin (2006), Chan and Chan (2010), Durowoju et al. (2012), Wang et al. (2012)
	Problem-solving aids	Çebi and Bayraktar (2003), Chan and Chan (2004)
	Service capability	Kahraman et al. (2003), Gencer and Güpinar (2007), Ramanathan (2007)
	Technical assistance	Florez-Lopez (2007)
	Repair and maintenance service	Perçin (2006), Chan et al. (2007), Xia and Wu (2007)
	Warranty policies	Chan et al. (2007), Xia and Wu (2007), Wang et al. (2012)

4.2.1.4 Manufacturing Capacity

The risk category of manufacturing capacity is assessed on the basis of the importance and risk level of the following criteria in the supplier selection process: volume and mix flexibility, process control capabilities, technological capabilities, production facility and capacity and product development capability.

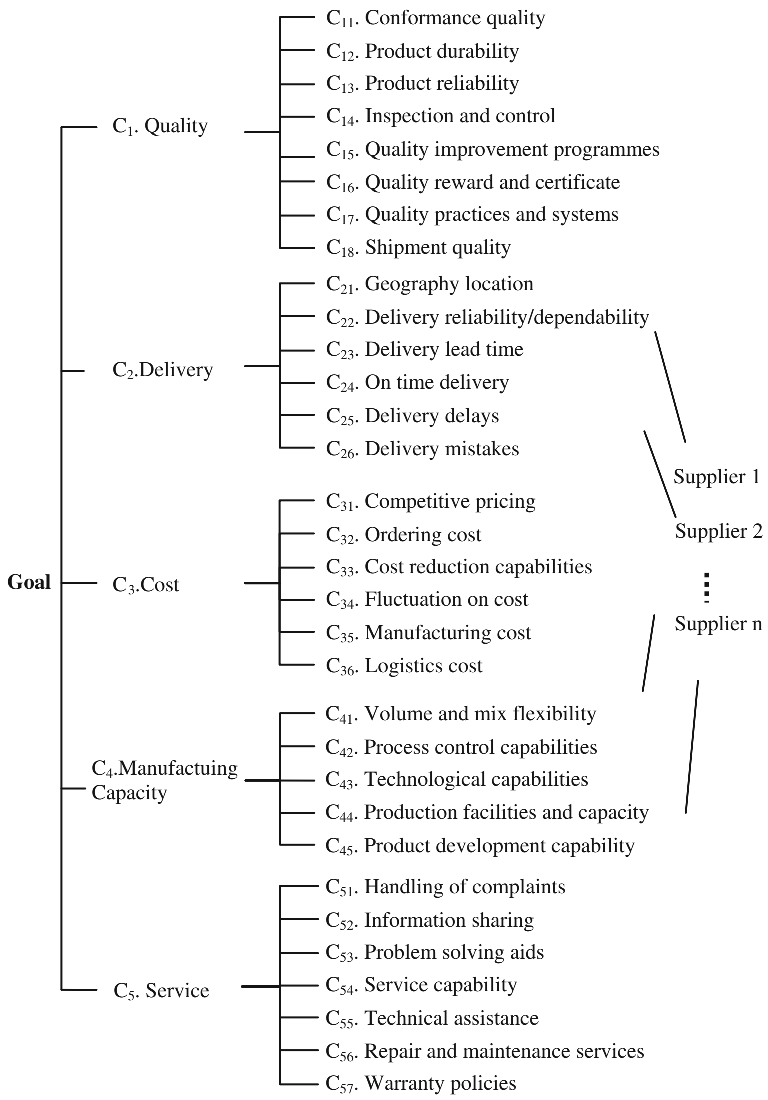


Fig. 4.2 Hierarchical structure model of aggregative supplier risk assessment

4.2.1.5 Service

The service factor has become more and more important in the decision-making process for the supplier selection. It also applies to the manufacturing sector. In this chapter, the criteria in the service category include handling of complaints, information sharing, problem-solving aids, service capability, technical assistance, repair and maintenance service and warranty policies.

4.2.2 Use Fuzzy Theory for Risk Assessment

In many cases, constraints in data quality, time personnel or resources may not permit a full systematic and quantitative risk assessment. In this chapter, the fuzzy approach is adopted here as a basis for transformation of qualitative risk evaluation into fuzzy values and consequently the quantitative assessment outcomes in the development of aggregative risk assessment model. Here, triangular fuzzy number (TFN) is used to characterise the fuzzy values of quantitative data, and linguistic terms are used in approximate reasoning.

When assessing risks, the severity and likelihood of the risk have to be considered. Here, the severity indicates the nature of the hazard, which means the level of an adverse effect that exposure of risk will result in. The likelihood refers to the probability of the risk occurring and its consequent effects based on known history of performance and complaints. In practice, companies have difficulties in evaluating these factors due to uncertainty and lack of knowledge and information. Instead, risk assessors and supply chain managers generally rank these risk factors in terms of linguistic variables such as high, moderate and low. In our research, the qualitative scales are expressed by TFNs to capture the vagueness in the linguistic subjectivity of risk definitions. Table 4.2 describes this qualitative scaling system for severity of the risk and likelihood of an adverse effect consequential to the risk. Two fuzzy numbers N_s and N_l with membership functions $N_s(x)$ and $N_l(x)$ represent the grades of the two factors, respectively. The membership functions of TFNs for the 11-level qualitative scales in Table 4.2 are described in Eq. 4.1. This approach has also been used by Lee (1996) in software risk assessment and by Sadiq and Husain (2005) in aggregative environmental risk assessment.

Table 4.2 Linguistic classification of grades of hazard factors and their corresponding triangular fuzzy numbers

Ranking level	A qualitative explanation for grade of hazard severity (*s*)	A qualitative explanation for grade of likelihood of the hazard (*l*)	Triangular fuzzy numbers (TFNs)
1	Definitely mild	Definitely low	(0.0, 0.0, 0.1)
2	Extremely mild	Extremely low	(0.0, 0.1, 0.2)
3	Quite mild	Quite low	(0.1, 0.2, 0.3)
4	Mild	Low	(0.2, 0.3, 0.4)
5	Slightly mild	Slightly low	(0.3, 0.4, 0.5)
6	Moderate	Moderate	(0.4, 0.5, 0.6)
7	Slightly severe	Slightly high	(0.5, 0.6, 0.7)
8	Severe	High	(0.6, 0.7, 0.8)
9	Quite severe	Quite high	(0.7, 0.8, 0.9)
10	Extremely severe	Extremely high	(0.8, 0.9, 1.0)
11	Definitely severe	Definitely high	(0.9, 1.0, 1.0)

$$\mu_{N1}(x) = \begin{cases} 1 - 10x, & 0 \le x < 0.1, \\ 0, & 0.1 \le x \le 1, \end{cases}$$

$$\mu_{Nn}(x) = \begin{cases} 0, & 0 \le x < \frac{n-2}{10} \\ 10x - (n-2), & \frac{n-2}{10} \le x \le \frac{n-1}{10} \\ n - 10x, & \frac{n-1}{10} \le x \le \frac{n}{10} \\ 0, & \frac{n}{10} \le x \le 1 \end{cases} \tag{4.1}$$

$(n = 2, 3, \cdots 10)$ and

$$\mu_{N11}(x) = \begin{cases} 0, & 0 \le x < 0.9, \\ 10x - 9, & 0.9 \le x \le 1, \end{cases}$$

To determine the magnitude and intensity of the risk, the two risk factors are multiplied to produce the risk evaluation. The product of two TFNs is also a fuzzy member, but not necessary a triangular one. To simplify multiplication calculations, a standard approximation is used. The standard approximation has been defined by authors such as Chen and Hwang (1993) and Giachetti and Young (1997) in the forms described as follows:

$$\begin{aligned} &A \to \langle a_1, a_2, a_3 \rangle \\ &B \to \langle b_1, b_2, b_3 \rangle \\ &C = A \otimes B \\ &C \to \langle a_1 b_1, a_2 b_2, a_3 b_3 \rangle \end{aligned} \tag{4.2}$$

To ensure the accuracy of the assessment, group risk assessment is incorporated in the model. First of all, a risk assessment team or group is formed. With reference to Table 4.2, a set of integers (from 1 to 11) are assigned to the two elements for each risk item in the hierarchical model by individual assessors according to her/his analysis of the hazard. Using fuzzy geometric mean, both fuzzy grading for the severity $(\tilde{s}_i)$ and likelihood $(\tilde{l}_i)$ of each item can be obtained using Eqs. (4.3) and (4.4), respectively:

$$\tilde{s}_i = (\tilde{s}_{i1} \otimes \tilde{s}_{i2} \otimes \ldots \otimes \tilde{s}_{in})^{1/n} \tag{4.3}$$

$$\tilde{l}_i = (\tilde{l}_{i1} \otimes \tilde{l}_{i2} \otimes \ldots \otimes \tilde{l}_{in})^{1/n} \tag{4.4}$$

With the fuzzy grading, the risk level of identified risk item can be calculated individually as follows:

$$\begin{aligned} \tilde{g}_i &= \tilde{s}_i \otimes \tilde{l}_i \\ &= (Lg_i, Mg_i, Ug_i) \end{aligned} \tag{4.5}$$

where Lg_i, Mg_i, Ug_i represent the lower, middle and upper values of the fuzzy grade of the ith risk item. Since the calculation so far involves fuzzy variables, the next step is to defuzzify the grades to form meaningful figures for analysis (e.g. ranking). Many methods exist in the literature, but centre of area (COA) is by far the most popular and easy to use one (e.g. Hsieh et al. 2004). Then, using the COA method, the non-fuzzy (i.e. defuzzified) risk value of the *i*th risk item is given as follows:

$$g_i = [(Ug_i - Lg_i) + (Mg_i - Lg_i)]/3 + Lg_i \tag{4.6}$$

The higher the value is, the higher the risk level of the assessed risk item.

4.2.3 Analysis of Criteria Weights with AHP

To incorporate all the criteria into an aggregated risk rate, it is essential to know how important one criterion or sub-criterion is over another for supplier selection. In other words, risk assessors have to determine the weights between main criteria. AHP has been widely used to address the multi-criterion decision-making problems. In a typical AHP method, the pairwise comparisons are established using a nine-point scale which converts human preferences into available alternatives such as equally, moderately, strongly, very strongly or extremely preferred. For example, if two elements are assumed equally important, the comparison will have a scale 1. If one element is moderately more important than the other, the analysis will have a scale 3. Subsequently, scales 5, 7 and 9 are used to describe strongly more important, very strongly more important and extremely more important, respectively. The corresponding reciprocals 1, 1/2, 1/3, …, 1/9 are used for the reverse comparison. The pairwise comparisons of the attributes at each level in the hierarchy are arranged into a reciprocal matrix (Saaty 1996). In general, the comparison matrices are defined as $A = \left(a_{ij}\right)$, where A = reciprocal matrix $a_{ij} = 1/a_{ji}$. The relative weights of the elements at each level with respect to an element are computed as the components of the normalised eigenvector associated with the largest eigenvalue of the comparison matrix A. There are a number of ways to derive the vector of priorities for the matrix. Table 4.3 shows an example using AHP matrix to estimate the weights for five main criteria in supply chain structure area by normalising the geometric means of the rows. Detailed solution of deriving the weights for criteria or attributes by using AHP can be found in Saaty (1980).

When conducting the pairwise comparisons, the assessors can incorporate their knowledge and experience about a particular supplier selection case with reference to the product nature and market environment. Those main criteria in each risk

Table 4.3 The pairwise comparisons of main criteria

	C_1	C_2	C_3	C_4	C_5	Weights
C_1	1	2	1/3	2	1/2	0.149
C_2	1/2	1	1/5	1	1/3	0.082
C_3	3	5	1	5	2	0.438
C_4	1/2	1	1/5	1	1/3	0.082
C_5	2	3	1/2	3	1	0.250

Note The consistency index CI = 0.0159 and the consistency ratio CR = 0.0176

assessment category would have to be weighted regarding to their individual importance to manage supply risk and improve supply chain performance.

4.2.4 Evaluation of Aggregative Risk

To evaluate an aggregative risk, all the risk factors and the weights of risk categories and their associated criteria must be incorporated into the assessment. Table 4.4 shows all the contents of the hierarchical structure for assessing supplier risk. In the table, W_i and W_{ij} are the comparative weights for the main risk categories and their associated criteria, respectively, whereas $g(s, l)$ is the rate of risk for each criterion, subject to s and l that are defined in Table 4.2.

Here, a three-step fuzzy assessment method for evaluating the aggregative risk rate is presented. The criteria ratings for risk are linguistic variables with linguistic values V_1, V_2, V_3, V_4, V_5, V_6, V_7, where V_1 = extra low, V_2 = very low, V_3 = low, V_4 = middle, V_5 = high, V_6 = very high, V_7 = extra high. These linguistic variables were then defined by TFNs with membership functions as follows:

$$\begin{aligned}
&V_1 = \left(0, 0, \tfrac{1}{6}\right) && \mu_{N1}(x) = \begin{cases} 1 - 6x, & 0 \le x < \frac{1}{6}, \\ 0, & \frac{1}{6} \le x \le 1, \end{cases} \\
&V_n = \left(\tfrac{n-2}{6}, \tfrac{n-1}{6}, \tfrac{n}{6}\right) && \mu_{N1}(x) = \begin{cases} 0, & 0 \le x < \frac{n-2}{6} \\ 6x - (n-2), & \frac{n-2}{6} \le x < \frac{n-1}{6} \\ n - 6x, & \frac{n-1}{6} \le x \le \frac{n}{6} \\ 0, & \frac{n}{6} \le x \le 1, \end{cases} \\
&n = 2, 3, 4, 5, 6 \text{ and} && \\
&V_7 = \left(\tfrac{5}{6}, 1, 1\right) && \mu_{N1}(x) = \begin{cases} 0, & 0 \le x < \frac{5}{6}, \\ 6x - 5, & \frac{5}{6} \le x \le 1, \end{cases}
\end{aligned} \tag{4.7}$$

Using the centroid method, the seven qualitative scales V_1, V_2, V_3, V_4, V_5, V_6, V_7 have centroids $V_G(1) = 0.0556$, $V_G\ (2) = 0.1667$, $V_G(3) = 0.3333$, $V_G(4) = 0.5000$, $V_G(5) = 0.6667$, $V_G(6) = 0.8334$, $V_G(7) = 0.9444$, respectively. Let $V = \{V_1, V_2, V_3, V_4, V_5, V_6, V_7\}$ be the set of rating for each sub-criterion. By fuzzy relation on $C_i \times V$, the fuzzy assessment matrix for risk attributes is established. For example, the criteria of C_{11}, C_{12}, C_{13}, C_{14}, C_{15}, C_{16}, C_{17} and C_{18} and the corresponding rates of risk are $g(s_{11}, l_{11})$, $g(s_{12}, l_{12})$, $g(s_{13}, l_{13})$, $g(s_{14}, l_{14})$, $g(s_{15}, l_{15})$, $g(s_{16}, l_{16})$, $g(s_{17}, l_{17})$ and $g(s_{18}, l_{18})$, respectively (see Table 4.4). Assume $V(s_{11}, l_{11}, n)$ and $V(s_{11}, l_{11}, n + 1)$ be the intersection of $x = g(s_{11}, l_{11})$, and $\mu_{V_n}(x)$, $\mu_{V_{n+1}}(x)$, $(n = 1, 2, \ldots, 6)$, respectively. Then, $V(s_{11}, l_{11}, n + 1) = 1 - V(s_{11}, l_{11}, n)$, and we may assume $V(s_{11}, l_{11}, m) = 0$ for every $m = 1, 2, \ldots, n$, but $m \neq n, n + 1$. Thus, a fuzzy assessment matrix $M(C_1)$ can be formulated as follows:

Table 4.4 A two-phase structure model of aggregative supplier risk assessment

Risk categories	Sub-criteria	W_i	W_{ij}	s	l	g (s, l)
C_1		W_1				
	C_{11}		W_{11}	s_{11}	l_{11}	g (s_{11}, l_{11})
	C_{12}		W_{12}	s_{12}	l_{12}	g (s_{12}, l_{12})
	C_{13}		W_{13}	s_{13}	l_{13}	g (s_{13}, l_{13})
	C_{14}		W_{14}	s_{14}	l_{14}	g (s_{14}, l_{14})
	C_{15}		W_{15}	s_{15}	l_{15}	g (s_{15}, l_{15})
	C_{16}		W_{16}	s_{16}	l_{16}	g (s_{16}, l_{13})
	C_{17}		W_{17}	s_{17}	l_{17}	g (s_{17}, l_{17})
	C_{18}		W_{18}	s_{18}	l_{18}	g (s_{18}, l_{18})
C_2		W_2				
	C_{21}		W_{21}	s_{21}	l_{21}	g (s_{21}, l_{21})
	C_{22}		W_{22}	s_{22}	l_{22}	g (s_{22}, l_{22})
	C_{23}		W_{23}	s_{23}	l_{23}	g (s_{23}, l_{23})
	C_{24}		W_{24}	s_{24}	l_{24}	g (s_{24}, l_{24})
	C_{25}		W_{25}	s_{25}	l_{25}	g (s_{25}, l_{25})
	C_{26}		W_{26}	s_{26}	l_{26}	g (s_{26}, l_{23})
C_3		W_3				
	C_{31}		W_{31}	s_{31}	l_{31}	g (s_{31}, l_{31})
	C_{32}		W_{32}	s_{32}	l_{32}	g (s_{32}, l_{32})
	C_{33}		W_{33}	s_{33}	l_{33}	g (s_{33}, l_{33})
	C_{34}		W_{34}	s_{34}	l_{34}	g (s_{34}, l_{34})
	C_{35}		W_{35}	s_{35}	l_{35}	g (s_{35}, l_{35})
	C_{36}		W_{36}	s_{36}	l_{36}	g (s_{36}, l_{33})
C_4		W_4				
	C_{41}		W_{41}	s_{41}	l_{41}	g (s_{41}, l_{41})
	C_{42}		W_{42}	s_{42}	l_{42}	g (s_{42}, l_{42})
	C_{43}		W_{43}	s_{43}	l_{43}	g (s_{43}, l_{43})
	C_{44}		W_{44}	s_{44}	l_{44}	g (s_{44}, l_{44})
	C_{45}		W_{45}	s_{45}	l_{45}	g (s_{45}, l_{45})
C_5						
	C_{51}		W_{51}	s_{51}	l_{51}	g (s_{51}, l_{51})
	C_{52}		W_{52}	s_{52}	l_{52}	g (s_{52}, l_{52})
	C_{53}		W_{53}	s_{53}	l_{53}	g (s_{53}, l_{53})
	C_{54}		W_{54}	s_{54}	l_{54}	g (s_{54}, l_{54})
	C_{55}		W_{55}	s_{55}	l_{55}	g (s_{55}, l_{55})
	C_{56}		W_{56}	s_{56}	l_{56}	g (s_{56}, l_{53})
	C_{57}		W_{57}	s_{57}	l_{57}	g (s_{57}, l_{57})

$$M(C_1) = \begin{array}{cc} \begin{pmatrix} V(s_{11}, l_{11}, 1) & V(s_{11}, l_{11}, 2) & \ldots & V(s_{11}, l_{11}, 7) \\ V(s_{12}, l_{12}, 1) & V(s_{12}, l_{12}, 2) & \ldots & V(s_{12}, l_{12}, 7) \\ \vdots & \vdots & \ddots & \vdots \\ V(s_{18}, l_{18}, 1) & V(s_{18}, l_{18}, 2) & \ldots & V(s_{18}, l_{18}, 7) \end{pmatrix} & \begin{array}{c} C_{11} \\ C_{12} \\ \vdots \\ C_{18} \end{array} \end{array} \tag{4.8}$$

By the same approach, we can form fuzzy assessment matrices $M(C_2)$, $M(C_3)$, $M(C_4)$ and $M(C_5)$, for risk categories C_2, C_3, C_4 and C_5, respectively. Now the first-stage aggregative supplier risk assessment can be evaluated for category C_1 as follows:

$$\begin{aligned}&(R(1,1), R(1,2), R(1,3), R(1,4), R(1,5), R(1,6), R, (1,7))_{1\times 7}\\&= (W_{11}, W_{12}, W_{13}, W_{14}, W_{15}, W_{16}, W_{17}, W_{18}) \times M(C_1)_{8\times 7}\end{aligned} \tag{4.9}$$

where $R(1,n) = \sum_{k=1}^{8} W_{1k} \times V(s_{1k}, l_{1k}, n) \quad \text{for } n = 1, 2, \ldots, 7.$

We denote $R(1) = (R(1,1),\ R(1,2),\ R(1,3),\ R(1,4),\ R(1,5),\ R(1,6), R(1,7))$ as the vector of the first-stage aggregative assessment for risk category C_1. Similarly, $R(2)$, $R(3)$, $R(4)$ and $R(5)$ are vectors of the first-stage aggregative risk for categories, C_2, C_3, C_4 and C_5, respectively.

The second step assessment for the aggregative risk is as follows:

$$\begin{aligned}&(R(1), R(2), R(3), R(4), R(5), R(6), R(7))_{1\times 7}\\&= (W_1, W_2, W_3, W_4, W_5)_{1\times 5} \times \begin{pmatrix} R1 \\ R2 \\ R3 \\ R4 \\ R5 \end{pmatrix}_{5\times 7}\end{aligned} \tag{4.10}$$

where $R2(n) = (R(1), R(2), R(3), R(4), R(5), R(6), R(7))_{1\times 7}$

The final rate of aggregative supplier risk is defuzzified by the centroid method as follows:

$$\text{ASRI} = \sum_{n=1}^{7} V_G(n) \times R2(n) \tag{4.11}$$

The above ASRI value gives a quantitative measure of the aggregative risk level associated with a supplier. This index is useful in evaluating different suppliers subject to the same set of judging criteria. In such a case, different ASRI values would have to be calculated using the same method, and the one with the lowest ASRI value implies that the corresponding supplier has the lowest risk level and hence should be selected.

4.3 An Application of the Proposed Model

4.3.1 Case Background

The company was set up at the south-east region of China in 2001 and produces customised stainless steel bands. The stainless steel bands are essential raw material for stainless steel tubes, cookware and stainless steel components for electronics and telecommunication equipments. An overview of its supply chain is

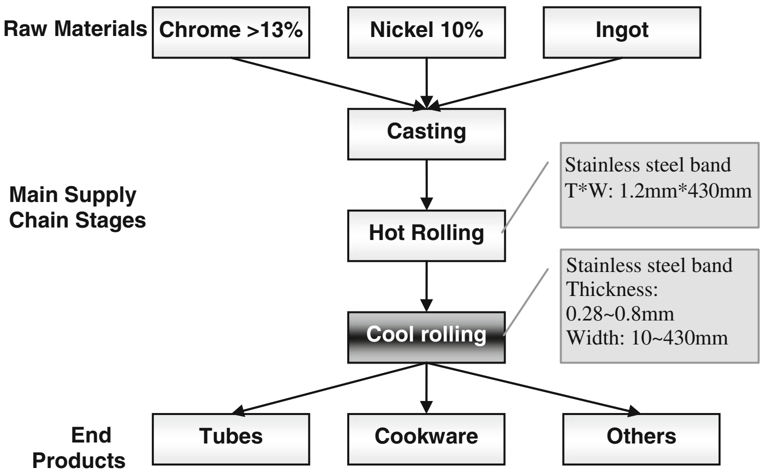
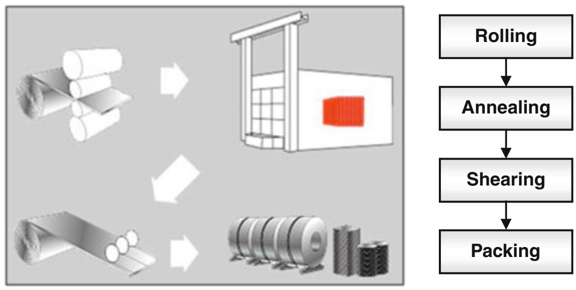


Fig. 4.3 Case company's supply chain

Fig. 4.4 Key production processes



described in Fig. 4.3. The case company specialises in cool rolling which transformed hot-rolled stainless steel materials into customised stainless steel bands through the key production processes illustrated in Fig. 4.4.

While the demand of stainless steel products increases significantly in recent years, the industry has experienced a great deal of change with global sourcing and high levels of price competition. In addition, high volatility of raw material price, low predictability and a level of impulse purchase add further uncertainty for the company. Moreover, all the products are customised in terms of types of raw materials, thickness and width of the product and packaging. To minimise the lead time to complete an order and maximise the production capacity at the same time, information management and effective production planning and scheduling become very crucial for the business. Product quality also plays a crucial role. As the company specialises in one value-adding process in the stainless steel supply chain, raw material cost consists 80 % of its total cost. Product waste during the production process and those finished products failed to meet customer quality standard can only be sold at half of its original purchasing price.

The management team wants to develop a more collaborative supply chain relationship with it supplier chain partners to overcome the business challenges and improve its supply chain performance. It is a challenging task in the current tough market environment due to the supply chain complexity and dynamic relationships between supply chain parties. Because of the product nature, the company considers the supply side as the starting point and is keen to identify a suitable supplier to develop a collaborative relationship. Three potential suppliers were targeted. Supplier 1 is a local company who specialises in hot-rolling process in the stainless steel supplier chain. The company has been in business for over 10 years and has grown considerably in the last few years. Located in the same city, supplier 2 is a newly established company. There is some uncertainty regarding the quality of product and services this supplier provides although they are offering competitive price at the moment. Supplier 3 is a well-established company which located 300 miles away. The company has good reputation for the quality of its product. The company also has very restricted payment requirement that often causes delivery delays. The proposed risk assessment method was applied to estimate the aggregative risk for three potential suppliers. Assessment questionnaires were given to the purchasing manager, the production manager and the managing director. Questionnaire responses were converted into inputs for AHP pairwise comparison and grading for risk factors. The assessment results are illustrated in the following sections.

4.3.2 Weights Evaluation by Pairwise Comparison

The risk assessment hierarchy is displayed in Fig. 4.2. The goal is to evaluate the ASRI for different suppliers. The five risk categories include quality, delivery, cost, manufacturing capacity and services. There are a number of criteria under five risk categories. The priority weights of five risk categories and their associated criteria are calculated using AHP approach. Evidently, as any AHP exercise would require, main risk categories and their associated criteria comprising the sub-levels of risk categories would have to be weighted regarding to their individual importance under the case scenario. The comparison of the importance or priority of one risk category or criterion over another can be done with the help of discussion of the assessment team or questionnaire to individual assessors. Tables 4.5, 4.6, 4.7, 4.8, 4.9 and 4.10 present the overall weighting information for risk categories and their associated criteria, respectively. At the same time, the consistency ratio of each judgement was calculated and checked to ensure that it is lower than or equal to 0.1.

Table 4.5 Weights of risk categories with respect to the case scenario

Main criteria	C_1	C_2	C_3	C_4	C_5	Weights
C_1	1	3	2	3	4	0.385
C_2	1/3	1	1/3	1	2	0.121
C_3	1/2	3	1	3	5	0.307
C_4	1/3	1	1/3	1	1	0.106
C_5	1/4	1/2	1/5	1	1	0.080

Note The consistency index CI = 0.029 and the consistency ratio CR = 0.026

Table 4.6 Criteria weights in the quality category

C_1	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}	C_{18}	Weights
C_{11}	1	3	3	4	4	3	3	2	0.283
C_{12}	1/3	1	1	3	3	1	1	1/2	0.112
C_{13}	1/3	1	1	3	3	1	1	1/3	0.108
C_{14}	1/4	1/3	1/3	1	1	1/3	1/3	1/4	0.044
C_{15}	1/4	1/3	1/3	1	1	1/3	1	1/2	0.057
C_{16}	1/3	1	1	3	3	1	1	1	0.122
C_{17}	1/3	1	1	3	1	1	1	1/2	0.098
C_{18}	1/2	2	3	4	2	1	2	1	0.176

Note The consistency index CI = 0.042 and the consistency ratio CR = 0.030

Table 4.7 Criteria weights in the delivery category

C_2	C_{21}	C_{22}	C_{23}	C_{24}	C_{25}	C_{26}	Weights
C_{21}	1	1/3	1/2	1/5	1/3	1/3	0.056
C_{22}	3	1	3	1	2	2	0.254
C_{23}	2	1/3	1	1/3	1/2	1/3	0.082
C_{24}	5	1	3	1	3	2	0.290
C_{25}	3	1/2	2	1/3	1	1/3	0.122
C_{26}	3	1/2	3	1/2	3	1	0.196

Note The consistency index CI = 0.044 and the consistency ratio CR = 0.036

Table 4.8 Criteria weights in the cost category

C_3	C_{31}	C_{32}	C_{33}	C_{34}	C_{35}	C_{36}	Weights
C_{31}	1	4	2	3	3	3	0.349
C_{32}	1/4	1	1/3	1/2	1/3	1/3	0.060
C_{33}	1/2	3	1	2	1	1	0.174
C_{34}	1/3	2	1/2	1	1	2	0.136
C_{35}	1/3	3	1	1	1	2	0.161
C_{36}	1/3	3	1	1/2	1/2	1	0.120

Note The consistency index CI = 0.045 and the consistency ratio CR = 0.036

Table 4.9 Criteria weights in the manufacturing capacity category

C_4	C_{41}	C_{42}	C_{43}	C_{44}	C_{45}	Weights
C_{41}	1	3	5	2	5	0.426
C_{42}	1/3	1	2	1/3	3	0.152
C_{43}	1/5	1/2	1	1/3	1	0.079
C_{44}	1/2	3	3	1	3	0.268
C_{45}	1/5	1/3	1	1/3	1	0.075

Note The consistency index CI = 0.029 and the consistency ratio CR = 0.026

Table 4.10 Criteria weights in the service category

C_5	C_{51}	C_{52}	C_{53}	C_{54}	C_{55}	C_{56}	C_{57}	Weights
C_{51}	1	2	1/2	3	4	3	2	0.215
C_{52}	1/2	1	1/3	2	3	2	1	0.129
C_{53}	2	3	1	4	5	4	3	0.331
C_{54}	1/3	1/2	1/4	1	2	1	1/2	0.075
C_{55}	1/4	1/3	1/5	1/2	1	1/2	1/3	0.046
C_{56}	1/3	1/2	1/4	1	2	1	1/2	0.075
C_{57}	1/2	1	1/3	2	3	2	1	0.129

Note The consistency index CI = 0.013 and the consistency ratio CR = 0.010

4.3.3 Two-Stage Assessment for Aggregative Risk Index

The risk of each criterion can be assessed by considering the severity and likelihood of the risk. These basic risk factors are expressed qualitatively, and TFNs are used to define the qualitative scales before the estimated indices at higher levels. After deciding the s and l values for each criterion, the rate of risk $g(s, l)$ is evaluated through the fuzzy method discussed in Sect. 4.2.2. It enables to obtain a numerical value representing the risk level of individual sub-criterion. The risk assessment starts with supplier 1. Based on the information that the assessment team has regarding to supplier 1. The severity and likelihood of each assessment criterion are graded for supplier 1. Through the fuzzy risk assessment method presented, the risk level of individual criteria can be calculated and the results are summarised in Table 4.11.

After that, all the basic risk indicators and importance weights are incorporated into fuzzy calculations for estimating the ASRI. For each $g(s, l)$, the membership $\mu_{V_n}(x)$ for linguistic variables (V_1–V_7) is estimated. Use the criterion C_{11}, for example, conformance quality, the individual risk is $g(8, 4)$, which is equal to 0.217 (see Table 4.11). The memberships $\mu_{V_n}(x)$ of linguistic variables are $V_1 = 0$, $V_2 = 0.70$, $V_3 = 0.30$ and V_4 to $V_7 = 0$ as shown in Fig. 4.5.

The same procedure is repeated for C_{12}–$C_{18.}$ Therefore, the $M(C_1)$ matrix is built in Eq. 4.12.

$$M(C_1) = \begin{array}{c} \begin{bmatrix} 0 & 0.70 & 0.30 & 0 & 0 & 0 & 0 \\ 0.60 & 0.40 & 0 & 0 & 0 & 0 & 0 \\ 0.36 & 0.64 & 0 & 0 & 0 & 0 & 0 \\ 0.24 & 0.76 & 0 & 0 & 0 & 0 & 0 \\ 0.60 & 0.40 & 0 & 0 & 0 & 0 & 0 \\ 0.72 & 0.28 & 0 & 0 & 0 & 0 & 0 \\ 0.60 & 0.40 & 0 & 0 & 0 & 0 & 0 \\ 0.24 & 0.76 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \end{array} \begin{array}{l} C_{11} \\ C_{12} \\ C_{13} \\ C_{14} \\ C_{15} \\ C_{16} \\ C_{17} \\ C_{18} \end{array} \tag{4.12}$$

Now, the $M(C_1)$ matrix can be multiplied by W_{1j} to determine the items for risk category C_1 as follows:

$$\begin{aligned} R(1) &= [0.283 \quad 0.112 \quad 0.108 \quad 0.044 \quad 0.057 \quad 0.122 \quad 0.098 \quad 0.176] \times M(C_1) \\ &= [0.340 \quad 0.575 \quad 0.085 \quad 0 \quad 0 \quad 0 \quad 0]_{1\times7} \end{aligned} \tag{4.13}$$

Similarly, assessment matrices $M(C_2)$, $M(C_3)$, $M(C_4)$ and $M(C_5)$ can be formed and $R(2)$, $R(3)$, $R(4)$ and $R(5)$ can be calculated as follows:

$$\begin{aligned} R(2) &= [0.246 \quad 0.718 \quad 0.036 \quad 0 \quad 0 \quad 0 \quad 0]_{1\times7} \\ R(3) &= [0.236 \quad 0.764 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0]_{1\times7} \\ R(4) &= [0.411 \quad 0.589 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0]_{1\times7} \\ R(5) &= [0.510 \quad 0.490 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0]_{1\times7} \end{aligned} \tag{4.14}$$

Table 4.11 Fuzzy-based risk assessment for criteria under the case scenario

Criterion	Severity (s)	Likelihood (l)	$g(s, l)$
C_{11}	8	4	0.217
C_{12}	4	3	0.067
C_{13}	6	3	0.107
C_{14}	5	4	0.127
C_{15}	4	3	0.067
C_{16}	3	3	0.047
C_{17}	4	3	0.067
C_{18}	5	4	0.127
C_{21}	3	3	0.047
C_{22}	7	3	0.127
C_{23}	5	3	0.087
C_{24}	6	3	0.107
C_{25}	8	4	0.217
C_{26}	9	3	0.167
C_{31}	5	4	0.127
C_{32}	5	4	0.127
C_{33}	4	3	0.067
C_{34}	8	3	0.147
C_{35}	6	4	0.157
C_{36}	6	4	0.157
C_{41}	5	3	0.087
C_{42}	6	3	0.107
C_{43}	4	4	0.097
C_{44}	7	3	0.127
C_{45}	3	3	0.047
C_{51}	6	3	0.107
C_{52}	5	3	0.087
C_{53}	7	2	0.067
C_{54}	5	4	0.127
C_{55}	3	3	0.047
C_{56}	4	2	0.037
C_{57}	5	3	0.087

Then, the matrix W_i is multiplied by $R2(i, n)$ to obtain the aggregative matrix $R2(n)$ as follows:

$$R2(n) = \begin{bmatrix} 0.385 & 0.121 & 0.307 & 0.106 & 0.080 \end{bmatrix}_{1\times 5} \times \begin{bmatrix} 0.340 & 0.575 & 0.085 & 0 & 0 & 0 & 0 \\ 0.246 & 0.718 & 0.036 & 0 & 0 & 0 & 0 \\ 0.236 & 0.764 & 0 & 0 & 0 & 0 & 0 \\ 0.411 & 0.589 & 0 & 0 & 0 & 0 & 0 \\ 0.510 & 0.490 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}_{5\times 7} \tag{4.15}$$

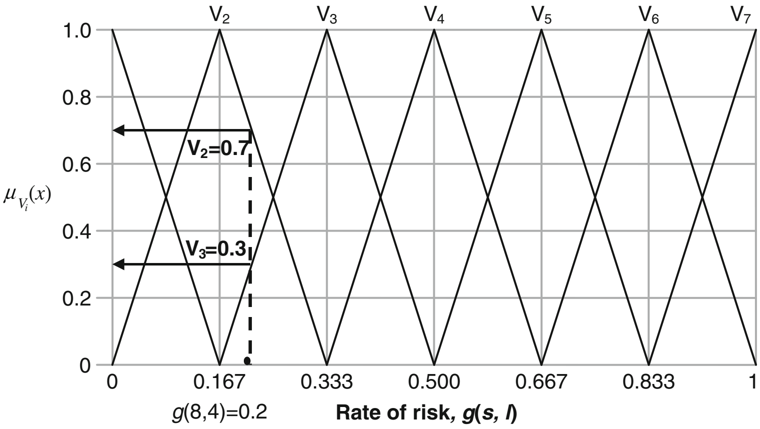


Fig. 4.5 Membership functions of the set of the criteria ratings of risk

The ASRI can then be calculated through defuzzification, which is 0.138 as reflected in the following calculation:

$$\text{ASRI} = \begin{pmatrix} 0.318 \times 0.0556 + 0.645 \times 0.1667 + 0.037 \times 0.3333 \\ +0 \times 0.5 + 0 \times 0.6667 + 0 \times 0.8333 + 0 \times 0.9444 \end{pmatrix} = 0.138$$

The main purpose of this research is to establish the ASRI for supplier selection. Such a quantified ASRI will be useful to compare the risk level between various suppliers under different supply chain environments. The lower the obtained ASRI is, the less risk the supplier has for the case company to develop a closer relationship. Further analysis is provided for another two potential suppliers. Similar to the supplier 1, the same procedure is repeated for supplier 2 and 3; the detailed calculations and assessment results are shown in Tables 4.12 and 4.13, respectively.

Among the three suppliers, supplier 2 has the highest ASRI, 0.184. It means that it is the most risky for the case company to select supplier 2 because relative importance weights and higher risk ratings in the conformance quality, delivery delays, delivery mistakes, fluctuation on cost and problem-solving aids contribute to a higher ASRI. Although supplier 2 is offering the most competitive price at the moment, supplier 2 should be screened out first because of the higher risk in quality, delivery and service compared to the other two suppliers. Supplier 3 has a lower risk level in quality categories due to its long-term commitment in product quality. Nevertheless, it has a higher risk level in both delivery and cost categories. By considering all the five main risk categories and their associated assessment criteria, supplier 1 has the lowest ASRI and therefore should be recommended for selection. Through this numerical example, the effectiveness of the proposed model can be observed undoubtedly.

Table 4.12 Estimation of the aggregative risk index for supplier 2

Criteria	$g(s, l)$	Wij	V_1	V_2	V_3	V_4	V_5	V_6	V_7
C_{11}	0.357	0.283	0	0	0.86	0.14	0	0	0
C_{12}	0.097	0.112	0.42	0.58	0	0	0	0	0
C_{13}	0.207	0.108	0	0.76	0.24	0	0	0	0
C_{14}	0.207	0.044	0	0.76	0.24	0	0	0	0
C_{15}	0.127	0.057	0.24	0.76	0	0	0	0	0
C_{16}	0.067	0.122	0.60	0.40	0	0	0	0	0
C_{17}	0.127	0.098	0.24	0.76	0	0	0	0	0
C_{18}	0.207	0.176	0	0.76	0.24	0	0	0	0
C_{21}	0.027	0.056	0.84	0.16	0	0	0	0	0
C_{22}	0.187	0.254	0	0.88	0.12	0	0	0	0
C_{23}	0.087	0.082	0.48	0.52	0	0	0	0	0
C_{24}	0.207	0.290	0	0.76	0.24	0	0	0	0
C_{25}	0.287	0.122	0	0.28	0.72	0	0	0	0
C_{26}	0.247	0.196	0	0.52	0.48	0	0	0	0
C_{31}	0.087	0.349	0.48	0.52	0	0	0	0	0
C_{32}	0.047	0.060	0.72	0.28	0	0	0	0	0
C_{33}	0.097	0.174	0.42	0.58	0	0	0	0	0
C_{34}	0.287	0.136	0	0.28	0.72	0	0	0	0
C_{35}	0.157	0.161	0.06	0.94	0	0	0	0	0
C_{36}	0.107	0.120	0.36	0.64	0	0	0	0	0
C_{41}	0.127	0.426	0.24	0.76	0	0	0	0	0
C_{42}	0.207	0.152	0	0.76	0.24	0	0	0	0
C_{43}	0.127	0.079	0.24	0.76	0	0	0	0	0
C_{44}	0.187	0.268	0	0.88	0.12	0	0	0	0
C_{45}	0.087	0.075	0.48	0.52	0	0	0	0	0
C_{51}	0.157	0.215	0.06	0.94	0	0	0	0	0
C_{52}	0.127	0.129	0.24	0.76	0	0	0	0	0
C_{53}	0.247	0.331	0	0.52	0.48	0	0	0	0
C_{54}	0.167	0.075	0	1.00	0	0	0	0	0
C_{55}	0.067	0.046	0.60	0.40	0	0	0	0	0
C_{56}	0.067	0.075	0.60	0.40	0	0	0	0	0
C_{57}	0.127	0.129	0.24	0.76	0	0	0	0	0

Criteria	Items	Wi	$R(i,1)$	$R(i,2)$	$R(i,3)$	$R(i,4)$	$R(i,5)$	$R(i,6)$	$R1(i,7)$
$C1$	$R(1,n)$	0.385	0.158	0.481	0.322	0.040	0	0	0
$C2$	$R(2,n)$	0.121	0.087	0.632	0.281	0	0	0	0
$C3$	$R(3,n)$	0.307	0.336	0.566	0.098	0	0	0	0
$C4$	$R(4,n)$	0.106	0.157	0.774	0.068	0	0	0	0
$C5$	$R(5,n)$	0.080	0.148	0.693	0.159	0	0	0	0

Aggregative risk		$R32(1)$	$R2(2)$	$R2(3)$	$R2(4)$	$R2(5)$	$R2(6)$	$R2(7)$
X	$R2(n)$	0.203	0.573	0.208	0.015	0	0	0
Centroid	$V_G(n)$	0.056	0.167	0.333	0.500	0.667	0.883	0.944
Risk	ASRI	0.184						

Table 4.13 Estimation of the aggregative risk index for case scenario 2

Criteria	$g(s, l)$	Wij	V_1	V_2	V_3	V_4	V_5	V_6	V_7
C_{11}	0.147	0.283	0.12	0.88	0	0	0	0	0
C_{12}	0.067	0.112	0.60	0.40	0	0	0	0	0
C_{13}	0.057	0.108	0.66	0.34	0	0	0	0	0
C_{14}	0.087	0.044	0.48	0.52	0	0	0	0	0
C_{15}	0.037	0.057	0.78	0.22	0	0	0	0	0
C_{16}	0.047	0.122	0.72	0.28	0	0	0	0	0
C_{17}	0.037	0.098	0.78	0.22	0	0	0	0	0
C_{18}	0.087	0.176	0.48	0.52	0	0	0	0	0
C_{21}	0.087	0.056	0.48	0.52	0	0	0	0	0
C_{22}	0.307	0.254	0	0.16	0.84	0	0	0	0
C_{23}	0.167	0.082	0	1.00	0	0	0	0	0
C_{24}	0.157	0.290	0.06	0.94	0	0	0	0	0
C_{25}	0.287	0.122	0	0.28	0.72	0	0	0	0
C_{26}	0.087	0.196	0.48	0.52	0	0	0	0	0
C_{31}	0.167	0.349	0	1.00	0	0	0	0	0
C_{32}	0.167	0.060	0	1.00	0	0	0	0	0
C_{33}	0.097	0.174	0.42	0.58	0	0	0	0	0
C_{34}	0.217	0.136	0	0.70	0.30	0	0	0	0
C_{35}	0.157	0.161	0.06	0.94	0	0	0	0	0
C_{36}	0.207	0.120	0	0.76	0.24	0	0	0	0
C_{41}	0.087	0.426	0.48	0.52	0	0	0	0	0
C_{42}	0.057	0.152	0.66	0.34	0	0	0	0	0
C_{43}	0.037	0.079	0.78	0.22	0	0	0	0	0
C_{44}	0.127	0.268	0.24	0.76	0	0	0	0	0
C_{45}	0.027	0.075	0.84	0.16	0	0	0	0	0
C_{51}	0.157	0.215	0.06	0.94	0	0	0	0	0
C_{52}	0.087	0.129	0.48	0.52	0	0	0	0	0
C_{53}	0.127	0.331	0.24	0.76	0	0	0	0	0
C_{54}	0.087	0.075	0.48	0.52	0	0	0	0	0
C_{55}	0.027	0.046	0.84	0.16	0	0	0	0	0
C_{56}	0.067	0.075	0.60	0.40	0	0	0	0	0
C_{57}	0.047	0.129	0.72	0.28	0	0	0	0	0
Criteria	Items	Wi	$R(i,1)$	$R(i,2)$	$R(i,3)$	$R(i,4)$	$R(i,5)$	$R(i,6)$	$R1(i,7)$
$C1$	$R(1,n)$	0.385	0.487	0.513	0	0	0	0	0
$C2$	$R(2,n)$	0.121	0.138	0.561	0.301	0	0	0	0
$C3$	$R(3,n)$	0.307	0.083	0.847	0.070	0	0	0	0
$C4$	$R(4,n)$	0.106	0.494	0.506	0	0	0	0	0
$C5$	$R(5,n)$	0.080	0.367	0.633	0	0	0	0	0
Aggregative risk			$R32(1)$	$R2(2)$	$R2(3)$	$R2(4)$	$R2(5)$	$R2(6)$	$R2(7)$
X	$R2(n)$		0.312	0.630	0.058	0	0	0	0
Centroid	$V_G(n)$		0.056	0.167	0.333	0.500	0.667	0.883	0.944
Risk	ASRI		0.142						

4.4 Conclusion

The proposed model considers all risk categories and their associated criteria in an integrated way for the assessment of supply risk. It provides a practical solution by which enterprises can systematically assess the supply risk associated with individual suppliers. By comparison with other risk assessment methods used for supplier selection purpose, the accuracy of the results in our model is considered sufficient to compare different suppliers and to act as a basis for supplier selection decisions. The assessment results can be used to identify the critical control points when managing existing suppliers. This will facilitate their quality control and lead to a consistent supply of quality products. An important property of this risk assessment approach is that risk can be aggregated over the various criteria and factors affecting them so as to provide an index of the overall level of supplier risk. The quantified final rate of aggregative risk can be used as an indicator to measure risk of different suppliers. In addition, the fuzzy-enabled risk assessment method proposed in this paper estimates the uncertainty inherent in input values and allows users to conveniently describe uncertainty. Furthermore, this fuzzy method can be easily changed to traditional probabilistic methods when sufficient information and knowledge about the supplier are available.

Despite the tangible benefits, there are some limitations and weaknesses. Some are general problems associated with risk assessment modelling, while others are specific to the model presented here. When modelling any complex and dynamic system, it is necessary to make assumptions in order to simplify the calculation but will inevitably detract the model from reality. To simplify calculations in both fuzzy multiplication and estimation of weightings using AHP, approximation approaches are used. In general, the approximation is a conservative estimate as the error introduced by the approximation is different from the actual calculation. However, as the same method was applied to all three alternative suppliers and the assessment results were used to make comparisons between them, the approximation is considered acceptable. Another weakness of the proposed model is that users have to make subjective decisions regarding to scales given to risk factors. In fact, the functionality of the model is highly dependent on the knowledge, expertise and communication skills of assessors. The assessment results are more comparable when the same assessor or assessment team performs all the assessments.

References

Akarte, M. M., Surendra, N. V., Ravi, B., & Rangaraj, N. (2001). Web based casting supplier evaluation using analytical hierarchy process. *Journal of the Operational Research Society, 52*(5), 511–522.

Bayazit, O. (2006). Use of analytic network process in vendor selection decisions. *Benchmarking: An International Journal, 13*(5), 566–579.

Bevilacqua, M., Ciarapica, F. E., & Giacchetta, G. (2006). A fuzzy-QFD approach to supplier selection. *Journal of Purchasing and Supply Management, 12*(1), 14–27.

Braglia, M., & Petroni, A. (2000). A quality assurance-oriented methodology for handling trade-offs in supplier selection. *International Journal of Physical Distribution and Logistics Management, 30*(2), 96–111.

Çebi, F., & Bayraktar, D. (2003). An integrated approach for supplier selection. *Logistics Information Management, 16*(6), 395–400.

Chan, F. T. S. & Chan, H. K. (2004). Development of the supplier selection model—a case study in the advanced technology industry. *Proceedings of the Institution of Mechanical Engineers, Part B*: *Journal of Engineering Manufacture, 218*(12), 1807–1824.

Chan, F. T. S., & Chan, H. K. (2010). An AHP model for selection of suppliers in the fast changing fashion market. *International Journal of Advanced Manufacturing Technology, 51*(9–12), 1195–1207.

Chan, F. T. S., & Kumar, N. (2007). Global supplier development considering risk factors using fuzzy extended AHP-based approach. *Omega—International Journal of Management Science, 35*, 417–431.

Chan, F. T. S., Chan, H. K., IP, R. W. L., & Lau, H. C. W. (2007). A decision support system for supplier selection in the airline industry. *Journal of Engineering Manufacture: Part B, 221*, 741–758.

Chen, Y. M., & Huang, P. N. (2007). Bi-negotiation integrated AHP in suppliers selection. *Benchmarking: An International Journal, 14*(5), 575–593.

Chen, S. J., & Hwang, C. L. (1993). *Fuzzy multiple attribute decision making: Methods and applications*. Berlin: Springer.

Chen, C. T., Lin, C. T., & Huang, S. F. (2006). A fuzzy approach for supplier evaluation and selection in supply chain management. *International Journal of Production Economics, 102*(2), 289–301.

Chou, S. Y., & Chang, Y. H. (2008). A decision support system for supplier selection based on a strategy-aligned fuzzy SMART approach. *Expert Systems with Applications, 34*(4), 2241–2253.

Choy, K. L., & Lee, W. B. (2003). A generic supplier management tool for outsourcing manufacturing. *Supply Chain Management: An International Journal, 8*(2), 140–154.

Choy, K. L., Lee, W. B., & Lo, V. (2002). Development of a case based intelligent customer—supplier relationship management system. *Expert Systems with Applications, 23*(3), 281–297.

Choy, K. L., Lee, W. B., & Lo, V. (2003). Design of a case based intelligent supplier relationship management system—the integration of supplier rating system and product coding system. *Expert Systems with Applications, 25*(1), 87–100.

Choy, K. L., Lee, W. B., & Lo, V. (2005). A knowledge-based supplier intelligence retrieval system for outsource manufacturing. *Knowledge-Based Systems, 18*(1), 1–17.

Davis, T. (1993). Effective supply chain management. *Sloan Management Review, 34*(4), 35–46.

Demirtas, E. A., & Üstün, Ö. (2008). An integrated multi-objective decision making process for supplier selection and order allocation. *Omega—International Journal of Management Science, 36*(1), 76–90.

Ding, H., Benyoucef, L., & Xie, X. (2005). A simulation optimization methodology for supplier selection problem. *International Journal Computer Integrated Manufacturing, 18*(2–3), 210–224.

Durowoju, O. A., Chan, H. K., & Wang, X. (2012). Entropy assessment of supply chain disruption: an information flow perspective. *Journal of Manufacturing Technology Management, 23*(8), 998–1014.

Florez-Lopez, R. (2007). Strategic supplier selection in the added-value perspective: A CI approach. *Information Sciences, 177*(5), 1169–1179.

Forker, L. B., & Mendez, D. (2001). An analytical method for benchmarking best peer suppliers. *International Journal of Operations and Production Management, 21*(1–2), 195–209.

Fynes, B., Búrca, S., & Marshall, D. (2004). Environmental uncertainty, supply chain relationship quality and performance. *Journal of Purchasing and Supply Management, 10*(4–5), 179–190.

Garfamy, R. M. (2006). A data envelopment analysis approach based on total cost of ownership for supplier selection. *Journal of Enterprise Information Management, 19*(6), 662–678.
Gencer, C., & Gürpinar, D. (2007). Analytic network process in supplier selection: A case study in an electronic firm. *Applied Mathematical Modelling, 31*(11), 2475–2486.
Ghodsypour, S. H., & O'Brien, C. (2001). The total cost of logistics in supplier selection, under conditions of multiple sourcing, multiple criteria and capacity constraint. *International Journal of Production Economics, 73*(1), 15–27.
Giachetti, R. G., & Young, R. E. (1997). Analysis of the error in the standard approximation used for multiplication of triangular and trapezoidal fuzzy numbers and the development of a new approximation. *Fuzzy Sets and Systems, 91*, 1–13.
Ha, S. H., & Krishnan, R. (2008). A hybrid approach to supplier selection for the maintenance of a competitive supply chain. *Expert Systems with Applications, 34*(2), 1303–1311.
Ho, W., Xu, X., & Dey, P. K. (2010). Multi-criteria decision making approaches for supplier evaluation and selection: A literature review. *European Journal of Operational Research, 202*(1), 16–24.
Hou, J., & Su, D. (2007). EJB–MVC oriented supplier selection system for mass customization. *Journal of Manufacturing Technology Management, 18*(1), 54–71.
Hsieh, T. Y., Lu, S.-T., & Tzeng, G.-H., (2004). Fuzzy MCDM approach for planning and design tenders selection in public office buildings. *International Journal of Project Management, 22*, 573–584.
Kahraman, C., Cebeci, U., & Ulukan, Z. (2003). Multi-criteria supplier selection using fuzzy AHP. *Logistics Information Management, 16*(6), 382–394.
Karpak, B., Kumcu, E., & Kasuganti, R. R. (2001). Purchasing materials in the supply chain: Managing a multi-objective task. *European Journal of Purchasing and Supply Management, 7*(3), 209–216.
Kwong, C. K., Ip, W. H., & Chan, J. W. K. (2002). Combining scoring method and fuzzy expert systems approach to supplier assessment: A case study. *Integrated Manufacturing Systems, 13*(7), 512–519.
Lau, H. C. W., Lee, C. K. M., Ho, G. T. S., Pun, K. F., & Choy, K. L. (2006). A performance benchmarking system to support supplier selection. *International Journal of Business Performance Management, 8*(2–3), 132–151.
Lee, H. M. (1996). Applying fuzzy set theory to evaluate the rate of aggregative risk in software development. *Fuzzy Sets and Systems, 79*(3), 323–336.
Liu, F. H. F., & Hai, H. L. (2005). The voting analytic hierarchy process method for selecting supplier. *International Journal of Production Economics, 97*(3), 308–317.
McCollum, B. D. (2001). How changing purchasing can change your business. *Production and Inventory Management Journal, 42*(2), 57–60.
Micheli, G., Cagnop, J. L. E., & Giulio, A. D. (2009). Reducing the total cost of supply through risk-efficiency-based supplier selection in the EPC industry. *Journal of Purchasing and Supply Management, 15*, 166–177.
Narasimhan, R., Talluri, S., & Mendez, D. (2001). Supplier evaluation and rationalization via data envelopment analysis: An empirical examination. *Journal of Supply Chain Management, 37*(3), 28–37.
Ng, W. L. (2008). An efficient and simple model for multiple criteria supplier selection problem. *European Journal of Operational Research, 186*(3), 1059–1067.
Park, D., & Krishnan, H. A. (2001). Understanding supplier selection practices: difference between US and Korean executives. *Thunderbird International Business Review, 43*(2), 243–255.
Perçin, S. (2006). An application of the integrated AHP–PGP model in supplier selection. *Measuring Business Excellence, 10*(4), 34–49.
Perona, M., & Miragliotta, G. (2004). Complexity management and supply chain performance assessment. A field study and a conceptual framework. *International Journal of Production Economics, 90*, 103–115.

Ramanathan, R. (2007). Supplier selection problem: integrating DEA with the approaches of total cost of ownership and AHP. *Supply Chain Management: An International Journal, 12*(4), 258–261.

Saaty, T. L. (1980). *The analytic hierarchy process*. New York: McGraw-Hill.

Saaty, T. L. (1996). *Decision making with dependence and feedback: The analytical hierarchy process*. Pittsburgh: RWS.

Sadiq, R., & Husain, T. (2005). A fuzzy-based methodology for an aggregative environmental risk assessment: A case study of drilling waste. *Environmental Modelling and Software, 20*(1), 33–36.

Sarkar, A., & Mohapatra, P. K. J. (2006). Evaluation of supplier capability and performance: A method for supply base reduction. *Journal of Purchasing and Supply Management, 12*(3), 148–163.

Sevkli, M., Koh, S. C. L., Zaim, S., Demirbag, M., & Tatoglu, E. (2007). An application of data envelopment analytic hierarchy process for supplier selection: A case study of BEKO in Turkey. *International Journal of Production Research, 45*(9), 1973–2003.

Talluri, S., & Narasimhan, R. (2004). A methodology for strategic sourcing. *European Journal of Operational Research, 154*(1), 236–250.

Talluri, S., & Narasimhan, R. (2005). A note on "a methodology for supply base optimization". *IEEE Transactions on Engineering Management, 52*(1), 130–139.

Wang, X., & Li, D. (2012). A dynamic product quality evaluation based pricing model for perishable food supply chains. *Omega—The International Journal of Management Science, 40*(6), 906–917.

Wang, G., Huang, S. H., & Dismukes, J. P. (2004). Product-driven supply chain selection using integrated multi-criteria decision-making methodology. *International Journal of Production Economics, 91*(1), 1–15.

Wang, X., Chan, H. K., Yee, W. Y., & Diaz-Rainey, I. (2012). A two-stage Fuzzy-AHP model for risk assessment of implementing green initiatives in the fashion supply chain. *International Journal of Production Economics, 135*(2), 595–606.

Wu, T., Blackhurst, J., & Chidambaram, V. (2006). A model for inbound supply risk analysis. *Computers in Industry, 57*, 250–265.

Xia, W., & Wu, Z. (2007). Supplier selection with multiple criteria in volume discount environments. *Omega—International Journal of Management Science, 35*(5), 494–504.

Xiao, Z., Chen, W., & Li, L. (2012). An integrated FCM and fuzzy soft set for supplier selection problem based on risk evaluation. *Applied Mathematical Modelling, 36*, 1444–1454.

Yang, C. C., & Chen, B. S. (2006). Supplier selection using combined analytical hierarchy process and grey relational analysis. *Journal of Manufacturing Technology Management, 17*(7), 926–941.

Chapter 5
Fuzzy AHP Approach for Analysing Risk Rating of Environmentally Friendly Product Designs

5.1 Introduction

This chapter presents a model that integrates fuzzy logic and analytic hierarchy process (AHP) for the selection of green product designs. Life cycle assessment (LCA) is a methodology commonly utilised to analyse the environmental impacts of a product from its origin (i.e. raw materials) to its end-of-life. LCA is a popular and comprehensive tool to accomplish the objective. Please refer to Appendix 1 for an introduction of LCA. Two common critiques of LCA lie in its non-consideration of "uncertainty" when evaluating alternative designs and its time-consuming data collection process as well as in its subsequent analysis. The former limitation is particularly important in the design stage as the final options are not well defined, whereas the latter requires substantial resources and expertise. This chapter proposes an approach that blends structured LCA with fuzzy AHP (FAHP). In doing so, some of the disadvantages of LCA can be remedied, and this provides a practical tool for performing LCA. The result is a tool that is easy to use by practitioners to obtain valuable information for evaluating various product designs and particularly useful in the early stages of design when different options can be evaluated and be screened out.

5.2 Fuzzy AHP (FAHP) Method

The proposed method utilises the advantages of fuzzy set theory, which was developed by Zadeh in the 1960s, that can incorporate imprecise and uncertain variables (Zadeh 1965). In the 1980s, some scholars started combining the fuzzy concepts with AHP (e.g. Van Laarhoven and Pedrycz 1983) to form the FAHP strand of research. Since then, FAHP has been applied in different applications (e.g. Weck et al. 1997; Kanda and Deshmukh 2007; Huang et al. 2008; Wang et al. 2011). In this chapter, FAHP is employed to help understand the risk of an environmentally friendly product design with respect to different assessment attributes. Obviously, the main rationale behind this is owing to the uncertain

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nature of the problem, which involves different combinations of material selection, process designs and so on.

One beauty of FAHP is that when assessors evaluate each environmental output of a design with different criteria, linguistic terms (e.g. high, very high) or a fuzzy number, which can be assigned instead of providing a precise numerical value, sometimes it is impossible. A fuzzy number is a special fuzzy set, such that $M = \{(x, \mu_M(x), x \in \mathrm{R})\}$, where the value of x lies on the real line $\mathrm{R} \rightarrow [0, 1]$. We define a fuzzy number M on R to be a triangular fuzzy number (TFN), and the membership function can be described as follows:

$$\mu_M(x) = \begin{cases} (x - m1)/(m2 - m1), & x \in [m1, m2] \\ (m3 - x)/(m3 - m2), & x \in [m2, m3] \\ 0, & \text{otherwise} \end{cases} \tag{5.1}$$

where $m_1 \leq m_2 \leq m_3$, m_1 and m_3 stand for the lower and upper values of the support of M, respectively, and m_2 denotes the most promising value. TFNs M_1, M_3, M_5, M_7 and M_9 are used to represent the pairwise comparison of decision variables from "Equal" to "Absolutely Better", and TFNs M_2, M_4, M_6 and M_8 represent the middle preference values between them. The membership functions of the TFNs are shown in Fig. 5.1, $M_z = (m_{z1}, m_{z2}, m_{z3})$, where $z = 1, 2, \ldots, 9$. Here, m_{z1}, m_{z2} and m_{z3} are the lower, middle and upper values of the fuzzy number m_z, respectively, where m_{z1} and m_{z3} represent a fuzzy degree of judgement. The greater the $m_{z3} - m_{z1}$ is, the greater is the fuzziness of the judgement. When $m_{z1} = m_{z2} = m_{z3}$, the judgment is a non-fuzzy number (i.e. the assessor knows the exact rating or value of the judgement).

The procedure for standard FAHP has been well documented in the literature, and the following is a summary of the procedures with reference to the study conducted by Hsieh et al. (2004):

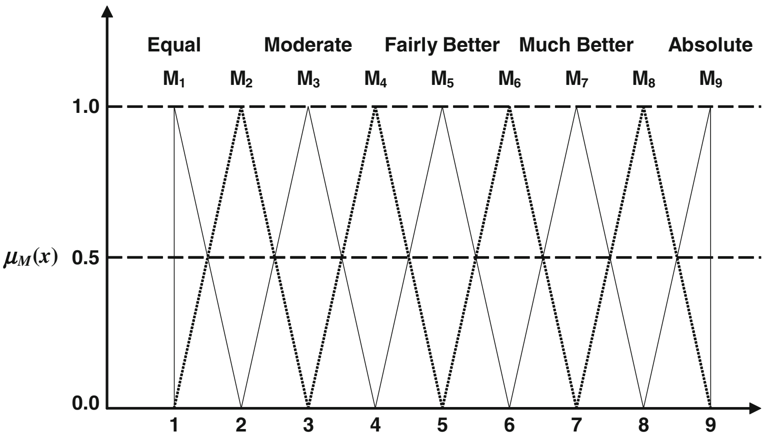

Fig. 5.1 Membership functions of triangular fuzzy numbers

Step 1: Construct pairwise comparison matrices from a panel of experts. Linguistic variables could be used, so the following matrix (per expert) is constructed by Eq. 5.2. For simplicity, reference to different experts is omitted (see Step 2):

$$\tilde{A} = \begin{bmatrix} 1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \tilde{a}_{21} & 1 & & \tilde{a}_{2n} \\ \vdots & & \ddots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n1} & \cdots & 1 \end{bmatrix} \tag{5.2}$$

where $\tilde{a}_{ij} = 1/\tilde{a}_{ji}$ and

$$\tilde{a}_{ij} = \begin{cases} \tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9} & \text{if criterion } \ i \text{ is relativelyimportant to criterion } j \\ 1 \quad \text{if } i = j \\ \frac{1}{1}, \frac{1}{3}, \frac{1}{5}, \frac{1}{7}, \frac{1}{9} & \text{if criterion } i \text{ isrelatively less important to criterion } j \end{cases}$$

Step 2: Since the evaluation of different experts would lead to different matrices, we need to integrate the opinion of different experts to form one synthetic pairwise comparison matrix. Obviously, this step can be skipped if there is only one expert in Step 1. The elements of the synthetic pairwise comparison matrix ($\tilde{a}_{ij}$) are calculated by using the geometric mean method proposed by Buckley (1985):

$$\tilde{a}_{ij} = \left(\tilde{a}_{ij}^{1} \otimes \tilde{a}_{ij}^{2} \otimes \cdots \otimes \tilde{a}_{ij}^{E}\right)^{1/E} \tag{5.3}$$

The superscript in Eq. 5.3 is the index which refers to different experts, and there are total of E experts.

Step 3: Make use of the synthetic pairwise comparison matrix from Step 2 and define the fuzzy geometric mean ($\tilde{r}_i$) and fuzzy weights of each criterion ($\tilde{w}_i$) using Eqs. 5.4 and 5.5, respectively:

$$\tilde{r}_i = (\tilde{a}_{i1} \otimes \tilde{a}_{i2} \otimes \cdots \otimes \tilde{a}_{in})^{1/n} \tag{5.4}$$

$$\tilde{w}_i = \tilde{r}_i \otimes (r_1 \oplus \cdots \oplus \tilde{r}_n)^{-1} \tag{5.5}$$

Step 4: Since the calculation so far involves linguistic variables, the next step is to defuzzify the weights to form meaningful figures for analysis (e.g. ranking). Many methods exist in the literature, but centre of area (COA) is by far the most popular and easy to use one (e.g. Hsieh et al. 2004). Assume that the fuzzy weights of each criterion (w_i) can be expressed in the following form:

$$\tilde{w}_i = (Lw_i, Mw_i, Uw_i) \tag{5.6}$$

where Lw_i, Mw_i, Uw_i represent the lower, middle and upper values of the fuzzy weight of the ith criterion.

Then, the non-fuzzy (i.e. defuzzified) weight value of the *ith* criterion (w_i) is given by Eq. 5.7:

$$w_i = [(Uw_i - Lw_i) + (Mw_i - Lw_i)]/3 + Lw_i \tag{5.7}$$

Step 5: The last step is to calculate the risk ratings of different criteria with respect to the five environmental assessment attributes (to be discussed in next section). The procedure is similar to Step 1 and Step 4, and the major difference is just in the object of the pairwise comparison. A similar matrix as in Eq. 5.1 should be constructed by different experts. A synthetic pairwise comparison matrix can then be calculated using the geometric mean method outlined in Step 2. After that, the fuzzy geometric mean and fuzzy weights of each criterion with respect to different environment attributes can be defined using Eqs. 5.4 and 5.5. This is referred to as fuzzy environmental risk ratings, in contrast to the regular weightings of different criteria. The rating of each attributed EA_i can be expressed in the following format, analogous to Eq. 5.6:

$$\tilde{E}A_i = (LEA_i, MEA_i, UEA_i) \tag{5.8}$$

In ranking the environmental assessment attributes, the final synthetic decision can be conducted and a fuzzy synthetic decision matrix $\tilde{R}$ can be computed as follows:

$$\tilde{R} = \tilde{E}A \otimes \tilde{W} \tag{5.9}$$

where $\tilde{W}$ is the criteria weight vector calculated in previous step.

Each element of the fuzzy synthetic decision matrix $\tilde{R}$, $\tilde{R}_{ij} = (LR_{ij}, \quad MR_{ij}, \quad UR_{ij})$, with respect to the criterion C_{ij} can be estimated by the following equations:

$$LR_{ij} = LEA_{ij} \times LW_{ij} \tag{5.10}$$

$$MR_{ij} = MEA_{ij} \times MW_{ij} \tag{5.11}$$

$$UR_{ij} = UEA_{ij} \times UW_{ij} \tag{5.12}$$

Finally, $\tilde{R}$ needs to be defuzzified using the COA method given by Eq. 5.7.

In this chapter, the objective is to analyse the weighting (i.e. contribution) of each criterion and life cycle phases of the overall LCA. Therefore, the above do not consider selection of alternatives. However, the remaining procedures will follow regular AHP analysis if the pairwise comparisons are not fuzzy in nature (i.e. crisp values are used). Even if the comparisons are carried out using fuzzy membership functions, the procedure would just repeat the above, so the discussion is omitted here. Below is a case study to illustrate how the FAHP method can be applied in the eco-design application.

5.3 Using FAHP for Green Design Evaluation: Constructing the Hierarchy of Green Design

One major drawback of LCA is to assess the potential environmental impact associated with a product by compiling an inventory of relevant inputs and outputs, which of course can help establish links between the environmental impacts, operations and economics of the process. Having said that, this will require substantial data, which should be scientifically proved, from the industry. This is a big hurdle to many organisations, especially small and medium enterprises, as they would not be able to devote resources or expertise to carry out a complete and systematic LCA. Therefore, a simple and cost-effective method is desired. Although AHP is a good candidate from this perspective as the discrete scale of AHP has the advantages of simplicity and ease of use for pairwise comparison of different designs, it is not without shortcomings. Most importantly, it cannot handle the uncertainty and ambiguity present in deciding the ratings of different attributes, and it is often difficult to compare different factors due to the lack of adequate information (Chan and Kumar 2007).

In this connection, an LCA-based FAHP is employed as an integrated methodology for assessing the risk associated with different environmental impacts of a product design over its entire product life cycle. The proposed method can address the aforementioned drawbacks of both LCA and AHP: a full LCA is not needed, the solution can come up quickly, and uncertainty can be taken into account. A step-by-step approach for the selection of green designs, considering all environmental issues from cradle to grave, is proposed as follows:

- Like many decision-making problems, the first step is to define the problem under study, which is the risk assessment of different criteria with respect to different environmental assessment attributes. A panel of experts, which can include product designers, engineers, production people and so on, is formed to participate in the evaluation process.
- The whole produce life cycle (including raw material selection and use, manufacturing, distribution, installation and maintenance, usage and end-of-life) is to be systematically analysed based on the LCA principle, although we do not need to go through the tedious LCA process. The output of this step is to identify the main criteria within each phase that are contributing factors to the analysis.
- The next step is the data collection process. Relevant data can be collected through documentations like the bill of material, plant visit to understand the manufacturing processes and associated consumption of energy and so on.
- Then, the hierarchical structure for green design selection can be constructed (to be discussed in the subsequent section).
- The final step involves the collection of relevant data for the environmental impact assessment with respect to the criteria defined in previous step. Since this is not a full LCA, comprehensive data are not required. Instead, expert opinions will be collected in the proposed approach to come up with the conclusion.

Once the hierarchy is constructed and data are collected, the proposed FAHP outlined in Sect. 5.2 is utilised to estimate comparative ratings for the environmental performance of alternative designs against each criterion. Moreover, it is also used to estimate comparative weightings of life cycle phases and associated criteria. Details of the key steps are discussed below.

Level 1: Overall Objective

The overall objective is obviously the selection of the best green design. The actual problem, however, is how the design can be broken down into a number of criteria (i.e. Level 2 to be discussed below). With the help of LCA principle, this can be done very easily.

Level 2: Six life cycle phases

Level 2 in the hierarchy consists of the life cycle phases. The definition of life cycle is different in various studies. Therefore, in this study, the definition from the energy using products (EuP) directive (European Council 2005) is adopted. "Life cycle" means the consecutive and interlinked stages of an EuP from raw material selection, through production and distribution, then customer usage till the final disposal. It is recommended that the analysis should be broken down into the following six phases: (1) raw material selection and use (L_1); (2) manufacturing (L_2); (3) packaging, transport and distribution (L_3); (4) installation and maintenance (L_4); (5) usage (L_5); and (6) end-of-life, that is, the state of an EuP having reached the end of its first use until its final disposal (L_6). In some applications, not all six phases are required (like the case study to be discussed). However, a generic diagram consists of six phases as illustrated in Fig. 5.2, together with Level 1.

Level 3: The decision criteria within each phase

This is the most important level in the analysis. In short, the main criteria under each phase should be identified. For example, in the "Material Selection" phase, plastics, metals or electronic components used, among others, are the main types of raw material used and should be put down as judging criteria. Relevant data, such as the bill of materials mentioned in previous steps, should be collected to support the identification process. In the next phase, "Manufacturing" phase, all the main manufacturing processes should be identified. This can be done by plant

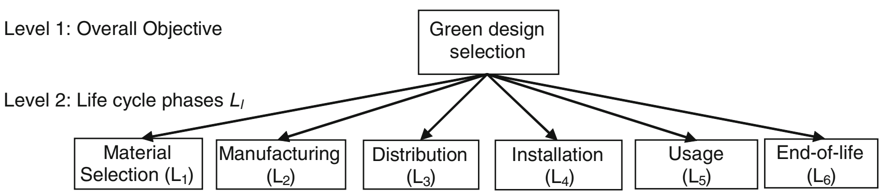

Fig. 5.2 First two levels of the hierarchical structure for green design selection

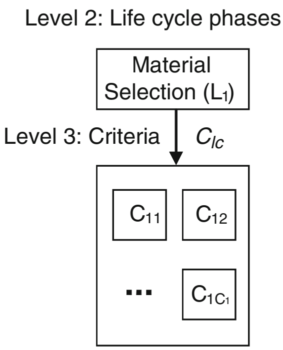

Fig. 5.3 Level 3 of the hierarchical structure (phase 1 as an example)

visit, interviews with production engineers and so on. In the "Distribution" phase, all elements affecting transportation, including the design of packaging, the means of transportation and so on, should be studied. In both "Installation" and "Usage" phases, energy consumption and wastes are common criteria to be considered. Lastly, in the "End-of-Life" phase, information about reuse, remanufacturing and recycling is under the spotlight and other criteria surrounding these practices. Details of common criteria under other life cycle phases will be further explained in the illustrative case study. A generic diagram of each phase is demonstrated in Fig. 5.3, using phase 1 as an example.

Level 4: The five attributes of environmental impact assessment for each criterion

Defining the performance measures of a multi-criteria decision-making problem is always difficult. One reason is that different measures can be used as a proxy of a performance evaluation. Fortunately, the EuP Directive proposes five assessment attributes, and hence, they are employed in this study at Level 4. They are (1) consumption of material, energy and other resources (EA_1); (2) emission to air, water or soil (EA_2); (3) anticipated pollution (EA_3); (4) generation of waste material (EA_4); and (5) possibility of reuse, recycling and recovery of materials and/or of energy (EA_5).

Level 5: Different product designs

Finally, the green product design alternatives (X_n) are located at Level 5 of the hierarchy. Figure 5.4 depicts the overall hierarchical structure.

5.4 Background Studies on Environmentally Friendly Design

In recent years, the awareness of environmentally conscious practices has been improving (Sarkis 1998; Carter and Carter 1998; Rao and Holt 2005; Yung et al. 2009). These practices include environmentally friendly design (sometimes

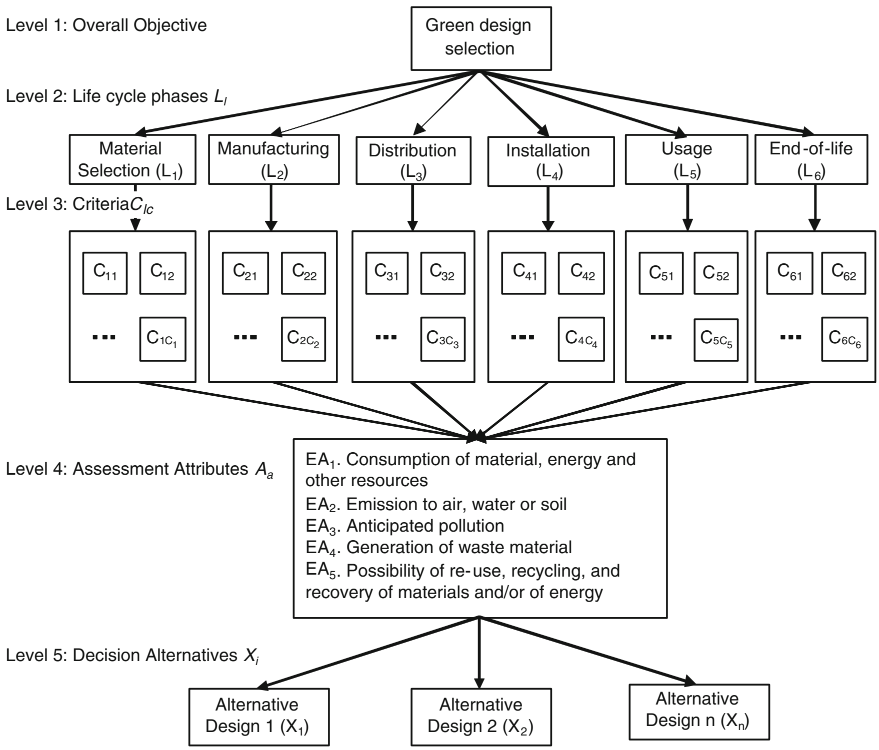

Fig. 5.4 Overall hierarchical structure for green design selection (Chan et al. 2012)

referred to as eco-design), green procurement, sustainable operations and also a number of end-of-life practices such as recycling and remanufacturing. The trend may be a consequence of regulatory pressures to protect the environment. For example, the European Council's Directive (2005) on EuP restricts manufacturers to comply with its eco-design principles in order to sell their products to the European Union. Preventive rather than corrective actions should be taken as early as possible during the design phase of EuP in order to identify and reduce the environmental impact of product's whole life cycle. It is becoming an important element when considering new product development. Decisions regarding raw material selection, electricity consumption during use phase, packaging design, end-of-life treatment, etc., can potentially have a profound environmental impact. Aforementioned trend may exert further burden to organisations, but on the other hand also help to boost the progression of organisations to reduce adverse effects on the environment (Zhu and Sarkis 2003).

In fact, the EuP Directive is not the only regulation that can be found in the electronics industry. In recent years, these include the Waste Electrical and Electronic Equipment (WEEE) Directive, Restriction of Hazardous Substances (RoHS) Directive and also the aforementioned EuP Directive (Trappey et al. 2011).

Given its short life cycle, the industry is considered as the fastest growing streams of waste generation (Gurauskienė and Varžinskas 2006). If a product cannot comply with any one of these directives, it is prohibited from being traded in the member states of the European Union. There is however no universally applicable tool to tackle this problem, and thus, the EuP Directive was set up partly to address this issue (Yung et al. 2011). This is the motivation why in this study an LCA-based FAHP method is proposed for eco-design.

LCA is a systematic and scientific tool that can help designers analyse the environmental impact of a product and has been applied in various applications over the last three decades (Guinée et al. 2011). In an LCA, the whole product life cycle of a product is taken into consideration (Junnila 2008). That means LCA can provide the designers a complete picture of the environmental output and hence impacts of the product. Because of this unique feature, LCA has attracted increasing attention in both the academy and practitioners, and hence, numerous studies can be found in the literature (e.g. Thoming and Erol 2005; Kobayashi 2005; Bovea and Gallardo 2006). LCA may also be employed to address legislative mandates, especially in the light of the requirements introduced in the European Union (e.g. the EuP Directive) (Trappey et al. 2011; Yung et al. 2012).

In essence, LCA is a multi-objective (with respect to different environmental impacts) approach for decision-making (Gerber et al. 2011). Therefore, LCA and AHP are perfect matches as both can address multi-criterion decision-making problem. For example, Sarkis (2003) proposed an AHP approach to evaluate the environmental output of different supply chain life cycle stages, despite the fact that the stages are not in line with the phases outlined in LCA. Lu et al. (2007) studied how AHP can be utilised for selecting suppliers based on a set of environmental criteria. Sarmiento and Thomas (2010) identified improvement areas (i.e. different criteria) when implementing green initiatives, among others.

As discussed, the major shortcoming of traditional AHP is that it cannot handle uncertain variables. In this connection, another stream of research focuses on FAHP. For example, Kang and Li (2010) presented a FAHP method for "green rationality evaluation" of degradable packaging with respect to LCA. Zheng et al. (2011) applied an FAHP assessment model to evaluate energy conservation in the building sector. In both studies, hierarchy models were developed based on the AHP concept, and then, the weightings of the evaluation factors were determined following the AHP procedures. In addition, fuzzy membership degrees were only employed in the lowest hierarchy to measure each criterion. Therefore, such approach is not full FAHP and cannot address the aforementioned shortcoming.

In the eco-design domain, Ng and Chuah (2010) employed TOPSIS as the fuzzy decision-making tool in FAHP for evaluating different eco-design alternatives. Their research outlined the advantages of FAHP. Different from this study, they ignored the life cycle issues and based their hierarchical model on the three factors: economic, environmental and social. As a matter of fact, fuzzy TOPSIS separates qualitative and quantitative variables and it is not designed for comparative analysis of different criteria (Ertuğrul and Karakaşoğlu 2008). As a consequence, fuzzy TOPSIS is limited to one-tier decision problem (Bottani and

Rizzi 2006). This is also the motivation for employing the FAHP outlined in previous section. A case study is used to demonstrate how the approach can be applied in real-life example, and details are discussed in the subsequent section.

5.5 Case Study: An Electronic Product

The case product in this study is a personal electronic product. The manufacturer of the product attempted to initiate eco-design program that aims to develop a tool (i.e. LCA) to help designers select the best design options of its products. A full LCA has been conducted, and details of the results are reported in Yung et al. (2011). In this study, the authors make reference to the case to demonstrate how the proposed model can simplify new product development from an eco-design perspective, especially when an LCA has already been conducted so that the result can be benchmarked against Yung et al. (2011) study.

Following the procedures outlined in Sect. 5.3, the overall objective is defined for the design selection. A closer look at the product reveals that the number of phases of the product life cycle only comprises of five phases as there is no installation and maintenance phase. This is because the product is a battery-driven product. Therefore, only five life cycle phases are defined in the selection hierarchy. The next step, which is the most challenging one, is to choose the criteria against which the alternatives will be evaluated. Fortunately, with reference to the case (Yung et al. 2011), the key criteria under each phase can be identified. The hierarchy of the LCA based on AHP was constructed, and it is shown in Table 5.1 (only selected criteria are shown here for demonstration purpose). If a full LCA has not been developed instead, associated information should be collected according to the procedures suggested in Sect. 5.3.

Then, the FAHP method is used to assign comparative ratings of environmental performance to different designs that are being assessed. The first step (Step 1 in Sect. 5.2) is to construct pairwise comparison between criteria from different experts. At the same time, the consistency ratio of each judgement is calculated and checked to ensure that it is lower than or equal to 0.1. For example, the following matrix is the comparison between different life cycle phases from one expert with respect to the membership functions defined in Fig. 5.1 (the reciprocal elements on the left-hand corner are omitted for simplicity):

$$\tilde{A} = \begin{array}{c} L_1 \\ L_2 \\ L_3 \\ L_4 \\ L_5 \end{array} \begin{bmatrix} 1 & \tilde{3} & \tilde{9} & \tilde{6} & \tilde{9} \\ . & 1 & \tilde{9} & \tilde{4} & \tilde{9} \\ . & . & 1 & \tilde{\frac{1}{5}} & \tilde{2} \\ . & . & . & 1 & \tilde{7} \\ . & . & . & . & 1 \end{bmatrix}$$

Table 5.1 An example of hierarchy structure for LCA-based green design selection

Life cycle phases	Criteria	Environmental assessment attributes
L_1. Material selection	C_{11}. Plastics	EA_1. Consumption of material, energy and other resources
	C_{12}. Electronic component	
	C_{13}. Metal	
L_2. Manufacturing	C_{21}. Solder paste painting	EA_2. Emission to air, water or soil
	C_{22}. SMD pick-and-place component	
	C_{23}. Reflow soldering	
	C_{24}. PAD cleaning	
	C_{25}. DIE sticking	
	C_{26}. Wire bonding	
	C_{27}. Packing	
L_3. Distribution	C_{31}. Packaging	EA_3. Anticipated pollution
	C_{32}. Transportation	
L_4. Usage	C_{41}. Energy consumption	EA_4. Generation of waste material
	C_{42}. Waste	
	C_{43}. Residue	
L_5. End-of-life	C_{51}. Reuse	EA_5. Possibility of reuse, recycling and recovery of materials and/or of energy
	C_{52}. Remanufacture	
	C_{53}. Recycling	
	C_{54}. Toxic material	
	C_{55}. Landfill for non-toxic material	

Table 5.2 Synthetic pairwise comparison matrix for different life cycle phases

	L_1			L_2			L_3			L_4			L_5		
L_1	1/1	1/1	1/1	5/4	17/9	5/2	19/6	23/6	13/3	19/7	10/3	4/1	19/6	13/3	21/4
L_2	2/5	1/2	4/5	1/1	1/1	1/1	16/7	10/3	4/1	17/9	5/2	22/7	2/1	10/3	13/3
L_3	1/4	1/4	1/3	1/4	1/3	3/7	1/1	1/1	1/1	1/3	4/9	5/8	5/8	5/4	17/9
L_4	1/4	2/7	3/8	1/3	2/5	1/2	8/5	9/4	26/9	1/1	1/1	1/1	9/5	5/2	19/6
L_5	1/5	1/4	1/3	1/4	1/3	1/2	1/2	4/5	8/5	1/3	2/5	5/9	1/1	1/1	1/1

Note above are all fuzzy membership functions, so they are in the form (L, M, U)

In the second step, evaluations from all experts are incorporated to formulate one fuzzy synthetic pairwise comparison matrix. It can be calculated by Eq. 5.3 as follows (Table 5.2):

The next step (Step 3) is to calculate the fuzzy geometric mean ($\tilde{r}_i$) and fuzzy weights ($\tilde{w}_i$) of all life cycle phases. Use Eq. 5.4 to obtain the fuzzy weights of dimensions for owners group, that is,

$$\begin{aligned}\tilde{r}_1 &= (\tilde{a}_{11} \otimes \tilde{a}_{12} \otimes \tilde{a}_{13} \otimes \tilde{a}_{14} \otimes \tilde{a}_{15})^{1/5} \\ &= \left(\left(1 \times \frac{5}{4} \times \frac{19}{6} \times \frac{19}{7} \times \frac{19}{6}\right)^{\frac{1}{5}}, \left(1 \times \frac{17}{9} \times \frac{23}{6} \times \frac{10}{3} \times \frac{13}{3}\right)^{\frac{1}{5}} \left(1 \times \frac{5}{2} \times \frac{13}{3} \times 4 \times \frac{21}{4}\right)^{\frac{1}{5}}\right) \\ &= (2.030, 2.536, 2.960)\end{aligned}$$

Similarly, we can obtain the remaining $\tilde{r}_i$, that is,

$$\begin{aligned}\tilde{r}_2 &= (1.280, 1.708, 2.132) \\ \tilde{r}_3 &= (0.416, 0.536, 0.696) \\ \tilde{r}_4 &= (0.745, 0.922, 1.123) \\ \tilde{r}_5 &= (0.374, 0.467, 0.673)\end{aligned}$$

For the weight of each dimension, they can be calculated by Eq. 5.5 as follows:

$$\begin{aligned}\tilde{w}_1 &= \tilde{r}_1 \otimes (\tilde{r}_1 \oplus \tilde{r}_2 \oplus \tilde{r}_3 \oplus \tilde{r}_4 \oplus \tilde{r}_5)^{-1} \\ &= (2.030, 2.536, 2.960) \otimes (1/(2.960 + \cdots + 0.673), 1/(1.708 + \cdots + 0.467), 1/(1.280 + \cdots + 0.374)) \\ &= (0.268, 0.411, 0.611)\end{aligned}$$

Likewise, the remaining weights of each life cycle phase can be obtained, and the results are displayed in Table 5.3.

Using the COA method (Eq. 5.6), the non-fuzzy value of the fuzzy weights of each life cycle phase can be calculated. To take the "Material Selection" phase as an example, the calculation process is as follows:

$$\begin{aligned}w_1 &= [(Uw_i - Lw_i) + (Mw_i - Lw_i)]/3 + Lw_i \\ &= [(0.611 - 0.268) + (0.411 - 0.268)]/3 + 0.268 = 0.430\end{aligned}$$

Table 5.4 shows the non-fuzzy weight values of all life cycle phases and their normalised value.

Similarly, the weights for the criteria within each life cycle phase can be obtained. Table 5.5 summarises the overall weightings' information for each element in the hierarchical model.

Table 5.3 Fuzzy weights for different life cycle phases

	L	M	U
$\tilde{w}_1$	0.268	0.411	0.611
$\tilde{w}_2$	0.169	0.277	0.440
$\tilde{w}_3$	0.055	0.087	0.144
$\tilde{w}_4$	0.098	0.149	0.232
$\tilde{w}_5$	0.049	0.076	0.139

Table 5.4 Non-fuzzy weights for different life cycle phases

	Non-fuzzy weights	Normalised weights
W_1	0.430	0.403
W_2	0.295	0.276
W_3	0.095	0.089
W_4	0.160	0.150
W_5	0.088	0.082

Table 5.5 Comparative weightings of life cycle phases and its associated criteria

Life cycle phase	Local weights			Integrated weights			Non-fuzzy weights
	Lw_i	Mw_i	Uw_i	Lw_i	Mw_i	Uw_i	
L_1	*0.268*	*0.411*	*0.611*				0.403
C_{11}	0.215	0.400	0.670	0.058	0.164	0.409	0.157
C_{12}	0.156	0.254	0.430	0.042	0.104	0.263	0.103
C_{13}	0.213	0.347	0.612	0.057	0.143	0.374	0.143
L_2	*0.169*	*0.277*	*0.440*				0.276
C_{21}	0.084	0.151	0.255	0.014	0.042	0.112	0.041
C_{22}	0.118	0.210	0.346	0.020	0.058	0.152	0.057
C_{23}	0.186	0.299	0.490	0.031	0.083	0.216	0.082
C_{24}	0.055	0.092	0.159	0.009	0.025	0.070	0.008
C_{25}	0.055	0.090	0.155	0.009	0.025	0.068	0.008
C_{26}	0.060	0.100	0.171	0.010	0.028	0.075	0.015
C_{27}	0.037	0.059	0.104	0.006	0.016	0.046	0.009
L_3	*0.055*	*0.087*	*0.144*				0.089
C_{31}	0.307	0.490	0.853	0.017	0.043	0.123	0.042
C_{32}	0.293	0.510	0.813	0.016	0.044	0.117	0.041
L_4	*0.098*	*0.149*	*0.232*				0.150
C_{41}	0.313	0.417	0.564	0.031	0.062	0.131	0.063
C_{42}	0.241	0.327	0.430	0.024	0.049	0.100	0.048
C_{43}	0.189	0.256	0.351	0.019	0.038	0.081	0.039
L_5	*0.049*	*0.076*	*0.139*				0.082
C_{51}	0.169	0.311	0.490	0.008	0.024	0.068	0.025
C_{52}	0.144	0.214	0.377	0.007	0.016	0.052	0.019
C_{53}	0.112	0.180	0.278	0.006	0.014	0.039	0.015
C_{54}	0.119	0.169	0.263	0.006	0.013	0.036	0.014
C_{55}	0.079	0.126	0.197	0.004	0.010	0.027	0.010

Now, the risk ratings of different criteria with respect to the five environmental assessment attributes are determined by following the same procedure discussed above (Step 5). Using the criterion C_{11}, plastics, as an example, firstly, the fuzzy evaluation matrix of environmental risk assessment is constructed by the pairwise comparison between different assessment attributes using triangular fuzzy numbers. The following is assignment from the same expert as in the life cycle phase above:

$$\tilde{A} = \begin{array}{c} EA_1 \\ EA_2 \\ EA_3 \\ EA_4 \\ EA_5 \end{array} \begin{bmatrix} 1 & \tilde{\frac{1}{5}} & \tilde{\frac{1}{7}} & \tilde{\frac{1}{2}} & \tilde{\frac{1}{8}} \\ . & 1 & \tilde{\frac{1}{3}} & \tilde{3} & \tilde{\frac{1}{6}} \\ . & . & 1 & \tilde{6} & \tilde{2} \\ . & . & . & 1 & \tilde{\frac{1}{4}} \\ . & . & . & . & 1 \end{bmatrix}$$

Again, by incorporating all experts' evaluation, the synthetic pairwise comparison matrix of the criterion with respect to the assessment attributes can be calculated by Eq. 5.3 as follows (Table 5.6):

Each weight can then be calculated by Eq. 5.5. The overall fuzzy environmental risk ratings can then be found as follows (Table 5.7):

From the integrated criteria weight vector, $\breve{W}$, and fuzzy risk ratings, $(\tilde{EA})$, the final fuzzy synthetic decision can be conducted. The derived result will be the fuzzy synthetic decision matrix $\breve{R}$ calculated by Eq. 5.9. For criterion C_{11} (plastics), the fuzzy synthetic decision matrix of EA_1, "Consumption of material, energy and other resources", is expressed as follows:

$$(0.109, 0.193, 0.325) \times (0.058, 0.164, 0.409)$$

The approximated result of the fuzzy multiplication is obtained as (0.006, 0.032, 0.133), using Eqs. 5.10–5.12. Using the COA method, its non-fuzzy value can be calculated as 0.057. Similarly, the remaining four environmental assessment attributes, EA_2, EA_3, EA_4 and EA_5, with respect to C_{11}, can be derived as 0.058, 0.081, 0.048 and 0.051, respectively. The derived results are useful for ranking the environmental risk with respect to individual criterion within each life cycle phase, which indicates important areas for design improvement.

Table 5.6 Synthetic pairwise comparison matrix for different environmental assessment attributes

	EA_1			EA_2			EA_3			EA_4			EA_5		
EA_1	1/1	1/1	1/1	5/9	1/1	1/1	2/5	2/3	4/5	1/4	1/3	5/9	4/5	1/1	8/5
EA_2	1/1	1/1	9/5	1/1	1/1	1/1	3/5	1/1	8/5	1/3	3/7	4/5	8/7	2/1	2/1
EA_3	5/4	13/9	5/2	5/8	10/9	5/3	1/1	1/1	1/1	2/5	2/3	4/5	3/4	1/1	9/5
EA_4	9/5	3/1	25/6	5/4	16/7	10/3	5/4	13/9	5/2	1/1	1/1	1/1	2/1	2/1	2/1
EA_5	5/8	10/9	5/4	1/2	1/2	7/8	5/9	1/1	4/3	1/2	1/2	1/2	1/1	1/1	1/1

Table 5.7 Fuzzy environmental risk ratings for different environmental assessment attributes

	LEA_i	MEA_i	UEA_i
EA_1	0.109	0.193	0.325
EA_2	0.132	0.203	0.323
EA_3	0.166	0.292	0.453
EA_4	0.094	0.153	0.276
EA_5	0.097	0.159	0.293

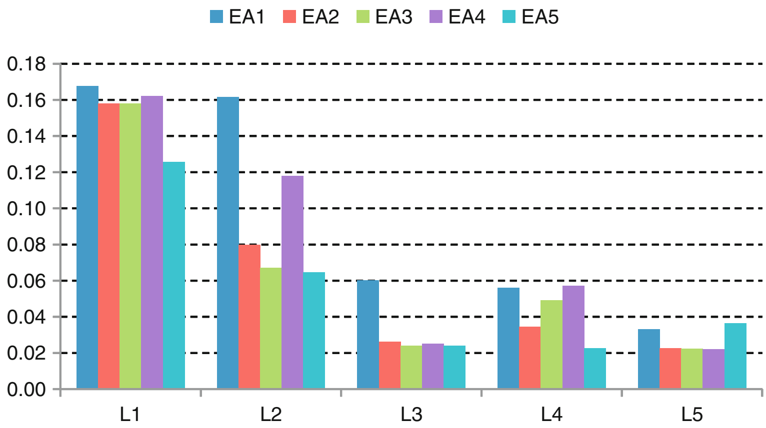

Fig. 5.5 Environmental performance of each assessment attribute with respect to the life cycle phases

5.6 Results and Discussion

Based on the above procedure, the environmental risk ratings of each assessment attribute with respect to the life cycle phases are depicted in Fig. 5.5. It shows that life cycle phases 1 and 2 are more significant if different environmental performances are taken into account. Obviously, more effort should be devoted to the material selection and the design of manufacturing processes in order to lower the risk of producing high environmental impact. In addition, EA_1 is always ranked top in different life cycle phases—this is where the designers can pay attention to. Above can be extended to criterion level, which is illustrated in Fig. 5.6. Similar observation can be deduced, so Fig. 5.6 is shown here for reference only.

Above briefly summarise the technical assessment of this case product; however, what is more important are the managerial implications of this study. Although LCA is a useful technique, conducting a full LCA is not without concerns. A survey indicated that 68 % of the respondents considered that LCA is time-consuming and 63 % of them felt that LA is costly (Cooper and Fava 2008). As a matter of fact, conducting an LCA requires proprietary software which maintains the database and handles the calculations. This often inhibits organisations from using LCA as a decision-making tool due to high cost of the software. The proposed method provides a practical and easy-to-use way to carry out environmental impact assessment and the evaluation of comparative weightings of life cycle phases and their associated criteria. All the calculations can be done in an Excel spreadsheet, so it can be adopted easily in the industry, without purchase of expensive software. Compared to conventional LCA, the FAHP approach outlined in this chapter is less demanding upon the computational power and time needed to make a decision.

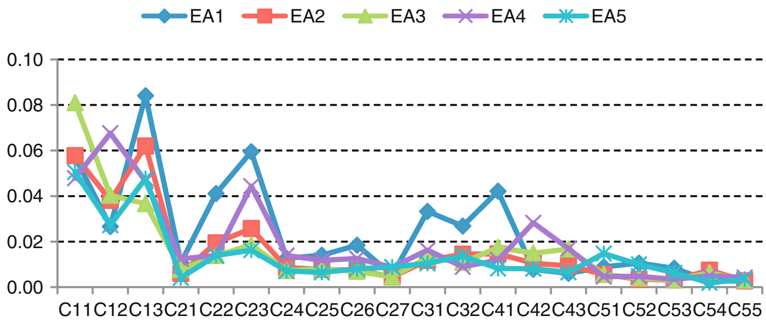

Fig. 5.6 Environmental performance of each assessment attribute with respect to the criteria

Another merit of the proposed FAHP is to incorporate uncertain parameters through the use of fuzzy numbers instead of precise numbers when evaluating the environmental performance. More specifically, the method incorporates fuzzy concepts, so uncertainty can be dealt with. This adds further advantages to the proposed method. It can be observed from the case example that the model does not involve complicated mathematical operations, but it is robust enough to consider uncertainty and is efficient to incorporate the knowledge of decision makers. In addition, this approach helps companies pinpoint the criteria that are worse in various environmental assessments (refer to Figs. 5.5 and 5.6), and hence, different options can then be considered. This will lead to consistent sustainable new product development.

5.7 Conclusions

In the electronics industry, product life cycles are getting shorter and shorter on the one hand; the demand for green product development is getting higher and higher due to regulatory pressure, customer awareness and so on, on the other hand. It is virtually impossible for companies to conduct LCA for all products and associated design alternatives nowadays. Therefore, the proposed method can cut short the development lead time to screen out various design options. This is very useful especially in the electronics industry as modular designs and mass customisation are very popular. These practices make the applications of the proposed approach even easier and can help to prioritise alternatives and select new design options for product improvement in a timely manner. Nevertheless, the aim of the proposed approach is not to replace LCA or undermine the usefulness of LCA.

Like many AHP-based models, one limitation of the proposal model is that users have to make subjective assessments of environmental impact and the relative weightings of life cycle phases and their associated criteria. In fact, that is highly dependent on the knowledge, expertise and communication skills of users. In addition, sufficient information is required to be able to analyse the product life cycle and main criteria within each of the life cycle phases. Having said that, the level of accuracy obtained on the basis of the proposed approach provides a comparatively fast approach to understand the entirety of the environmental impact of a new design.

References

Bottani, E., & Rizzi, A. (2006). A fuzzy TOPSIS methodology to support outsourcing of logistics services. *Supply Chain Management: An International Journal, 11*(4), 294–308.

Bovea, M. D., & Gallardo, A. (2006). The influence of impact assessment methods on materials selection for eco-design. *Materials and Decision, 27*(3), 209–215.

Buckley, J. (1985). Fuzzy hierarchical analysis. *Fuzzy Sets and Systems, 17*, 233–247.

Carter, C. R., & Carter, J. R. (1998). Inter-organizational determinants of environmental purchasing: initial evidence from the consumer products industry. *Decision Sciences, 29*(3), 659–684.

Chan, F. T. S., & Kumar, N. (2007). Global supplier development considering risk factors using fuzzy extended AHP-based approach. *Omega, 35*(4), 417–431.

Chan, H. K., Wang, X., White, G., & Nick, Y. (2012). An extended fuzzy AHP approach for the evaluation of green product designs. *IEEE Transactions on Engineering Management, 2012*, 1–13. doi:10.1109/TEM.2012.2196704.

Cooper, J. S., & Fava, J. A. (2008). Life-cycle assessment practitioner survey: Summary of results. *Journal of Industrial Ecology, 10*(4), 12–14.

Ertuğrul, İ., & Karakaşoğlu, N. (2008). Comparison of fuzzy AHP and fuzzy TOPSIS methods for facility location selection. *International Journal of Advanced Manufacturing Technology, 39*(7–8), 783–795.

Council, European. (2005). Directive 2005/32/EC of the European Parliament of the council of 6 July 2005 establishing a framework for the settings of ecodesign requirements for energy-using products and amending council directive 92/42/EEC and directive 96/57/EC and 2000/55/EC of the European Parliament and of the council. *Official Journal of the European Union, L191*(48), 29058.

Gerber, L., Gassner, M., & Maréchal, F. (2011). Systematic integration of LCA in process systems design: Application to combined fuel and electricity production from lignocellulosic biomass. *Computers and Chemical Engineering, 35*(7), 1265–1280.

Guinée, J. B., Heijungs, R., Huppes, G., Zamagni, A., Masoni, P., Buonamici, R., et al. (2011). Life cycle assessment: past, present, and future. *Environmental Science and Technology, 45*(1), 90–96.

Gurauskienė, I., & Varžinskas, V. (2006). Eco-design methodology for electrical and electronic equipment industry. *Environmental Research, Engineering and Management, 37*(3), 43–51.

Hsieh, T. Y., Lu, S.-T., & Tzeng, G.-H. (2004). Fuzzy MCDM approach for planning and design tenders selection in public office buildings. *International Journal of Project Management, 22*, 573–584.

Huang, C., Chu, P., & Chiang, Y. (2008). A fuzzy AHP application in government-sponsored R&D project selection. *Omega, 36*, 1038–1052.

Junnila, S. (2008). Life cycle management of energy-consuming products in companies using IO-LCA. *International Journal of Life Cycle Assessment, 13*(5), 432–439.

Kanda, A. A., & Deshmukh, S. G. (2007). Coordination in supply chains: an evaluation using fuzzy logic. *Production Planning and Control, 18*(5), 420–435.

Kang, Y., & Li, J. (2010). Green rationality evaluation of degradable packaging based on LCA and fuzzy AHP. In *Proceedings of the IEEE 17th International Conference on Industrial Engineering and Engineering Management* (IE&EM), 329-332.

Kobayashi, H. (2005). Strategic evaluation of eco-products: a product life cycle planning methodology. *Research in Engineering Design, 16*, 1–16.

Lu, L. Y. Y., Wu, C. H., & Kuo, T.-C. (2007). Environmental principles applicable to green supplier evaluation by using multi-objective decision analysis. *International Journal of Production Research, 45*(18–19), 4317–4331.

Ng, C. Y., & Chuah, K. B. (2010). Evaluation of eco design alternatives using fuzzy AHP methodology. *Design Principles and Practices: An International Journal, 4*(1), 1–14.

Rao, P., & Holt, D. (2005). Do green supply chains lead to competitiveness and economic performance? *International Journal of Operation & Production Management, 25*(9), 898–916.

Sarkis, J. (1998). Evaluating environmentally conscious business practices. *European Journal of Operational Research, 107*(1), 159–174.

Sarkis, J. (2003). A strategic decision framework for green supply chain management. *Journal of Cleaner Production, 11*(4), 397–409.

Sarminento, R., & Thomas, A. (2010). Identifying improvement areas when implementing green initiatives using a multitier AHP approach. *Benchmarking: An International Journal, 17*(3), 452–463.

Thoming, J., & Erol, P. (2005). Eco-design of reuse and recycling networks by multi-objective optimization. *Journal of Cleaner Production, 13*, 1492–1503.

Trappey, A. J. C., Ou, J. J. R., Lin, G. Y. P., & Chen, M.-Y. (2011). An eco- and inno-product design system applying integrated and intelligent QFDE and TRIZ methodology. *Journal of Systems Science and Systems Engineering, 20*(4), 443–459.

Van laarhoven, P. J. M., & Pedrycz, W. (1983). A fuzzy extension of Saaty's priority theory. *Fuzzy Sets and Systems, 11*, 229–241.

Wang, X., Li, D., & Shi, X. (2011). A fuzzy enabled model for aggregative food safety risk assessment in food supply chains. *Production Planning and Control, 23*, 377–395. doi: 10.1080/09537287.2001.561812.

Weck, M., Klocke, F., Schell, H., & Ruenauver, E. (1997). Evaluating alternative production cycles using the extended fuzzy AHP method. *European Journal of Operational Research, 100*(2), 351–366.

Yung, W. K. C., Chan, H. K., Wong, D. C. W., So, J. H. T., Choi, A. C. K., & Yue, T. M. (2009). Life cycle assessment of two personal electronic products—a note with respect to the energy-using product directive. *International Journal of Advanced Manufacturing Technology, 42*(3–4), 415–419.

Yung, K. C., Chan, H. K., So, H. T., Wong, W. C., Choi, C. K., & Yue, T. M. (2011). A life-cycle assessment for eco-redesign of a consumer electronic product. *Journal of Engineering Design, 22*(2), 69–85.

Yung, W. K. C., Chan, H. K., So, J. H. T., Wong, D. C. W., Choi, A. C. K., & Yue, T. M. (2012). Environmental impact of two electrical products with reference to the energy-using products directive. *International Journal of Sustainable Engineering, 5*(2), 86–90.

Zadeh, L. A. (1965). Fuzzy sets. *Information and control, 8*(3), 338–353.

Zhu, Q., & Sarkis, J. (2003). Relationships between operational practices and performance among early adopters of green supply chain management practices in Chinese manufacturing enterprises. *Journal of Operations Management, 22*(3), 265–289.

Zheng, G., Jing, Y., Huang, H., & Gao, Y. (2011). Applying LCA and fuzzy AHP to evaluate building energy conservation. *Civil Engineering and Environmental Systems, 28*(2), 123–141.

Chapter 6
Fuzzy Extent Analysis for Food Risk Assessment

6.1 Introduction

The analytical hierarchy process (AHP) provides an effective way to deal with complex decision making. However, AHP requires decision makers to determine the relative importance of each criterion/factor by means of pairwise comparisons between the relevant criteria/factors included in the analysis. The decision maker may feel uncertain about the pairwise comparison or may consider that it is not a method capable of reflecting a human being's vague thoughts (Kahraman et al. 2003). Often, the uncertainty inherent in some situations and in some problems cannot be expressed simply by using crisp values from the nine-point scale. To address the limitations of AHP, some scholars have made use of fuzzy set theory, as introduced by Zaddeh (1965), to create the fuzzy AHP approach. The main benefit introduced by fuzzy AHP is that it enables a more accurate description of the decision-making process that takes place in real applications where ill-defined uncertainties are not uncommon (Huang et al. 2008).

Different methods for the fuzzification of AHP have been proposed since Van Laarhoven and Pedrycz (1983) and Buckley (1985) presented their preliminary work in fuzzy AHP. Van Laarhoven and Pedrycz (1983) used fuzzy ratios based on triangular fuzzy number. Buckley (1985) determined fuzzy priorities for comparison ratios which were defined by trapezoidal membership functions. The previous chapter demonstrates the operations of fuzzy AHP via a case study. In addition, many approaches have been developed to refine fuzzy AHP models on multiple criteria decision-making (MCDM) problems (Chang 1996; Xu 2000; Csutora and Buckley 2001; Mikhailov 2003; Wang et al. 2006). Amongst these, fuzzy extent analysis introduced by Chang (1996) is a relatively easier and less computational exercise compared with the other approaches to fuzzy AHP. In this approach, triangular fuzzy numbers are used to construct pairwise comparison scales for fuzzy AHP, and then the fuzzy extent analysis method is deployed to determine the synthetic extent values of the pairwise comparison.

In this chapter, fuzzy extent analysis is integrated with the hierarchical model to provide aggregative risk assessment. An application of the aggregative risk assessment model in the food supply chain is presented. Quality and safety are

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always the top priorities in the industry. The fuzzy hierarchical model provides a practical and easy-to-use risk assessment model that will help in conducting risk analysis and in quantifying risk in such a way that different operational processes and material batches can be compared in terms of food safety and quality. The model is able to effectively analyse, quantify and enable comparative assessment of the risks of the different processes along a food supply chain, and thereby support the decision-making process at critical control points.

6.2 Fuzzy Extent Analysis

Here, the fuzzy synthetic extent analysis method is introduced to calculate the synthetic extent value of the pairwise comparison. An extent analysis adaptation to fuzzy AHP was proposed by Chang (1996), in order to obtain a crisp priority vector from a triangular fuzzy comparison matrix. The triangular fuzzy scale of preferences is given in Fig. 6.1, in which TFNs' M_1, M_3, M_5, M_7 and M_9 are used to represent the pairwise comparison of decision variables in the range from "Equal" to "Absolute", when these are employed as descriptive terms attached to the level of importance of paired variables, and TFNs' M_2, M_4, M_6 and M_8 represent the mid-point preference values lying between them.

In terms of an equation-based approach, let $P = \{p_1, p_2, \ldots p_n\}$ be an object set, and $Q = \{q_1, q_2, \ldots q_m\}$ be a goal set. According to the method of extent analysis (Chang 1996), each object is taken and extent analysis is performed for each goal, respectively. Therefore, the m extent analysis values for each object are obtained as $M_{g_i}^1, M_{g_i}^2, \ldots M_{g_i}^m, i = 1, 2, \ldots, n$, where all the $M_{g_i}^j (j = 1, 2, \ldots, m)$ are TFNs. The value of fuzzy synthetic extent with respect to the ith object is defined as:

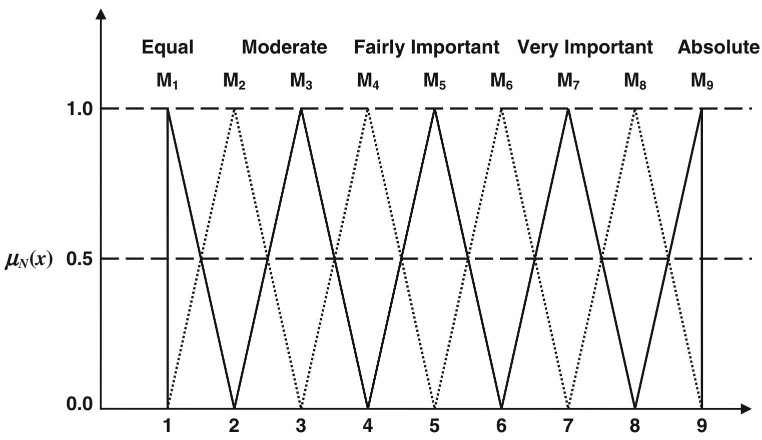

Fig. 6.1 Membership functions of TFN

$$S_i = \sum_{j=1}^{m} M_{g_i}^{j} \otimes \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^{j} \right]^{-1} \tag{6.1}$$

and $\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1}$ can be calculated as:

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^{j} \right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} m_{3i}}, \frac{1}{\sum_{i=1}^{n} m_{2i}}, \frac{1}{\sum_{i=1}^{n} m_{1i}} \right) \tag{6.2}$$

The degree of possibility of $M_1 \geq M_2$ is defined as:

$$V(M_1 \geq M_2) = \sup_{x \geq y} [\min(u_{M_1}(x), u_{M_2}(y))] \tag{6.3}$$

When a pair (x, y) exists, such that $x \geq y$ and $u_{M_1}(x) = u_{M_2}(y) = 1$, then we have $V(M_1 \geq M_2) = 1$. Since M_1 and M_2 are convex fuzzy numbers, we have that

$$\begin{aligned} V(M_1 \geq M_2) &= 1 \text{ if } m_{12} \geq m_{22}, \\ V(M_1 \geq M_2) &= hgt(M_1 \cap M_2) = u_{M_1}(d) \end{aligned} \tag{6.4}$$

where d is the ordinate of the highest intersection point D between u_{M_1} and u_{M_2} (see Fig. 6.2). When $M_1 = (m_{11},\ m_{12},\ m_{13})$ and $M_2 = (m_{21},\ m_{22},\ m_{23})$, then ordinate of D is computed by

$$\begin{aligned} V(M_2 \geq M_1) &= hgt(M_1 \cap M_2) \\ &= \frac{m_{11} - m_{23}}{(m_{22} - m_{23}) - (m_{12} - m_{11})} \end{aligned} \tag{6.5}$$

To compare M_1 and M_2, both the values of $V(M_1 \geq M_2)$ and $V(M_2 \geq M_1)$ are required. The degree of possibility for a convex fuzzy number to be greater than k convex fuzzy numbers M_i ($i = 1, 2,\ldots,k$) can be defined by

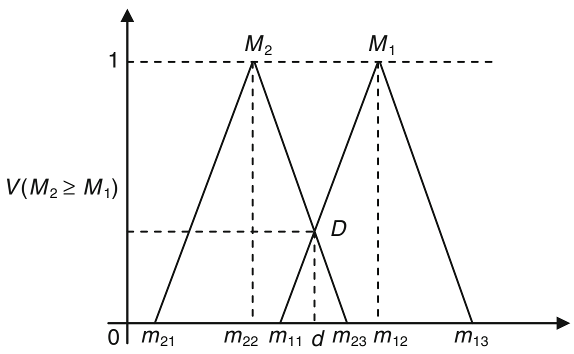

Fig. 6.2 Membership functions of the set of importance ratings

$$\begin{aligned} & V(M \geq M_1, M_2, \ldots, M_k) \\ = V[(M \geq M_1)\, and\, (M \geq M_2) & \text{ and}, \ldots, \text{and } (M \geq M_2)] \\ & = \min V(M \geq M_i), i = 1, 2, \ldots, k \end{aligned} \tag{6.6}$$

If

$$d(X_i) = \min\, V(S_i \geq S_k), \tag{6.7}$$

For k = 1, 2,…, n; $k \neq i$, then the rating vector is given by

$$W' = (d(X_1), d(X_2), \ldots, d(X_n))^T \tag{6.8}$$

where X_i (i = 1, 2,…., n) are n different criteria. Via normalisation, the normalised rating vectors are:

$$W = (R(X_1), R(X_2), \ldots, R(X_n))^T \tag{6.9}$$

where W is a non-fuzzy number that provides priority weights of an uncertainty criterion or sub-criterion over others.

For the accuracy of the method to be verified, the consistency measure is performed to screen out inconsistency between responses. Since M_i is a triangular number, it has to be defuzzified into a crisp number to compute the consistency ratio (CR). The centre of area (COA) approach is used here for defuzzifying M_i. According to the COA approach discussed earlier in Chap. 5, a TFN $\tilde{M} = (m_1, m_2, m_3)$ can be defuzzified into a crisp value by:

$$P(\tilde{M}) = [(m_3 - m_1) + (m_2 - m_1)]/3 + m_1 \tag{6.10}$$

Therefore, the CR of each judgment can be calculated and checked to ensure that it is lower than or equal to 0.1.

Chang's extent analysis has been widely applied in different problem environments in the literature: Weck et al. (1997) applied this method to evaluate alternative production cycles and rank them in terms of the main objective set; Kwong and Bai (2003) used fuzzy extent analysis to prioritise customer requirements in quality function deployment (QFD); Kahraman et al. (2004) developed an analytical selection tool to measure the customer satisfaction in catering firms in Turkey; Chan and Kumar (2007) applied fuzzy AHP to investigate the risk associated with various options for global supplier selection; Celik et al. (2009) developed fuzzy AHP methodology based on Chang's extent analysis to model shipping registry selection; Cho et al. (2012) employed extended fuzzy AHP to measure the performance of service supply chain management; Lee et al. (2012) used fuzzy extent analysis to determine the criteria for green supplier selection; Kutlu and Ekmekçioğlu (2012) integrated fuzzy extent analysis with fuzzy technique for order of preference by similarity to Ideal solution (TOPSIS) for failure mode and effects analysis; and Wang et al. (2012) applied fuzzy extent analysis to develop a risk assessment model that enabled a structured analysis of aggregative risk in the food supply chain. The trends in utilising fuzzy extent analysis in fuzzy

AHP evident in the literature have been continued in many of the operational disciplines due to its ease of use and computational simplicity. There is, however, criticism of its accuracy in estimating the respective weights of variables from a fuzzy comparison matrix. Further, Wang et al. (2008) stated that the fuzzy extent analysis method is not a method appropriate for deriving priorities from a fuzzy comparison matrix, demonstrating this through three numerical examples. Nevertheless, they also acknowledged that it is useful for showing to what degree the priority of one decision criterion or its alternative in a pair is greater than others in a fuzzy comparison matrix. The purpose of this research is to assess risk in different supply chains and highlight those risk factors that are significant, in order for organisations to take appropriate actions to address them. The fuzzy extent analysis approach to AHP allows a more accurate evaluation of the uncertainty inherent in the decision-making process and, therefore, merits inclusion in this book.

6.3 Risk Assessment in the Food Industry

Food contamination incidents, food quality concerns and outbreaks of animal diseases of all kinds are frequently reported in the media, and these have been responsible for spreading significant anxiety amongst consumers over food safety. To ensure consumers' confidence is retained, a series of food safety policies and regulations have been created and adopted, to varying degrees, all over the world. Along these same lines, the application of risk assessment techniques to food safety issues is being promoted strongly by international organisations (WHO/FAO 1999). Risk assessment is but one of three parts of the food risk analysis process, which also includes risk management and risk communication.

6.3.1 Hazard Analysis and Critical Control Points

Alongside the series of global food safety policies and regulations, the preventative approach of hazard analysis and critical control points (HACCP) is increasingly used as a means of providing enhanced food safety assurance. HACCP principles can be applied throughout the food chain from the primary producer to final consumer, and the application of HACCP systems can also aid inspection by regulatory authorities, as well as promote international trade, by increasing confidence in food safety (Codex Alimentarius Commission 1997). Most food manufacturers are now required to apply the principles of HACCP to ensure the safety of their products. Consequently, HACCP principles have been internationally accepted and approved.

The goal of a HACCP plan is to minimise risks by establishing control procedures at certain critical points during food processing. Walker and Jones (2002) stated that the use of HACCP is an approach for prevention and control of foodborne disease, by identifying hazards and risks at every stage of food production and determining where controls are required. Sun and Ockerman (2005) discussed the needs, current applications and the prospects of HACCP in food service areas in their research and suggested that the development of a HACCP in all food businesses is essential to ensure the safety of the whole production line in the food chain.

There are seven standard principles underpinning the HACCP system, as recommended by the US Food and Drug Administration's Food Code (McSwame et al. 2003). They are (1) hazard analysis, (2) identification of the critical control points (CCPs) in food preparation, (3) establishment of critical control limits (thresholds) which must be met at each identified critical control point, (4) establishment of procedures to monitor CCPs, (5) establishment of the corrective action procedures to be taken when monitoring indicates that a critical limit has been exceeded, (6) establishment of procedures to verify that the HACCP system is working and (7) implementation of effective record keeping systems that document the HACCP system. Hazard analysis is the collection and evaluation of information regarding the characteristics and extent of contaminants and other conditions leading to threats to food safety. Hazard identification is a qualitative approach of systematically identifying potential adverse health effects of the hazard. The impacts of hazardous agents vary in terms of the materials quality, process environment, composition, packaging and storage conditions of the product.

6.3.2 Food Risk Assessment

The application of risk assessment methods to food safety has been reported extensively in the literature. It is a scientific evaluation of known or potential adverse health effects resulting from exposure to biological, chemical or physical factors in food (Codex Alimentarius Commission 2002). The ultimate goal of a risk assessment process is to estimate the probability of occurrence, and this may be based on qualitative and/or quantitative information (Davidson et al. 2006).

Risk is defined as a function of the probability of an adverse health effect happening and the severity of that effect and is consequential to a hazard (European Commission 2002). Here, hazard means a biological, chemical or physical agent in, or the overall condition of, food with the potential to cause an adverse health effect (European Commission 2002). The risk assessment process consists of four steps: hazard identification, hazard characterisation, exposure assessment and risk characterisation. Hazard identification is the identification of biological, chemical and physical agents capable of causing adverse health effects and which may be present in a particular food or group of foods (Codex Alimentarius Commission 1999). Hazard characterisation is the qualitative and/or quantitative evaluation of the nature of the adverse health effects associated with these biological, chemical and physical agents, which may be presented in food (Codex Alimentarius Commission 1999). It is, therefore, the process of obtaining quantitative information (dose–response assessment) on the magnitude of adverse effects on human health following exposure to a hazardous entity. Exposure assessment is defined as the qualitative and/or quantitative evaluation of the likely intake of biological, chemical and physical agents via food, as well as exposures to other sources, if relevant (Codex Alimentarius Commission 1999). Risk characterisation is the qualitative and/or quantitative estimation, including any attendant uncertainties, of the probability of occurrence and severity of known, or potential, adverse health effects in a given population based on hazard identification, hazard characterisation and exposure assessment (Codex Alimentarius Commission 1999).

Various risk assessment methodologies and approaches have been developed and are used increasingly to quantitatively assess risks to human health presented by the food chain (Serra et al. 1999; Hoornstra et al. 2001; Parsons et al. 2005). Sperber (2001) indicated that risk assessment is a quantitative and globally applicable process in which a numerical degree of risk can be calculated for a particular hazard. Quantitative risk assessment, in particular when using stochastic models, is a specialised task that requires skills in mathematics and statistics, in addition to microbiological and technological knowledge (European Commission 2002). As a consequence, it is usually conducted by a large consortium of experts that normally involves regulatory, public health, academic and industry participation.

Traditionally, risk assessment has mainly focused on assessing the risk of the end product impacting adversely on consumers' health and on making decisions about food safety objectives that comply with regulatory and customer requirements (Hoornstra et al. 2001; European Commission 2002). End point testing of products is not a good way of ensuring food safety (Walker et al. 2003). By the time the results are obtained, the food has been served and consumed, and it is subsequently hard to trace effects, or even conduct a recall in the event of product safety being compromised. The question of the level of application of risk assessment is related to the reason for conducting the risk assessment in the first place, that is, to provide information sufficient to make robust risk management decisions. There is also a need to provide an additional focus on risk assessment application from a production perspective, and so more risk assessment procedures must be carried out during the processing itself. For example, "Pre-screening" of the risk by simpler qualitative methods can aid decisions about the value of investing resources in fully quantitative risk assessment (Ross and Sumner 2002). From a company's perspective, by using elements of quantitative risk assessment, the HACCP system can be transformed into a more meaningful managerial tool. In reality, many companies, and particularly small- and medium-sized enterprises (SMEs), struggle with the practical application of HACCP, because of a lack of expertise, training, time, motivation and commitment, all compounded by their lack of ability to implement a systematic and quantitative risk assessment.

In the food supply chain, the risk assessment process needs both sufficient information and effective tools. As previously discussed, HACCP is broadly established as a tool for promoting food safety assurance. Walker and Jones (2002) stated that HACCP is an approach for prevention and control of foodborne disease by identifying hazards and risks at every stage of food production and determining where controls are required. An important principle of HACCP is hazard analysis, but it should be emphasised that hazard analysis and risk assessment are fundamentally different and independent processes (Sperber 2001). However, both contain a common step: hazard identification, which is a qualitative approach of systematically identifying the potentially adverse health effects of the hazard. The main basis of hazard identification is starting from the knowledge of existing hazards, established either from an analysis of ingredient lists or from brainstorming by the HACCP team.

6.3.3 Using Fuzzy Theory in Food Risk Assessment

The process of conducting risk assessments is well described as a formal, structured process that is both complex and evolving. More and more extended quantitative risk assessments are being carried out. However, the outputs represent only those hazards incorporated in the original design of the assessment. In reality, many companies, particularly SMEs, struggle with their application in implementing systematic and quantitative risk assessment, due to lack of expertise, training, time, motivation, commitment and funding. Furthermore, tailor-made quantitative risk assessments are not always possible, either because of a lack of specific quantitative data or because of a lack of understanding of the available models or the implications of each model's parameter. However, these obstacles do not necessarily prevent risk estimation entirely. In such situations, qualitative risk assessment can assist risk managers in priority setting, policy decision making and allocating risk resources to sampling (Coleman and Marks 1999) while acknowledging that the assessment is often carried out with inadequate data for comprehensive numerical risk estimation (Codex Alimentarius Commission 2001). Accordingly, various semi-quantitative scoring systems and decision trees, etc., have also been introduced to bridge the gap between qualitative and fully quantitative methods (Marks et al. 1998; Huss et al. 2000; Ross and Sumner 2002, Davidson 2006).

In many cases, however, problems with a significant degree of uncertainty cannot be addressed simply by using the concept of probability, let alone crisp values. Since fuzzy set theory was introduced by Zadeh (1965), it has been frequently used to solve such problems of an uncertain nature. The fuzzy set theory resembles human reasoning, in its use of approximate information and allowance of uncertainty, as a tool to support decision making. It has the advantage of mathematically representing uncertainty and vagueness. The use of fuzzy methods in risk assessment has covered a range of applications: earthquake risks (Huang 1996), environmental risk (Sadiq and Husain 2005), contaminated groundwater (Li et al. 2007) and software development (Lee 1996; Lee et al. 2003). More recently, Davidson et al. (2006) proposed a general framework that allows simple computations (for microbial risk assessment) using fuzzy values to represent uncertainty and/or lack of knowledge of associated values. However, similar to most risk assessment models, the research only focuses on individual hazards and still requires some degree of knowledge to properly construct a food hazard identification system.

6.4 Fuzzy Hierarchical Model for Aggregative Food Risk Assessment

In a food production network, risk can be accumulated as food passes through the different stages in supply chains (Li et al. 2001; Parsons et al. 2005). The application of quality assurance (QA) systems is required at each step in the food supply chain to ensure safety of food and to show compliance with regulatory and customer requirements (Domenech et al. 2007). In order to enable a structured analysis of food safety risk in food supply chains to be carried out, a hierarchical structure model for aggregative risk assessment needs to be established, based on the input of hazards obtained through a hazard identification process. As previously stated, knowledge of existing or potential hazards may come from commonly used methods, for example, brainstorming by the HACCP team or the analysis of sensitive ingredient lists. Individual hazards in the hierarchical structure are then assessed using the fuzzy enabled risk assessment method. Fuzzy extent analysis is used to determine the weights of identified hazards. After that, fuzzy values are computed and it is possible to move on to establish an aggregative food safety risk indicator (AFSRI).

6.4.1 Hierarchical Structure

Contrary to current risk assessment techniques that focus on classifying particular types of hazards, this research aims to establish an aggregative food safety risk indicator (AFSRI) which provides a single value representing the risk rating. Risk assessment, according to the Codex Alimentarius Commission (2002), is a scientific evaluation of known or potentially adverse health effects resulting from exposure to hazardous agents. Impacts of hazardous agents vary in terms of material quality, process environment, packaging and storage conditions of the product, etc. Hazards can be classified into three categories: biological, chemical and physical hazards (Codex Alimentarius Commission 2002). To determine a value for the aggregative risk, biological, chemical and physical hazards (and all the severity factors associated with them) have to be incorporated into the calculation. Figure 6.3 represents a hierarchical model for the aggregative risk involving these three categories. Then, all the known and/or potential hazards in each category should be identified and listed. For example, physical hazards could be glass, bone, metal, wire, sand, dirt and stones, pits or shells, and pests or parts of pests, etc. The fuzzy set theory is then used to evaluate the identified individual hazards.

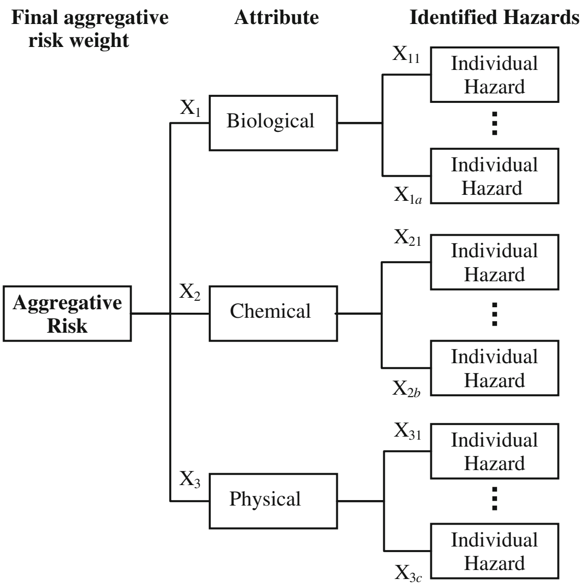

Fig. 6.3 Hierarchical structure model of aggregative food safety risk

6.4.2 Use of Fuzzy Theory in the Evaluation of Food Risk

In many cases, constraints in data quality, time, personnel or resources may not permit a full systematic and quantitative risk assessment. In this chapter, the fuzzy theory approach is adopted as a basis for the transformation of the qualitative risk evaluation factors into fuzzy values and, consequently, the use of more refined quantitative assessment outcomes in the development of the supply chain–oriented risk assessment model. Here, the commonly used concept of the triangular fuzzy number (TFN) is employed to characterise the fuzzy values of quantitative data, and additionally, linguistic terms are used in approximate reasoning. There are many other fuzzy theory representations, such as standardised trapezoidal fuzzy number and the Gaussian method, which are used to capture and convert experts' fuzzy information and subjective judgements into quantitative values. Trapezoidal, Gaussian and triangular membership functions are all popularly used representations. Trapezoidal and triangular membership functions describe the fuzzy membership linearly. On the other hand, the Gaussian function describes fuzzy membership nonlinearly and more flexibly, with a smoothed presentation in variations of membership by degrees. With more parameters characterising the function, the Gaussian method may describe the membership more accurately in some situations, particularly when the function of an item can be quantitatively defined and calculated. However, it is more complex than the methods employing linear functions, in terms of definition of a membership function. When an item is subjectively measured, the complexity of the definition may generate even more inaccuracy. Additionally, Gaussian membership functions are not normal, and they do not have the consistency property (Zeng and Singh 1994). Besides these complications, the triangular membership functions are easier to generate and are, thus, the most frequently used functions in applications (Lee 1996; Lee et al. 2003; Sadiq and Husain 2005).

Lee (1996) has developed an 11-level ranking system by which grade and importance of risk factors are classified. This approach was also used by Sadiq and Husain (2005) in estimating aggregative risk of various environmental activities. In Lee's approach, the linguistic values from 1 to 11 were used to represent corresponding fuzzy numbers with triangular membership functions, as listed in Table 6.1. The membership functions of triangular fuzzy numbers for the 11-level qualitative scales in Table 6.1 are described in Eq. 6.11.

$$\mu_{N1}(x) = \begin{cases} 1 - 10x, & 0 \le x < 0.1, \\ 0, & 0.1 \le x \le 1, \end{cases}$$

$$\mu_{Nn}(x) = \begin{cases} 0, & 0 \le x < \frac{n-2}{10} \\ 10x - (n-2), & \frac{n-2}{10} \le x \le \frac{n-1}{10} \\ n - 10x, & \frac{n-1}{10} \le x \le \frac{n}{10} \\ 0, & \frac{n}{10} \le x \le 1 \end{cases} \tag{6.11}$$

$$(n = 2, 3, \cdots 10)\text{and}$$

$$\mu_{N11}(x) = \begin{cases} 0, & 0 \le x < 0.9, \\ 10x - 9, & 0.9 \le x \le 1, \end{cases}$$

Once the linguistic values from 1 to 11 had been made into corresponding fuzzy numbers with triangular membership functions, two fuzzy numbers N_r and N_i with membership functions $u_{N_r}(x)$ and $u_{N_i}(x)$ were used to represent the grade of risk and the grade of importance, respectively. The next stage of the conversion of the

Table 6.1 Linguistic classifications of grades of risk and importance and their corresponding TFNs [Modified after Lee (1996)]

Grade of risk	Eleven ranks of grade of risk (r)	Eleven ranks of grade of importance (i)	Triangular fuzzy numbers (TFNs)
1	Definitely low	Definitely unimportant	(0.0, 0.0, 0.1)
2	Extremely low	Extremely unimportant	(0.0, 0.1, 0.2)
3	Very low	Very unimportant	(0.1, 0.2, 0.3)
4	Low	Unimportant	(0.2, 0.3, 0.4)
5	Slightly low	Slightly unimportant	(0.3, 0.4, 0.5)
6	Middle	Middle	(0.4, 0.5, 0.6)
7	Slightly high	Slightly important	(0.5, 0.6, 0.7)
8	High	Important	(0.6, 0.7, 0.8)
9	Very high	Very important	(0.7, 0.8, 0.9)
10	Extremely high	Extremely important	(0.8, 0.9, 1.0)
11	Definitely high	Definitely important	(0.9, 1.0, 1.0)

resulting combined fuzzy values into a non-fuzzy form is called defuzzification. The COA approach (see Eq. 6.10) is used for this defuzzification.

When assessing risks, the nature of the hazard, the likelihood that an individual or population will be exposed to the hazard and the likelihood that exposure will result in an adverse health effect have all to be considered (Walls 2006). As the assessment results are used as a comparative measure of risk and the same population target is contained in the assessment, the risk is assumed to be independent of population size. Therefore, the following factors are instead considered when the risk assessment is carried out:

1. Severity of the hazard
2. Likelihood of the hazard
3. Effect of the hazard

Here, the *severity* indicates the nature of the hazard; the *likelihood* refers to the probability of the hazard occurring and its consequent effects based on known history of performance and complaints; and the *effect* includes the potential numbers exposed, as well as the age and vulnerability of those exposed.

In practice, companies have difficulty in evaluating these factors due to uncertainty and lack of both knowledge and information. Instead, risk assessors and QA managers generally rank these risk factors qualitatively in terms of linguistic variables such as high, moderate and low. In the fuzzy theory approach, the qualitative scales are expressed as TFNs to capture the vagueness in the linguistic subjectivity of risk definitions. Table 6.2 describes this qualitative scaling system for severity of the hazard, likelihood of an adverse health effect consequential to the hazard, and probability of exposure. Three fuzzy numbers N_s, N_l and N_e with membership functions, $u_{N_s}(x)$, $u_{N_l}(x)$, and $u_{N_e}(x)$ represent the grading of these three factors, respectively. To determine the magnitude and intensity of the risk, these three factors are multiplied by themselves to produce the risk evaluation:

$$\text{Risk} = \text{Hazard Severity} \times \text{Hazard likelihood} \times \text{Hazard Effect} \tag{6.12}$$

All the calculations in this risk assessment involve multiplication. Note that the product of two TFNs is also a fuzzy number, which itself is not necessarily a triangle. To simplify the multiplication calculations, a standard approximation is used. The standard approximation has been defined by authors such as Chen and Hwang (1993) and Giachetti and Young (1997) in the forms described in Eq. 6.13.

$$\begin{aligned} &A \rightarrow \langle a_1, a_2, a_3 \rangle \\ &B \rightarrow \langle b_1, b_2, b_3 \rangle \\ &C = A \otimes B \\ &C \rightarrow \langle a_1 b_1, a_2 b_2, a_3 b_3 \rangle \end{aligned} \tag{6.13}$$

Generally, the product calculated by standard approximation is a conservative estimate, as the error introduced by the standard approximation is the difference between the membership function of the actual product and the membership

Table 6.2 Linguistic classification of grades of hazard factors and their corresponding TFNs

Ranking level	A qualitative explanation for grade of hazard severity (s)	A qualitative explanation for grade of likelihood of the hazard (l)	A qualitative explanation for grade of number of product exposed (e)	Triangular fuzzy numbers (TFNs)
1	Definitely mild	Definitely low	Minimal	(0.0, 0.0, 0.1)
2	Extremely mild	Extremely low	Extremely few	(0.0, 0.1, 0.2)
3	Quite mild	Quite low	Quite few	(0.1, 0.2, 0.3)
4	Mild	Low	Few	(0.2, 0.3, 0.4)
5	Slightly mild	Slightly low	Slightly few	(0.3, 0.4, 0.5)
6	Moderate	Moderate	Some	(0.4, 0.5, 0.6)
7	Slightly severe	Slightly high	Slightly many	(0.5, 0.6, 0.7)
8	Severe	High	Many	(0.6, 0.7, 0.8)
9	Quite severe	Quite high	Quite many	(0.7, 0.8, 0.9)
10	Extremely severe	Extremely high	Extremely many	(0.8, 0.9, 1.0)
11	Definitely severe	Definitely high	All	(0.9, 1.0, 1.0)

function of the standard approximation. However, it had been argued that the approximation is only appropriate for early-stage risk assessment (Davidson et al. 2006). In this chapter, the product of three TFNs is calculated by this standard approximation as shown in Eq. 6.14.

$$\begin{aligned} N_s &\rightarrow \langle a_s, m_s, b_s \rangle, a_s < m_s < b_s \\ N_l &\rightarrow \langle a_l, m_l, b_l \rangle, a_l < m_l < b_l \\ N_e &\rightarrow \langle a_e, m_e, b_e \rangle, a_e < m_e < b_e \\ N_g &= N_s \times N_l \times N_e \rightarrow \langle a_s\, a_l\, a_e,\ m_s\, m_l\, m_e,\ b_s\, b_l\, b_e \rangle \end{aligned} \tag{6.14}$$

Fuzzy mathematics is then used to determine the risk of a given magnitude and intensity. The COA method is exploited to transform the TFNs into a numerical value for the computation. We define these as follows:

$$P(N_g) = \left[(b_g - a_g) + (m_g - a_g) \right] / 3 + a_g \tag{6.15}$$

where a and b are the lower and upper limits of the integral, respectively. $\mu_{\mathrm{Ng}}(x)$ is the new membership function of multiplication result as:

$$\mu_{N_g}(x) = \begin{cases} 0, & x \le a_g \\ \frac{x - a_g}{m_g - a_g}, & a_g \le x \le m_g \\ \frac{b_g - x}{b_g - m_g}, & m_g \le x \le b_g \\ 0, & x \ge b_g. \end{cases} \tag{6.16}$$

For $a_g = a_s\, a_l\, a_e,\ m_g = m_s\, m_l\, m_e,\ b_g = b_s\, b_l\, b_e$

The grades of the three main risk factors for each hazard can be determined by a risk manager or a risk assessor in this manner, according to their analysis of the hazard. A set of integers between 1 and 11 are assigned to the individual hazard.

With the transformation of these descriptive scales into TFN values, the risk of identified hazards can be calculated.

6.4.3 Analysis of Aggregative Food Safety Risk Indicator with Fuzzy Analytical Hierarchy Process

To incorporate all of the identified hazards into an aggregated risk indicator, it is essential to know how important one hazard is over another for any given product in a particular process environment. In other words, risk assessors have to determine the respective variance in weighting between individual hazards. AHP has been widely used to address such multi-criteria decision-making (MCDM) problems. However, it has been generally criticised in the literature because of the use of a scale with discrete steps in value of 1 to 9, which in turn cannot handle the uncertainty and vagueness present in representing the relative importance of different decision criteria. Here, fuzzy AHP, which is an important extension of the typical AHP method, is used to rank how important one hazard is over another for a product in a particular process environment. The approach adopts the fuzzy synthetic extent analysis method (Chang 1996) and uses the triangular fuzzy numbers (TFNs) as a pairwise comparison scale for deriving the weights of identified hazards.

As discussed in Sect. 6.4.1, a two-stage hazard classification structure has been developed (see Fig. 6.3). At the first stage, there are three main hazard categories: biological, chemical and physical hazards. At the second stage, all the known and/or potential hazards within these three categories should be identified and listed. For each identified hazard, there are three risk factors: hazard severity, hazard likelihood and hazard effect. In converting these considerations to an equation, let N be the total number of identified hazards in the hierarchy model. For each identified hazard, we denote $w(X_i)$ as the comparative weight of hazard X_i. (where $0 \leq w(X_i) \leq 1$ and $\sum_{i=1}^{N} w(X_i) = 1$ for $i = 1, 2,\ldots N$). The hierarchical structure for above statements is given in Table 6.3.

Members of the company's risk assessment team are required to provide their value judgements on the basis of their knowledge and experience for each identified hazard. Assessors can either provide a precise numerical value or a linguistic term or a fuzzy number. They are encouraged to give fuzzy scales where they are not sure about the exact numerical values. The membership functions of the TFNs are shown in Fig. 6.1, $M_i = (m_{i1}, m_{i2}, m_{i3})$, where $i = 1, 2,\ldots,9$. Here, m_{i1}, m_{i2}, m_{i3} are the lower, middle and upper values of the fuzzy number m_i, respectively, where m_1, and m_{i3} represent a fuzzy degree of judgement. The greater m_{i3}–m_{i1} is, the greater the fuzziness of the judgement. When $m_{i1} = m_{i2} = m_{i3}$, the judgment is a non-fuzzy number.

Table 6.3 The structure model of aggregative food safety risk

Individual hazard	Weight of hazards	Hazard severity (s)	Likelihood of hazard (l)	Effect of hazard (e)	Rate of risk $g(s, l, e)$
X_1	$w(X_1)$	s_1	l_1	e_1	$g(s_1, l_1, e_1)$
X_2	$w(X_2)$	s_2	l_2	e_2	$g(s_2, l_2, e_2)$
…	…	…	…	…	…
X_n	$w(X_n)$	s_n	l_n	e_n	$g(s_n, l_n, e_n)$

Through this fuzzy extent analysis, the relative importance and weight of identified hazards can be obtained. The final value of aggregative risk is then calculated by the weighted average method as:

$$\mathrm{AFSRI} = [w(X_1), w(X_2), \ldots, w(X_n)]_{1\times n} \times g_n(s.l, e) \tag{6.17}$$

This index is useful in evaluating the aggregative risk of different production processes, and the identification of the highest AFSRI value implies that the associated process has the highest risk level.

6.5 Case Study

In this section, an application of the proposed model is presented based on a case study of a medium-sized food manufacturer in the UK. Numerical examples are provided to show how the model was applied and tested.

6.5.1 The Existing Risk Assessment Methodology in the Case Study Company

The case study is based on a supplier of ready-to-eat cooked meats (beef, pork, lamb, chicken and turkey) to major UK supermarkets. Due to the nature of cooked meat products, a strict QA scheme is currently deployed to ensure compliance with relevant legislation and industrial hygiene codes. Raw materials are purchased in chilled or frozen condition and stored appropriately within the factory. All production and associated chilled and frozen work-in-progress storage areas are temperature controlled throughout manufacturing. All finished cooked products are stored at chilled temperatures in designated facilities where a high-risk control environment can be maintained through measures such as air conditioning, separate drain systems and strict control of work wear.

The current risk assessment process in the company is integrated with the HACCP scheme. Table 6.4 shows an example of the risk assessment of the injection process currently conducted in the case company. For each process,

Table 6.4 Current risk assessment practice for injection process

Hazard		Severity	Likelihood	Effect
Biological hazards	Growth of pathogenic and spoilage bacteria caused by inadequate temperature control of brine solution	Moderate	Rare	Some
	Growth of pathogenic and spoilage bacteria caused by inadequate nitrite addition for cured meat products	Moderate	Rare	Some
Chemical hazards	Chemical contamination of brine solution or ingredients caused by insufficient control of hygiene chemicals	*Severe*	Rare	*All*
	Excessive quantity of nitrite added	Moderate	Rare	Some
Physical hazards	Metal contamination from needles/knives	Moderate	Occasional	Some

all known or potential hazards are identified and their causes are listed. The identified hazards are put into three categories: biological, chemical and physical hazards. Each hazard is measured by factors: **severity** (mild, moderate and severe), **likelihood** (rare, occasional and frequent) and **effect** (minimal, some and all). Each factor is ranked by the HACCP team. Control measures are then decided.

6.5.2 An Application of the Proposed Approach

Here, the aggregative risk assessment model is applied to perform a structured analysis of safety risk for specific products along their production process path. Firstly, the process flow in the manufacturing plant for a specific product is constructed including the stages of intake, storage, defrosting, meat preparation, brine make-up, injection, tumbling, filling and netting, cooking, cooling, roasting, slicing, and packing, etc. Data from each process stage are input into the analysis. In each process stage, all known or potential hazards are identified and the main potential sources inducing these hazards are listed and placed into the three categories: biological, chemical and physical. A hierarchical structure is then developed for these hazards, with the grades of severity (s), likelihood (l) and effect (e) of the hazard decided. After the s, l and e values for each hazard are estimated, risk grading $g(s, l, e)$ is evaluated through the fuzzy method discussed earlier to give a value for each hazard. As an example, the assessment results for the injection process of a selected product are presented in Table 6.5. Here, the scales of s, l and e values are estimates taken from the existing qualitative risk assessment gradings in the HACCP record (see Table 6.4). Compared with the current practice shown in Table 6.4, more options are provided with which to rank a particular risk factor, which allows users to better estimate the uncertainty inherent in input values. Furthermore, this provides a numerical value more accurately differentiating the risk level of individual hazards.

Table 6.5 Fuzzy-based risk assessment for injection process

Processes	Hazards category	Individual hazard		*s*	*l*	*e*	*g(s, l, e)*
Injection	Biological	Growth of pathogenic and spoilage bacteria caused by inadequate temperature control of the brine solution	X_1	6	3	6	0.127
		Growth of pathogenic and spoilage bacteria caused by inadequate nitrite addition for cured meat products	X_2	5	2	5	0.049
	Chemical	Chemical contamination of the brine solution or ingredients caused by insufficient control of hygiene chemicals	X_3	9	2	10	0.192
		Excessive quantity of nitrite added	X_4	5	2	4	0.039
	Physical	Metal contamination from needles/knives	X_5	8	4	4	0.156

Note The assessment is based on the information in Table 6.4 combined with the advice from the QA team in the case company

Then, the fuzzy AHP method is used to assign comparative weights to identified hazards for a particular process of the product under assessment. The different values of fuzzy synthetic extent with respect to the five different hazards are denoted by S_1, S_2, S_3, S_4 and S_5, respectively. By applying Eq. 6.1, we have

$$\begin{aligned}
S_1 &= (4.7, 5.8, 7.1) \otimes (1/43.4, 1/36.6, 1/30.4) \\
&= (0.11, 0.16, 0.23) \\
S_2 &= (2.9, 3.6, 4.4) \otimes (1/43.4, 1/36.6, 1/30.4) \\
&= (0.07, 0.10, 0.14) \\
S_3 &= (12.5, 15, 17.5) \otimes (1/43.4, 1/36.6, 1/30.4) \\
&= (0.29, 0.41, 0.58) \\
S_4 &= (2.4, 2.7, 3.3) \otimes (1/43.4, 1/36.6, 1/30.4) \\
&= (0.05, 0.07, 0.11) \\
S_5 &= (7.9, 9.5, 11.2) \otimes (1/43.4, 1/36.6, 1/30.4) \\
&= (0.18, 0.26, 0.37)
\end{aligned}$$

The degree of possibility of S_i over S_j $(i \neq j)$ can be determined by Eqs. 6.3–6.5.

$$\begin{aligned}
&V(S_1 \geq S_2) = 1, \\
&V(S_1 \geq S_3) = \frac{0.29 - 0.23}{(0.16 - 0.23) - (0.41 - 0.29)} = 0.28, \\
&V(S_1 \geq S_4) = 1, \\
&V(S_1 \geq S_5) = 0.34.
\end{aligned}$$

Similarly,

$$V(S_2 \geq S_1) = 0.37, V(S_2 \geq S_3) = 0.87, V(S_2 \geq S_4) = 0.37, V(S_2 \geq S_5) = 0.31;$$
$$V(S_3 \geq S_1) = 1, V(S_3 \geq S_2) = 1, V(S_3 \geq S_4) = 1, V(S_3 \geq S_5) = 1;$$
$$V(S_4 \geq S_1) = 0.02, V(S_4 \geq S_2) = 0.63, V(S_4 \geq S_3) = 1.13, V(S_4 \geq S_5) = 0.64;$$
$$V(S_5 \geq S_1) = 1, V(S_5 \geq S_2) = 1, V(S_5 \geq S_3) = 0.35, V(S_5 \geq S_4) = 1;$$

Based on Eq. 6.7, we obtain

$$\begin{aligned} d(X_1) &= \min V(S_1 \geq S_2, S_3, S_4, S_5) \\ &= \min(1,\ 0.28, 1,\ 0.34) \\ &= 0.28 \end{aligned}$$

Similarly, $d(X_2) = 0.31, d(X_3) = 1, d(X_4) = 0.02, d(X_5) = 0.35$

Therefore, $W' = (0.28, 0.31, 1, 0.02, 0.35)$ after the normalisation process, so the weight vector with respect to identified hazards, X_1, X_2, X_3, X_4, and X_5, can be expressed as:

$$W = (0.144, 0.160, 0.510, 0.008, 0.177)$$

The complete result is shown in Table 6.6. Now, the risk values of individual hazards, $g_n(s,l,e)$, are multiplied by W to determine the aggregative risk as follows

$$\begin{aligned} \text{AFSRI} &= (0.127 \times 0.144 + 0.049 \times 0.160 + 0.192 \times 0.510 + 0.039 \\ &\quad \times 0.008 + 0.156 \times 0.177) \\ &= 0.152 \end{aligned}$$

Therefore, in this example, 0.152 is the rate of aggregative safety risk for the injection process. The same procedure is repeated for the "raw material intake", "brine make-up" and "tumbling processes" to further demonstrate the proposed approach. The calculation results for these processes are shown in Table 6.7. The main difference between the proposed aggregative risk assessment model and the company's current practice is that the aggregative model does not only provide an assessment of individual hazards, but also gives an index of the overall food safety risk level for a particular process or product batch. More scoring options are also provided to rank a particular risk factor, which allow users to better estimate the uncertainty inherent in input values. In addition, this approach also provides an overview of the risk level for a particular process or product batch. Although the integrated risk index for a production or supply process does not scientifically measure a specific hazard, and though indices for different processes might only be slightly different, such a quantified AFSRI will be of significantly greater effectiveness in comparing the risk levels between different processes and product batches. Equally importantly, the aggregative risk assessment approach provides an opportunity for innovation in operations planning through incorporating safety factors associated with operational process change decisions in a quantitative manner. This is critical in properly taking

Table 6.6 Weights estimated through the fuzzy AHP

	X_1	X_2	X_3	X_4	X_5	W
X_1	(1, 1, 1)	(3/2, 2, 5/2)	(2/7, 1/3, 2/5)	(3/2, 2, 5/2)	(2/5, 1/2, 2/3)	0.144
X_2	(2/5, 1/2, 2/3)	(1, 1, 1)	(2/9, 1/4, 2/7)	(1, 3/2, 2)	(2/7, 1/3, 2/5)	0.160
X_3	(5/2, 3, 7/2)	(7/2, 4, 9/2)	(1, 1, 1)	(4, 5, 6)	(3/2, 2, 5/2)	0.510
X_4	(2/5, 1/2, 2/3)	(1/2, 2/3, 1)	(1/6, 1/5, 1/4)	(1, 1, 1)	(2/7, 1/3, 2/5)	0.008
X_5	(3/2, 2, 5/2)	(5/2, 3, 7/2)	(2/5, 1/2, 2/3)	(5/2, 3, 7/2)	(1, 1, 1)	0.177

Note
(1) The consistency index $CI = 0.0088$, the random consistency index $RI = 1.12$ and the consistency ratio $CR = CI/RI = 0.0079$
(2) Since CR is 0.0079 that is less than 10 %, the consistency test is satisfied (Saaty and Vargas 2001)

Table 6.7 Estimation of the aggregative food safety risk for various processes

Processes	Raw material intake			Brine make-up			Tumbling		
		$g(s, l, e)$	W_i		$g(s, l, e)$	W_i		$g(s, l, e)$	W_i
	X_{11}	0.412	0.226	X_{21}	0.127	0.125	X_{31}	0.127	0.142
	X_{12}	0.316	0.138	X_{22}	0.049	0.125	X_{32}	0.17	0.142
	X_{13}	0.221	0.292	X_{23}	0.053	0.167	X_{33}	0.039	0.119
	X_{14}	0.049	0.129	X_{24}	0.017	0.083	X_{34}	0.125	0.358
	X_{15}	0.148	0.214	X_{25}	0.085	0.071	X_{35}	0.032	0.239
				X_{26}	0.257	0.265			
				X_{27}	0.032	0.165			
AFSRI	0.239			0.112			0.099		

account of potential safety-related costs (e.g. recall cost) into operational decisions, but has been notably absent in present supply chain management practice (Wang et al. 2009).

Managing risk plays a vital role in food supply chain management. Most food production processes contain a certain degree of risk. The magnitude of risk directly affects the safety of food in terms of public health and aims to identify the possibility of a resulting food crisis that may require a product recall. However, few researches simultaneously consider operational objective and risk in the production planning process. The aggregative risk assessment approach provides an overview of the risk level for a particular process or product batch. It is able to integrate with the estimation of other operational factors and be used to obtain an optimal production plan, so as to improve the overall manufacturing performance, for example, by avoiding the uneconomic mixing of high- and low-quality raw materials and thus reducing the risk of cross-contamination.

In operations research, a major interest in both theory and practice is to determine economic production batch size, meaning that various cost factors need to be incorporated in production planning models. In addition to the traditional cost factors such as set-up cost, inventory holding cost and product deteriorating cost, from within a risk management perspective, product recall cost emerges as another important cost factor. Some product recalls are so potentially costly they could even put food companies out of business. The batch size plays an important role in the potential recall cost. For example, a large production batch may require separate raw material batches from different suppliers to be mixed together in order to fulfil a batch production operation. In the event of a food safety incident resulting from a problem with one the raw material sources used in the production, all the products containing this contaminated raw material from the batch must be recalled. A large batch size will have much greater economic consequences in such an event. Another important element that affects the probability of such an event is the safety risk level of the raw materials used in the production. A high-risk level for raw materials used, and the mixing of these raw materials required in the production operation, will increase the probability of product recall. One origin of the food safety risk level is associated with the potential development of different kind of bacteria such as botulism, listeriosis and salmonella, meaning product quality could be compromised due to inappropriate production or storage conditions. As more investment is required to ensure that good quality production and storage conditions are maintained throughout the different supply chain processes, suppliers may, in turn, charge a premium price for good quality raw materials which contain a relatively lower food safety risk.

An aggregative and tangible risk assessment for the food supply chain processes would assist a manufacturer to minimise its overall operational costs while maintaining food safety standards, leading to reduced risk of product recall and incurring recall-related costs. The quantified AFSRI values for material batches can play an important role in the decision-making process of determining the best ways to constitute raw material batches (Wang et al. 2010). This is especially applicable to products with high vulnerability in quality and safety terms, where it could help manufacturers to choose the optimal raw material supplies, with the backup of an integrated view on economic and safety factors, and so reduce the cross-contamination risk by minimising unnecessary raw material mixing.

6.6 Discussion

The AFSRI aggregative food risk assessment model considers all hazard agents in an integrated way for the comprehensive assessment of food safety risks. It provides a practical solution by which enterprises can systematically assess the risk of supply chain processes. A step-by-step approach for conducting an aggregative food safety risk assessment is shown in the flow chart in Fig. 6.4.

Compared with the risk assessment approach presently used in the case study company, the proposed model provides more options with which to grade the hazard factors. The quantified risk for individual hazards through the fuzzy approach sets the relative significance level for identified hazards, and the AFSRI then builds on these to give an indication of overall risk level for different production processes. The results could be used to support the decision-making

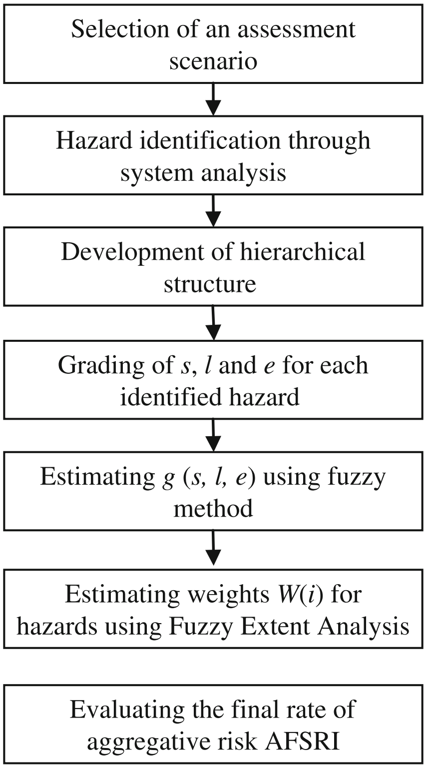

Fig. 6.4 Procedures for aggregative food safety risk assessment

process for the QA team, enabling them to focus on the most important hazards or processes, and take appropriate actions. The processes with higher AFSRI values highlight those containing higher-risk levels and indicate those areas where further in-depth risk assessment might be essential. Referring to the analysis in the case study application, the results derived through the aggregative risk assessment justify the perception of food safety risk from its raw materials as a critical control point for the case company. By comparison with other methods (Ross and Sumner 2002; Tuominen et al. 2003; Davidson et al. 2006) used for early-stage food risk assessment, the accuracy of the results in our model is considered sufficient to promote it as a more clearly focussed comparison of different products and processes. The AFSRI model could play a key complementary role in HACCP planning. All significant hazards identified in a process by this model can be further evaluated using more product-specific production analysis approaches. This helps food companies to focus on the factors that most affect food safety risk and to identify risks requiring more rigorous assessment. This will facilitate their quality control and provide the conditions likely to lead to a consistent supply of safe food products.

At present, the manual documentation process used in following the HACCP framework cannot be used to assess the overall risk level for a supply source, production process or a product batch. The proposed aggregative risk assessment method fills this gap by incorporating relevant multiple hazards and their associated risk factors into a quantified AFSRI value. It can be used as a safety indicator to measure the varying level of risk attached to raw materials from different suppliers and production batches from different processes. With this safety indicator, an optimal production plan becomes possible, both avoiding the uneconomic mixing of raw materials and reducing the risk of cross-contamination at the same time. Apart from its importance in the QA process for food production, the proposed method can also be used as a new decision-making tool for recipe testing of new products or for supporting the supplier selection process in order to improve product quality and safety management while maintaining operational efficiency.

In situations where knowledge about origins of risk generation is limited, point estimate approaches (Huss et al. 2000; Tuominen et al. 2003) have often been employed to evaluate the risk simply due to their simplicity of application. Although there is a reasonable justification for their use in the early stages of risk assessment, such approaches convey a false sense of certainty when risk is estimated as a numerical value. The fuzzy enabled risk assessment method proposed in this chapter estimates the uncertainty inherent in input values and allows users to conveniently describe uncertainty. Furthermore, this fuzzy method can be easily transformed into traditional probabilistic methods when sufficient information and knowledge about the food production system are available. In addition, the proposed methodology offers a new way of assessing, tracking and tracing risks at a supply chain level and so provides quantitative evaluation for all production stages. It also provides insight into potential risk mitigation options and identifies the weak links in food supply chain activities.

Despite these tangible benefits, there are some limitations and weaknesses in the model. Some are general problems associated with all forms of risk assessment modelling, while others are specific to the model. The main challenge of this research is to demonstrate a model which can provide a single value risk indicator (AFSRI) to represent the overall risk rating of the production process/batch. All hazards need to be identified, risk attributes have to be accounted for and both of these aggregated in the assessment. The complexity of the model lies in establishing the degrees of risk [$g(s, l, e)$] of all identified hazards, which itself requires complex fuzzy calculations. In addition, using fuzzy AHP and synthetic extent analysis to obtain comparative hazard weightings requires a certain amount of computational effort. Referring to Chang (1996), for an $n \times n$ fuzzy pairwise comparison, the time complexity value under synthetic extent analysis is $n(n + 6)$. The complexity of calculations often inhibits organisations from implementing those sophisticated methods in their daily operations. In order to make the proposed methodology more practical and easy-to-use, the fuzzy method is only introduced when there is a difficulty in accurately representing uncertainty or a lack of knowledge about associated values, so as to reduce the additional complexity brought in by fuzzy operations. In addition, while the model is developed as a potential early-stage approach to risk assessment, sufficient information is still required to adequately characterise the food production system and a long list of values (grades of risk factors for all identified hazards) must be provided, before the risk quantification is possible.

6.7 Conclusion

This chapter proposes a new risk assessment methodology that enables manufacturers to perform a structured analysis of aggregative food safety risk for all processes throughout the different stages of the food supply chain. The qualitative scales were converted into values by using TFNs to capture the vagueness in the linguistic subjectivity of food risk definitions. A hierarchical structure model was developed for various categories of hazards identified, in order to determine the AFSRI for a given process or product. An example of its application was presented via a case study, wherein the method's approach was illustrated with a medium-sized cooked meat producer. Numerical examples of the aggregative risk assessment were presented together with the application of AFSRI in the production planning process.

One key purpose of this study is to develop a methodology for determining a quantified food safety risk indicator to support operational decisions. The aggregative risk assessment approach provides an opportunity for innovation in operations planning through incorporating safety factors within operational decisions in a quantitative form. However, the model presented here may also function as a more limited but supportive part of practical food safety management tools in the food sector. It gives insight into potential risk mitigation between supply chain processes, which can help managers to understand how risks change and transfer across the supply chain. The approach has the ability to capture the vagueness of human judgment and effectively solve multi-attribute decision problems. This consequently provides support when making decisions on which interventions and actions might be applied to enhance food safety. With these advantages, and the fact that AFSRI focuses on products and their production processes, it can be a valuable component of a HACCP system. In this role, it can be used proactively to support decisions on the optimisation of production processes according to the aggregated risk level.

Additional to the various advantages of the proposed approach for food risk management, this research work can be extended further by modelling the process effects (such as growth, inactivation, removal, partitioning and cross-contamination) on risk transmission along the food supply chain. This will provide a more systemic view of how risks are developed and migrated along the food chain and thereby support risk management decisions. This can further increase the computational complexities involved, but constitutes a further piece of research work we would like to carry out in the future.

References

Buckley, J. (1985). Fuzzy hierarchical analysis. *Fuzzy Sets and Systems, 17*(3), 233–247.

Celik, M., Er, I. D., & Ozok, A. F. (2009). Application of fuzzy extended AHP methodology on shipping registry selection: The case of Turkish maritime industry. *Expert Systems with Applications, 36*(1), 190–198.

Chan, F. T. S., & Kumar, N. (2007). Global supplier development considering risk factors using fuzzy extended AHP-based approach. *Omega, 35*(4), 417–431.

Chang, D. Y. (1996). Applications of the extent analysis method on fuzzy AHP. *European Journal of Operational Research, 95*(3), 649–655.

Chen, S. J., & Hwang, C. L. (1993). *Fuzzy Multiple Attribute Decision Making—Methods and Applications*. Berlin: Springer.

Cho, D. W., Lee, Y. H., Ahn, S. H., & Hwang, M. K. (2012). A framework for measuring the performance of service supply chain management. *Computers and Industrial Engineering, 62*(3), 801–818.

Codex Alimentarius Commission. (1997). Hazard Analysis and Critical Control Point (HACCP) System and Guidelines for its application, Published in Codex Alimentarius Commission Food Hygiene Basic Texts, Revision 3, 1997, ISBN 92-5-104021-4 Incorporated into the General Principles of Food Hygiene CAC/RCP 1–(1969) Rev 3 (1997).

Codex Alimentarius Commission. (1999). Principles and guidelines for the conduct of a microbiological risk assessment. CA Commission. Rome, CAC/GL30, FAO.

Codex Alimentarius Commission. (2001). *Principles and guidelines for the conduct of microbiological risk assessment*, 2nd ed. The Codex general principles of food hygiene.

Codex Alimentarius Commission. (2002). *Food Hygiene Basic Texts*, Second Edition, the Codex Alimentarius Commission and the FAO/WHO Food Standard Programme.

Coleman, M. E., & Marks, H. M. (1999). Qualitative and quantitative risk assessment. *Food Control, 10*(4–5), 289–297.

Csutora, R., & Buckley, J. J. (2001). Fuzzy hierarchical analysis: The Lamda-Max method. *Fuzzy Sets and Systems, 120*(2), 181–195.

Davidson, V. J., Ryks, J., & Fazil, A. (2006). Fuzzy risk assessment tool for microbial hazards in food system. *Fuzzy Sets and Systems, 157*(9), 1201–1210.

Domenech, E., Escriche, I., & Martorell, S. (2007). Quantification of risks to consumers' health and to company's incomes due to failures in food safety. *Food Control, 18*(11), 1419–1427.

European Commission. (2002). Risk assessment of food borne bacterial pathogens: Quantitative methodology relevant for human exposure assessment, *European Commission Preliminary Report*.

Giachetti, R. G., & Young, R. E. (1997). Analysis of the error in the standard approximation used for multiplication of triangular and trapezoidal fuzzy numbers and the development of a new approximation. *Fuzzy Sets and Systems, 91*(1), 1–13.

Hoornstra, E., Northolt, M. D., Notermans, S., & Barendsz, A. W. (2001). The use of quantitative risk assessment in HACCP. *Food Control, 12*(4), 229–234.

Huang, C. (1996). Fuzzy risk assessment of urban natural hazards. *Fuzzy Sets and Systems, 83*(2), 271–282.

Huang, C., Chu, P., & Chiang, Y. (2008). A fuzzy AHP application in government-sponsored R&D project selection. *Omega, 36*(6), 1038–1052.

Huss, H., Reilly, A., & Embarek, P. (2000). Prevention and control of hazards in seafood. *Food Control, 11*(2), 149–156.

Kahraman, C., Cebeci, U., & Ulukan, Z. (2003). Multi criteria supplier selection using fuzzy AHP. *Logistics Information Management, 16*(6), 382–394.

Kahraman, C., Cebeci, U., & Ruan, D. (2004). Multi-attribute comparison of catering service companies using FAHP: The case of Turkey. *International Journal of Production Economics, 87*(2), 171–184.

Kutlu, A. C., & Ekmekçioğlu, M. (2012). Fuzzy failure modes and effects analysis by using fuzzy TOPSIS-based fuzzy AHP. *Expert Systems with Applications, 39*(1), 61–67.

Kwong, C. K., & Bai, H. (2003). Determining the importance weights for the customer requirements in QFD using a FAHP with an extent analysis approach. *IIE Transactions, 35*(7), 619–626.

Lee, H. M. (1996). Applying fuzzy set theory to evaluate the rate of aggregative risk in software development. *Fuzzy Sets and Systems, 79*, 323–336.

Lee, H. M., Lee, S. Y., Lea, T. Y., & Chen, J. J. (2003). A new algorithm for applying fuzzy set theory to evaluate the rate of aggregative risk in software development. *Information Science, 153*, 177–197.

Lee, T., Le, T. P. N., Genovese, A., & Koh, L. S. C. (2012). Using FAHP to determine the criteria for partner's selection within a green supply chain: The case of hand tool industry in Taiwan. *Journal of Manufacturing Technology Management, 23*(1), 25–55.

Li, D., McKay, A., de Pennington, A., & Barnes, C. (2001). A web-based system and a heuristic method for cooperation of manufacturing supply chain decisions. *Journal of Intelligent Manufacturing, 12*(5–6), 433–453.

Li, J., Huang, G. H., Zheng, G., Maqsood, I., & Huang, Y. (2007). An integrated fuzzy-stochastic modeling approach for risk assessment of groundwater contamination. *Journal of Environmental Management, 82*(2), 173–188.

Marks, H. M., Coleman, M. E., Lin, C. T., & Roberts, T. (1998). Topics in microbial risk assessment: Dynamic flow tree process. *Risk Analysis, 18*, 309–328.

McSwane, D., Rue, N., & Linton, R. (2003). *Essentials of food safety and sanitation*. New Jersey: Pearson Education.

Mikhailov, L. (2003). Deriving priorities from fuzzy pairwise comparison judgments. *Fuzzy Sets and Systems, 134*(3), 365–385.

Parsons, D. J., Orton, T. G., Souza, J. D., Moore, A., Jones, R., & Dodd, C. E. R. (2005). A comparison of three modelling approaches for quantitative risk assessment using the case study of Salmonella spp. *In Poultry Meat, International Journal of Food Microbiology, 98*, 35–51.

Ross, T., & Sumner, J. (2002). A simple, spread-sheet based, food safety risk assessment tool. *Journal of Food Microbiology, 77*, 39–53.

Saaty, T. L., & Vargas, L. G. (2001). *Models methods, concepts and applications of the analytical hierarchy process*. Boston: Kluwer Academic Publishers.

Sadiq, R., & Husain, T. (2005). A fuzzy-based methodology for an aggregative environmental risk assessment: A case study of drilling waste. *Environmental Modelling and Software, 20*, 33–36.

Serra, J. A., Domenech, E., Escrche, I., & Martorell, S. (1999). Risk assessment and critical control points from the production perspective. *International Journal of Food Microbiology, 66*, 9–26.

Sperber, W. H. (2001). Hazard identification: From a quantitative to a qualitative approach. *Food Control, 12*(4), 223–228.

Sun, Y., & Ockerman, H. W. (2005). A review of the needs and current applications of hazard analysis and critical control point (HACCP) system in foodservice areas. *Food Control, 16*(4), 325–332.

Tuominen, P., Hielm, S., Aarnisalo, K., Raaska, L., & Maijala, R. (2003). Trapping the food safety performance of a small or medium-size food company using a risk-based model: The HYGRAM system. *Food Control, 14*(8), 573–578.

Van Laarhoven, P. J. M., & Pedrycz, W. (1983). A fuzzy extension of Saaty's priority theory. *Fuzzy Sets and Systems, 11*(1–3), 229–241.

Walker, E., & Jones, N. (2002). An assessment of value of documenting food safety in small and less developed catering businesses. *Food Control, 13*(4/5), 307–314.

Walker, E., Pritchard, C., & Forsythe, S. (2003). Hazard analysis critical control point and prerequisite programme implementation in small and medium size food business. *Food Control, 14*(3), 169–174.

Walls, I. (2006). Role of quantitative risk assessment and food safety objectives in managing Listeria monocytogenes on ready-to-eat meats. *Meat Science, 74*, 66–75.
Wang, Y. M., Elhag, T. M. S., & Hua, Z. S. (2006). A modified fuzzy logarithmic least squares method for fuzzy analytic hierarchy process. *Fuzzy Sets and Systems, 157*(23), 3055–3071.
Wang, Y., Luo, Y., & Hua, Z. (2008). On the extent analysis method for fuzzy AHP and its applications. *European Journal of Operational Research, 186*(2), 735–747.
Wang, X., Li, D., & O'Brien, C. (2009). Optimisation of traceability and operations planning: An integrated model for perishable food production. *International Journal of Production Research, 47*(11), 2865–2886.
Wang, X., Li, D., O'Brien, C., & Li, Y. (2010). A production planning model to reduce risk and improve operations management. *International Journal of Production Economics, 124*(2), 463–474.
Wang, X., Li, D., & Shi, X. (2012). A fuzzy enabled model for aggregative food safety risk assessment in food supply chains. *Production Planning and Control, 23*(5), 377–395.
Weck, M., Klocke, F., Schell, H., & Rüenauver, E. (1997). Evaluating alternative production cycles using the extended fuzzy AHP method. *European Journal of Operational Research, 100*(2), 351–366.
WHO/FAO (1999). Risk assessment of microbiological hazards in foods. Report of a Joint FAO/WHO Expert Consultation, World Health Organisation, Geneva, Switzerland, 24.
Xu, R. (2000). Fuzzy least-squares priority method in the analytic hierarchy process. *Fuzzy Sets and Systems, 112*(3), 359–404.
Zadeh, L. A. (1965). Fuzzy sets. *Information and Control, 8*(3), 338–353.
Zeng, X. J., & Singh, M. G. (1994). Approximation theory of fuzzy systems-SISO case. *IEEE Transactions on Fuzzy Systems, 2*(2), 162–176.

Chapter 7
A Hierarchical Fuzzy TOPSIS Approach for the Risk Assessment of Green Supply Chain Implementation

7.1 Introduction

Green supply chain management (GSCM) has emerged as an organisational philosophy in recent years. GSCM helps organisation and their business to improve competitive advantages and profits (Sarkis 2003; Rao and Holt 2005; Srivastava 2007; Zhu et al. 2008; and Azevedo et al. 2011). Nevertheless, introducing new green initiatives might require the use of new technologies in supply and production processes, as well as the development of new quality systems. Purchasing-wise, it might need the procurement of new raw materials and affect the supplier selection process. Logistics-wise, it might require new inbound and outbound logistics along with new packaging. Considering potential adjustments in their internal and external operations, the adoption of greener practices could also increase the probability of experiencing adverse events in supply chains that significantly threaten normal business operations of organisations in the supply chain. Consequently, any strategic investments in green initiatives based on poorly considered "competencies" could be detrimental, which could lead to an increase in total costs and risk from failures along the supply chain. It is, therefore, clear that just like any strategic policy change, implementing green initiatives, consists of a certain degree of risk. The decision of adopting appropriate strategies for GSCM requires a trade-off between the benefits and cost involved.

Making such a decision, however, is never an easy task as there are many factors concerned with the decision-making process. This is a typical multi-criteria decision-making (MCDM) problem. MCDM methods have been widely used in many research fields. Different approaches have been proposed by many researchers, including the analytic hierarchy process (AHP) (Saaty 1980) and technique for order preference by similarity to ideal solution (TOPSIS) (Hwang and Yoon 1981). However, both approaches are often criticised regarding its inability to process ambiguous variables. When assessing risk for GSCM implementation, uncertainty is inherent to the assessment. Fuzzy set theory is used to address this issue, and a hierarchical fuzzy TOPSIS approach is proposed to make more rational decision. The remainder of the chapter is organised as follows: Sect. 7.2 introduces the TOPSIS method. Section 7.3 presents a review of back ground study. Section 7.4

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presents how we adopt the methodology, hierarchical fuzzy TOPSIS, for risk assessment when implementing green supply chain initiatives. Then, an illustrative application is presented in Sect. 7.5 to demonstrate how the model works. Finally, conclusions and remarks are then given in Sect. 7.6.

7.2 TOPSIS

TOPSIS is a technique to evaluate the performance of alternatives through the similarity with the ideal solution proposed by Hwang and Yoon (1981). The main concept of TOPSIS is to define the positive ideal solution and negative ideal solution. The positive ideal solution is one that maximises the benefit criteria and minimises the cost criteria. The negative ideal solution maximises the cost criteria and minimises the benefit criteria. The most preferred alternative should have the shortest distance from the positive ideal solution and the longest distance from the negative ideal solution. The procedure for standard TOPSIS has been well documented in the literature, and the following is a summary of the procedures with reference to study conducted by Krohling and Campanharo (2011):

Consider the decision matrix D, which consists of alternatives and criteria, described as follow:

$$D = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix} \tag{7.1}$$

where $A_1, A_2, \ldots, A_m$ are available alternatives, and $C_1, C_2, \ldots, C_n$ are criteria, x_{ij} specifies the rating of the alternative A_i according to criteria C_j. The weight vector $W = (w_1, w_2 \ldots, w_n)$ composed of the individual weights w_j $(j = 1, \ldots, n)$ for each criterion C_j satisfying $\sum_{i=1}^{n} W_j = 1$.

In general, the criteria can be classified into two types: benefit and cost. The benefit criterion means that a higher value is better, while for the cost criterion is valid the opposite. The data of the decision matrix D may come from different sources. Therefore, it is essential to normalise it in order to transform it into a dimensionless matrix, which allows the comparison of the various criteria. Using the normalised decision matrix $R = \left[r_{ij}\right]_{m \times n}$ with $i = 1, \ldots, m$, and $j = 1, \ldots, n$, its normalised value r_{ij} is calculated as:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \text{ with } i = 1, \ldots, m, \text{ and } j = 1, \ldots, n \tag{7.2}$$

The normalised decision matrix R represents the relative rating of the alternatives. After normalisation, the weighted normalised decision matrix $V = \left[v_{ij}\right]_{m \times n}$ with $i = 1, \ldots, m$, and $j = 1, \ldots, n$, is calculated by multiplying the normalised decision matrix by its associated weights. The weighted normalised value v_{ij} is calculated as:

$$p_{ij} = w_i \times r_{ij},\ \text{with}\ i = 1, \ldots, m,\ \text{and}\ j = 1, \ldots, n \tag{7.3}$$

The TOPSIS is expressed in the following steps:

Step 1: Identify the positive ideal solutions A^+ (benefits) and negative ideal solutions A^- (costs) as follow:

$$A^+ = \left(v_1^+, v_2^+, \ldots v_m^+,\right) \tag{7.4}$$

$$A^- = \left(v_1^-, v_2^-, \ldots v_m^-,\right) \tag{7.5}$$

where

$$v_j^+ = \left(\max_i\ v_{ij},\ j \in J_1; \min_i\ v_{ij},\ j \in J_2\right)$$

$$v_j^- = \left(\min_i\ v_{ij},\ j \in J_1; \max_i\ v_{ij}, j \in J_2\right)$$

where J_1 and J_2 represent the criteria benefit and cost, respectively.

Step 2: Calculate the Euclidean distances from the positive ideal solution A^+ and the negative ideal solution A^- for each alternative A_i, respectively, as follow:

$$d_i^+ = \sqrt{\sum_{j=1}^{n} \left(d_{ij}^+\right)^2} \tag{7.6}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} \left(d_{ij}^-\right)^2} \tag{7.7}$$

where

$$d_{ij}^+ = v_j^+ - v_{ij},\ \text{with}\ i = 1, \ldots, m.$$

$$d_{ij}^- = v_j^- - v_{ij},\ \text{with}\ i = 1, \ldots, m.$$

Step 3: Calculate the relative closeness $\check{C}_i$ for each alternative A_i with respect to positive ideal solution as:

$$\check{C}_i = \frac{d_i^-}{d_i^{-+} + d_i^-} \tag{7.8}$$

Step 4: Rank the alternatives according to the relative closeness. The best alternatives are those that have higher value $\check{C}_i$ and, therefore, should be selected because they are close to the positive ideal solution.

7.3 Risk Assessment for GSCM Implementation

With increased public awareness of the need to protect the environment, there is urgency for businesses to introduce and promote business practices that help to ease the negative impacts of their actions on environment. Businesses are more sensitive on decisions of what items are purchased, the effect of manufacturing processes, how products are packaged and delivered, and the recycle (or reuse) policies. In recent years, GSCM has drawn increased attention from both practitioners and academics. According to Srivastava (2007), GSCM is the process of incorporating environmental concerns into supply chain management, including product design, material sourcing and selection, manufacturing process, deliver of the final product to the consumers as well as end-of-life management of the product after its useful life. Srivastava (2007) classified the literature on GSCM on the basis of the problem context in supply chain's major influential areas, which include green design, green manufacturing and remanufacturing, reverse logistics and network design, and waste management. Shang et al. (2010) identified six dimensions of GSCM including green manufacturing and packaging, environmental participation, green marketing, green suppliers, green stock and green eco-design.

The main reason for implementing these GSCM practices is that organisations can generate more business opportunities than their competitors if they can address environmental issues successfully. A greener product design may improve brand image and stimulate demand from "green consumers" (Peattie 2001). Using environmentally friendly raw materials and green production process address issues such as environmental material substitution, waste reduction and decreasing the consumption of hazardous and toxic materials (Rao and Holt 2005; Vachon 2007; Zhu et al. 2007). Green logistics and packaging enhance cost savings by cutting energy consumption and packaging waste in times of rising commodities and energy costs being a particular concern (Zhu et al. 2008; Holt and Ghobadian 2009). Zhu and Sarkis (2004) thought that the economic performance is the main driver for enterprises which seeks to implement green initiatives. Rao and Holt (2005) studied the relationship between the implementation of green supply chains and the economic performance and competitiveness of a sample of Asian firms. Their research shows that GSCM can improve competitiveness, which is in line with Bacallan (2000). Zhu et al. (2007) evaluated the effectiveness of GSCM in Chinese manufacturing enterprises and the automobile industry, respectively, and delivered a similar message as above. Moreover, Azevedo et al. (2011) investigated the relationships between GSCM practices and supply chain performance in the context of the automotive industry. Their research reveals that, on the one hand, green practices have positive effects on quality, customer satisfaction and efficiency, and on the other hand, some factors of green practices have negative effects on supply chain performance. Furthermore, the introduction of greener practices requires different sets of sources and capabilities which might put different firms in the supply network a better position to adopt such practices than others. Therefore, it is crucial for decision makers to understand the potential ramifications of adopting green practices and initiatives (Sarkis 2003).

However, evaluating GSCM initiatives is a complex task which does not only require a trade-off between benefits and cost involved, but also take the operational and environmental performance into consideration. Several MCDM approaches have been developed to solve such type of real-world problems. One of these techniques known as TOPSIS is a technique to evaluate the performance of alternatives through the similarity with the ideal solution proposed by Hwang and Yoon (1981). Despite its popularity and simplicity in concept, TOPSIS is often criticised because of its inability to deal adequately with uncertainty and imprecision inherent in the process of mapping the perceptions of decision makers (Krohling and Campanharo 2011). In fact, implementing GSCM initiatives involves considerable amount of uncertainty causing elements arising from both internal and external sources including technical, operational and commercial issues. To address the limitation of TOPSIS, some scholars have made use of fuzzy logic, which can be employed to deal with uncertain parameters and information. Fuzzy logic resembles human reasoning in its use of approximate information and uncertainty to support decision making (Zadeh 1965). TOPSIS has been expanded to deal MCDM with an uncertain decision matrix resulting in fuzzy TOPSIS, which has successfully been applied to solve various MCDM problems such as plant location selection (Yong 2006; Ertuğrul and Karakaşoğlu 2008), customer evaluation (Chamodrakas et al. 2009), supplier selection and evaluation (Chen et al. 2005; Bottani and Rizzi 2006; Boran et al. 2009; Roghanian et al. 2010; Büyüközkan and Çifçi 2012), bridge risk assessment (Wang and Elhag 2006), evaluation of new product design (Kahraman et al. 2007; Gao et al. 2010; Ng and Chuah 2010) and personnel selection (Kelemenis and Askounis 2010; Kelemenis et al. 2011).

AHP has been extensively applied by academics and professionals, and the literature on AHP in various applications is very rich (e.g. Lee and Kozar 2006; Chan et al. 2006; Chang et al. 2007; Korpela et al. 2007; Ramanathan 2007; Dağdeviren 2008; Sharma and Agrawal 2009; Chan and Chan 2010). In relation to GSCM, AHP approaches have been utilised to investigate issues such as evaluating the environmental impacts of different stages of a supply chain life cycle (Sarkis 2003), selection of preferred partners and final product concept (Yan et al. 2008), supplier development based on environmental criteria (Lu et al. 2007), matching of product characteristics with supplier characteristics to select potential vendors (Chen and Huang 2007), identifying improvement areas when implementing green initiatives (Sarminento and Thomas 2010; Wang et al. 2012), evaluation of a product's impact and influence on the environment for early product planning and development (Yang et al. 2010), and selection and evaluation of innovative designs (Li 2010). Among these studies, the work carried by Sarminento and Thomas (2010) is most relevant to this research. They proposed a multi-tier AHP approach to analyse the problems firms taking part in a supply chain might encounter when implementing green initiatives. Although the research examines various potential challenges firms and supply chains might face when adopting green initiatives, their investigation is conceptual in nature and it is important to develop a more accurate, effective and systematic decision support tool to help industrial practitioners to perform such an assessment.

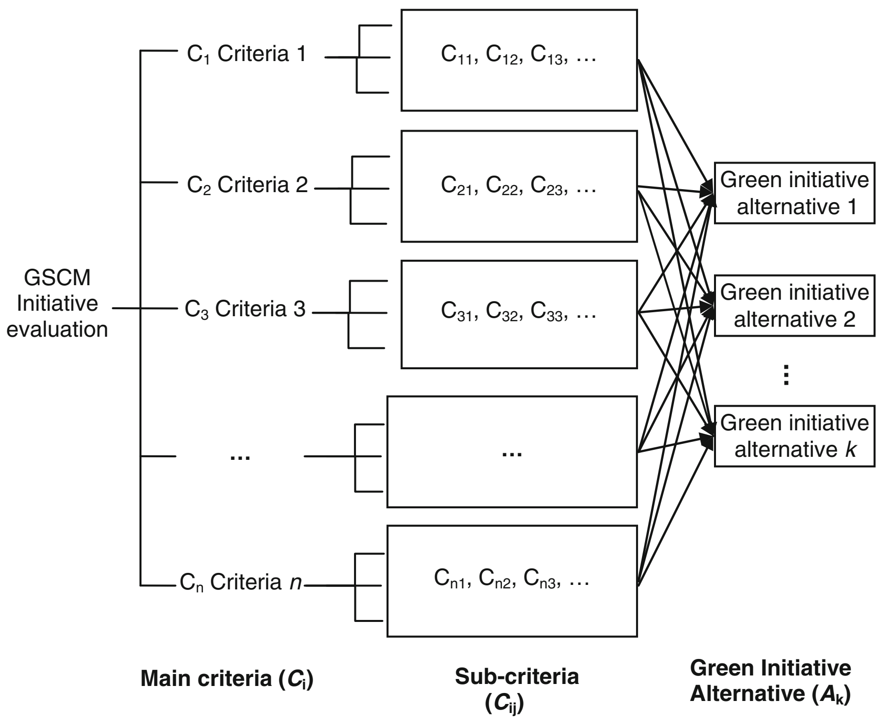
This chapter addressed the gap in the literature by proposing a hierarchical fuzzy TOPSIS approach to assess risks when implementing green supply chain initiatives. The proposed approach will benefit both from the superiority of the hierarchical structure of AHP and easiness of implementation of TOPSIS in a fuzzy environment. It helps decision makers to take the operational, technical and strategic issues in the consideration, thus providing the best options to be used in the implementation of GSCM initiatives.

7.4 Proposed Hierarchical Fuzzy TOPSIS Approach

In this section, a hierarchical fuzzy TOPSIS approach is proposed. First of all, the evaluation framework is presented to identify improvement areas when introducing green initiatives. Then, AHP is used to determine weights of evaluation criteria through pairwise comparison. After that, fuzzy TOPSIS is employed to acquire the comparative ratings of alternative options when introducing GSCM initiatives.

7.4.1 Hierarchical Model

The adoption of GSCM initiatives will lead to better economic performance through enhanced environmental performance such as less waste, enhanced energy efficiency and an improved recyclability of the end product. At the same time, new green initiatives might require organisations to redesign and improve various aspects of their exiting processes in order to adopt these innovations successfully. It is essential for the organisation to identify those areas at both the individual organisation and supply chain levels that are least prepared to handle the green innovation successfully. Sarminento and Thomas (2010) proposed a multi-tier AHP framework to assess supply chain resources and capabilities for implementing green initiatives. Nevertheless, the hierarchical model in Sarminento and Thomas's research only focuses on four main criteria: manufacturing, purchasing, logistics and marketing. In this research, a more generic model is proposed in which organisations have the flexibility to incorporate both environmental and operational aspects and include more criteria and relevant sub-criteria referring to their business concerns. Within each main criterion, the relevant sub-criteria are identified. Important data such as the bill of materials, manufacturing process and making strategies should be collected to support the identification process. The alternatives at the bottom end of the hierarchy are the time windows by which an organisation could successfully implement the selected green initiatives in the condition of the potential limitations in internal processes and resources. The AHP approach would address the diverse aspects associated with the implementation of green initiatives and enable the decision maker to make distinctions in the assignation of the weights of each individual factor. A general framework of the AHP used in the chapter is depicted in Fig. 7.1.



Where: i is the index of main criteria (i= 1,2,…, n)
j is the index of sub-criteria within each main criteria (j=1,2, …, C_i, and $m = \sum_{i=1}^{n} C_i$
k is the index of alternative green initiatives (k= 1,2,…, l)

Fig. 7.1 Hierarchical framework for assessing improvement areas when implementing GSCM initiatives

7.4.2 Analysis of Criteria Weights with AHP

When assessing the improvement areas for implementing green initiatives, it is essential to know how important one criterion or sub-criterion is over another. In other words, assessors have to determine the weights between main criteria. AHP is employed to obtain the weights. In a typical AHP method, the pairwise comparisons are established using a nine-point scale which converts human preferences into available alternatives such as equally, moderately, strongly, very strongly or extremely preferred. For example, if two elements are assumed equally important, the comparison will have a scale of 1. If one element is moderately more important than the other, the analysis will have a scale of 3. Subsequently, scales 5, 7 and 9 are used to describe strongly more important, very strongly more important and extremely more important, respectively. The corresponding reciprocals 1, 1/2, 1/3, …, 1/9 are used for the reverse comparison. The pairwise comparisons of the attributes at each level in the hierarchy are arranged into a reciprocal matrix (Saaty 1996). In general, the comparison matrices are defined as:

$$A = \left(a_{ij}\right) \tag{7.9}$$

where A = reciprocal matrix with the elements $a_{ij} = {}^{1}\!/_{a_{ji}}$. The relative weights of the elements at each level with respect to an element are computed as the components of the normalised eigenvector associated with the largest eigenvalue of the comparison matrix A.

AHP has proven its effectiveness in decision making. However, when conducting the pairwise comparisons, the assessors can incorporate their own knowledge and experience. Inconsistency can be an issue. For the accuracy of the method, the consistency measure (Saaty 1980) is performed to screen out inconsistency of responses.

7.4.3 Hierarchical Fuzzy TOPSIS

In this section, hierarchical fuzzy TOPSIS is used as a comprehensive decision support system for the evaluation of GSCM initiatives. To evaluate the performance of a set of alternative solutions, a fuzzy decision matrix, $\tilde{D}$, is constructed based on a given set of criteria and sub-criteria. Referring to the hierarchy model in figure, there are l alternatives A_k ($k = 1, 2, \ldots, l$) and n main criteria. Each main criterion has c_i sub-criteria where the total number of sub-criteria is equal to $\sum_{i=1}^{n} C_i$. $\tilde{x}_{kij}$ represents the value of the jth sub-criterion within ith main criterion of the kth alternative, which can be crisp data or appropriate linguistic variables which can be further represented by fuzzy numbers [e.g. $\tilde{x}_{kij} = \left(a_{kij}, m_{kij}, b_{kij}\right)$]. A hierarchical MCDM problem can be concisely expressed in a fuzzy decision matrix as:

$$\tilde{D} = \begin{array}{c} \\ \\ A_1 \\ A_2 \\ \vdots \\ A_K \end{array} \begin{array}{c} \begin{array}{ccccccccccccc} & C_1 & & & & C_2 & & \cdots & & C_n & & \\ C_{11} & C_{12} & \cdots & C_{1C_1} & C_{21} & C_{22} & \cdots & C_{2C_2} & \cdots & C_{n1} & C_{n2} & \cdots & C_{nC_n} \end{array} \\ \begin{bmatrix} \tilde{x}_{111} & \tilde{x}_{112} & \cdots & \tilde{x}_{11C_1} & \tilde{x}_{121} & \tilde{x}_{122} & \cdots & \tilde{x}_{12C_2} & \cdots & \tilde{x}_{1n1} & \tilde{x}_{1n2} & \cdots & \tilde{x}_{1nC_n} \\ \tilde{x}_{211} & \tilde{x}_{212} & \cdots & \tilde{x}_{21C_1} & \tilde{x}_{221} & \tilde{x}_{222} & \cdots & \tilde{x}_{22C_2} & \cdots & \tilde{x}_{2n1} & \tilde{x}_{2n2} & \cdots & \tilde{x}_{2nC_n} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \cdots & \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{K11} & \tilde{x}_{K12} & \cdots & \tilde{x}_{K1C_1} & \tilde{x}_{K21} & \tilde{x}_{K22} & \cdots & \tilde{x}_{K2C_2} & \cdots & \tilde{x}_{Kn1} & \tilde{x}_{Kn2} & \cdots & \tilde{x}_{KnC_n} \end{bmatrix} \end{array}$$

$$k = 1, 2, \ldots, l;\ i = 1, 2, \ldots, n;\ j = 1, 2, \ldots, C_i \tag{7.10}$$

$$\tilde{x}_{kij} = \frac{1}{S}\left(\tilde{x}^1_{kij} \oplus \cdots \oplus \tilde{x}^s_{kij} \oplus \cdots \oplus \tilde{x}^S_{kij}\right)$$

where $\tilde{x}_{kij}$ is the fuzzy evaluation score of alternative A_k with respect to sub-criterion C_{ij} evaluated by sth expert and $\tilde{x}^s_{kij} = \left(a^s_{kij}, m^s_{kij}, b^s_{kij}\right)$.

In general, the criteria can be classified into two categories: benefit and cost. The benefit criterion means that a higher value is better, while for the cost criterion is valid the opposite. The data of the decision matrix $\tilde{D}$ come from different sources. Therefore, it is necessary to normalise it in order to transform it into a dimensionless matrix, which allows the comparison of the various criteria. In this research, the normalised fuzzy decision matrix is denoted by $\tilde{R}$ shown as:

$$\begin{aligned} &\tilde{R} = \left[\tilde{r}_{kij}\right]_{l \times m}, \\ &k = 1, 2, \ldots, l; i = 1, 2, \ldots, n; j = 1, 2, \ldots, C_i; m = \sum_{i=1}^{n} C_i \end{aligned} \tag{7.11}$$

The normalisation process can then be performed by the following fuzzy operations:

$$\tilde{r}_{kij} = \begin{cases} \left(\frac{a_{kij}}{\mathcal{U}^+_{ij}}, \frac{m_{kij}}{\mathcal{U}^+_{ij}}, \frac{b_{kij}}{\mathcal{U}^+_{ij}}\right), & \forall_{ij},\ \tilde{x}_{ij} \text{ is a benefit criterion} \\ \left(\frac{\mathcal{U}^-_{ij}}{a_{kij}}, \frac{\mathcal{U}^-_{ij}}{m_{kij}}, \frac{\mathcal{U}^-_{ij}}{b_{kij}}\right), & \forall_{ij},\ \tilde{x}_{ij} \text{ is a cost criterion} \end{cases} \tag{7.12}$$

where $\mathcal{U}^+_{ij}$ and $\mathcal{U}^-_{ij}$ present the largest and the lowest value of each sub-criterion, respectively. The weighted fuzzy normalised decision matrix is shown as:

$$\tilde{V} = \left[\tilde{v}_{kij}\right]_{k \times m}, k = 1, 2, \ldots, l; i = 1, 2, \ldots, n; j = 1, 2, \ldots, C_i; m = \sum_{i=1}^{n} C_i \tag{7.13}$$

where $\tilde{v}_{kij} = \tilde{r}_{kij} \otimes W_{ij}$.

Here, W_{ij} is the final weight score for each sub-criterion which is the product of the main criterion weight score and the sub-criterion weight score with respect to the corresponding main criterion as follows:

$$W_{ij} = w_{C_i} \otimes w_{C_{ij}} = w_i \otimes \begin{bmatrix} w_{i1} \\ w_{i2} \\ \vdots \\ w_{iC_i} \end{bmatrix}, \quad (i = 1, 2, \ldots, n) \tag{7.14}$$

where w_{C_i} and $w_{C_{ij}}$ denote the ith main criterion weight score and the sub-criterion weight score with respect to this main criterion, respectively. Both w_{C_i} and $w_{C_{ij}}$ are obtained through the AHP method discussed in Chap. 3 and Sect. 7.4.2. The results of Eq. 7.13 can be summarised as:

$$\tilde{v} = \begin{array}{c c} & \begin{array}{ccccccccccccc} & & C_1 & & & C_2 & & & \cdots & & C_n & & \\ C_{11} & C_{12} & \cdots & C_{1C_1} & C_{21} & C_{22} & \cdots & C_{2C_2} & \cdots & C_{n1} & C_{n2} & \cdots & C_{nC_n} \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_K \end{array} & \begin{bmatrix} \tilde{v}_{111} & \tilde{v}_{112} & \cdots & \tilde{v}_{11C_1} & \tilde{v}_{121} & \tilde{v}_{122} & \cdots & \tilde{v}_{12C_2} & \cdots & \tilde{v}_{1n1} & \tilde{v}_{1n2} & \cdots & \tilde{v}_{1nC_n} \\ \tilde{v}_{211} & \tilde{v}_{212} & \cdots & \tilde{v}_{21C_1} & \tilde{v}_{221} & \tilde{v}_{222} & \cdots & \tilde{v}_{22C_2} & \cdots & \tilde{v}_{2n1} & \tilde{v}_{2n2} & \cdots & \tilde{v}_{2nC_n} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \cdots & \vdots & \vdots & \ddots & \vdots \\ \tilde{v}_{K11} & \tilde{v}_{K12} & \cdots & \tilde{v}_{K1C_1} & \tilde{v}_{K21} & \tilde{v}_{K22} & \cdots & \tilde{v}_{K2C_2} & \cdots & \tilde{v}_{Kn1} & \tilde{v}_{Kn2} & \cdots & \tilde{v}_{KnC_n} \end{bmatrix} \end{array} \tag{7.15}$$

Subsequently, the fuzzy addition principle is used to aggregate the values within each main criterion as follows:

$$\tilde{v}'_{ki} = \sum_{j=1}^{C_i} \tilde{v}_{kij}, \; k = 1, 2, \ldots, l; \; i = 1, 2, \ldots, n \tag{7.16}$$

The matrix $\tilde{V}$ is thus converted into the final weighted normalised fuzzy decision matrix $\tilde{V}'$,

$$\tilde{V}' = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & \ldots & C_N \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_l \end{array} & \begin{bmatrix} \tilde{v}'_{11} & \tilde{v}'_{12} & \cdots & \tilde{v}'_{1n} \\ \tilde{v}'_{21} & \tilde{v}'_{22} & \cdots & \tilde{v}'_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{v}'_{l1} & \tilde{v}'_{l2} & \ldots & \tilde{v}'_{ln} \end{bmatrix} \end{array} \tag{7.17}$$

This addition operation is important as the final weighted normalised fuzzy decision matrix becomes a one-layer fuzzy TOPSIS model after the calculation of the final weight score for each sub-criterion (Bao et al. 2012). Therefore, the hierarchical structure can be reflected only when aggregation of the weighted values within each main criterion is conducted.

Now, let A^+ and A^- denote the fuzzy positive idea solution (FPIS) and fuzzy negative ideal solution (FNIS), respectively. According to the weighted normalised fuzzy decision matrix, we have:

$$A^{+} = \left(\tilde{v}_1^{+}, \cdots, \tilde{v}_i^{+}, \cdots \tilde{v}_n^{+}\right)$$
$$A^{-} = \left(\tilde{v}_1^{-}, \cdots, \tilde{v}_i^{-}, \cdots \tilde{v}_n^{-}\right) \tag{7.18}$$

where $\tilde{v}_i^{+}$ and $\tilde{v}_i^{-}$ are the fuzzy numbers with the largest and the smallest generalised mean, respectively. The generalised mean for the fuzzy number $\tilde{v}_{ki} = (a_{ki}, m_{ki}, b_{ki})$, $\forall_i$ is defined as:

$$M(\tilde{v}_{ki}) = \frac{-a_{ki}^2 + b_{ki}^2 - a_{ki}m_{ki} + m_{ki}b_{ki}}{3(-a_{ki} + b_{ki})} \tag{7.19}$$

For each column i, the greatest generalised mean of $\tilde{v}_i^{+}$ and the lowest generalised mean of $\tilde{v}_i^{-}$ can be obtained, respectively. Consequently, the FPIS (A^{+}) and the FNIS (A^{-}) are derived. Then, the distances (d^{+} and d^{-}) of each alternative from A^{+} and A^{-} can be calculated by the area compensation method as

$$\tilde{d}_k^{+} = \sum_{i=1}^{n} d\left(\tilde{v}_{ki}, \tilde{v}_i^{+}\right), \quad k = 1, 2, \ldots, l;\ i = 1, 2, \ldots, n \tag{7.20}$$

$$\tilde{d}_k^{-} = \sum_{i=1}^{n} d\left(\tilde{v}_{ki}, \tilde{v}_i^{-}\right), \quad k = 1, 2, \ldots, l;\ i = 1, 2, \ldots, n \tag{7.21}$$

By combining the difference distances d^{+} and d^{-}, the relative closeness index is calculated as follows:

$$\check{C}_{\mathrm{k}} = \frac{\tilde{d}_k^{-}}{\tilde{d}_k^{+} + \tilde{d}_k^{-}} \tag{7.22}$$

According to the index value, the set of alternatives can be ranked from the most preferred to the least preferred feasible solutions.

7.5 An Illustrative Case Application

Implementing a GSCM practice is a challenging task due to conflicting nature of the objectives. Organisations want to generate substantial revenue increase and minimise negative environmental impact. Meanwhile, they do not want to increase the cost to a larger extent. The implementation of green practices could improve the business performance. It also brings a substantial amount of uncertainty as it requires potential adjustments in internal and external operations which may increase the risk of experiencing adverse events across the supply chain. In this section, a case study concerned with a fashion retail chain is presented to illustrate how the proposed fuzzy hierarchical TOPSIS approach can be applied to support the decision making.

The fashion industry is highly diverse and heterogeneous. The industry has experienced a great deal of change with global sourcing and high levels of price competition. In addition, the unique characteristics such as short product life cycle, high volatility, low predictability and a level of impulse purchase add further uncertainty for those organisations want greening their supply chain operations. Despite its reputation for both operational expertise and marketing excellence, the company made a strategic decision to use new green materials in their products. They believe that such a movement could improve saleability and secure future growth in the wide market. In the following sections, the proposed fuzzy hierarchical TOPSIS approach is employed to evaluate the organisation's readiness of implementing green raw material.

An expert panel was formed to conduct the assessment. After the overall objective was defined which is to successfully implement green raw material in the case organisation, the evaluation process began by analysing main criteria, their associated sub-criteria, required for the evaluation. Through the panel discussion, the detailed sub-criteria under four main criteria (manufacturing, purchasing, logistics and marketing) were identified. The results are illustrated in Table 7.1, in which the hierarchy is descended from the general criteria in the second level to more detailed sub-criteria. In addition to the factors that are recommended by Sarminento and Thomas (2010) to assess supply chain resources and capabilities for implementing green initiatives, those important factors that are critical to the fashion supply chain such as production capacity, assurance of supply, shipment accuracy and customer services were incorporated in the corresponding criteria of the hierarchy model. At the right side of the hierarchy, there are three time windows by which the organisation could successfully implement the selected green initiative in the condition of the potential limitations in internal processes and resources.

Then, the AHP method discussed in Sect. 7.4.2 is used to rate the importance of individual criteria over another with respect to the overall objective. Within each main criterion, the decision makers were required to give importance ratings of individual sub-criterion over another with respect to their corresponding main criterion. The comparison of the importance or priority of criteria or sub-criteria over another was carried out through a panel discussion. The AHP weightings were computed by using Microsoft Excel. The consistency ratio of each judgement was calculated and checked to ensure that it is lower than or equal to 0.1. The results are displayed in Table 7.2, in which the final weight scores for each sub-criterion were obtained by calculating the product of each main criterion weight scores and the sub-criteria weight scores with respect to the corresponding main criteria. Among the identified sub-criteria, production capacity, saleability and marketability have the highest weight scores. From the weight scores, we can understand that, for the case company, these are the important areas that the company should pay more attention to when implementing green raw material in their products.

Then, the three alternative implementation time windows in Table 7.1 were evaluated with respect to detailed sub-criteria in terms of the readiness of

Table 7.1 Hierarchical structure for the evaluation of three alternative timescales for the implementation of GSCM initiatives in the case organisation

Goal	Criteria	Sub-criteria	Alternative initiatives
Implementing green raw material	C_1 manufacturing	C_{11} processes	A_1 implement now
		C_{12} technical capability	A_2 implement in 6 months
		C_{13} innovation capability	A_3 implement in 12 months
		C_{14} innovation capability production capacity	
	C_2 purchasing	C_{21} raw material availability	
		C_{22} suppliers	
		C_{23} inventory level	
		C_{24} assurance of supply	
	C_3 logistics	C_{31} inbound logistics	
		C_{32} outbound Logistics	
		C_{33} packaging	
		C_{34} shipment accuracy	
	C_4 marketing	C_{41} saleability	
		C_{42} growth	
		C_{43} marketability	
		C_{44} customer service	

implementing green raw material. Decision makers can provide a precise numerical value or a linguistic term to express their opinions. The qualitative explanation of rating level and its corresponding triangular fuzzy numbers is described in Table 7.3. The linguistics terms were then converted into triangular fuzzy numbers. The results are then used to constitute a hierarchical decision-making matrix $\tilde{D}$ as illustrated in Table 7.4. The hierarchical decision-making matrix is normalised using Eq. 7.12. The result is displayed in Table 7.5.

Subsequently, through computing the product of the normalised hierarchical decision matrix $\tilde{D}$ and the final weight scores for each sub-criterion, the weighted normalised fuzzy decision matrix $\tilde{V}$ is obtained as Table 7.6.

By aggregating the values belong to each main criterion by fuzzy addition principle (see Eq. 7.18), the final weighted normalised fuzzy decision matrix $\tilde{V}'$ is obtained as Table 7.7.

Since each element in $\tilde{V}'$ is a fuzzy number, its generalised mean $M(\tilde{v}_{ki})$ is then calculated according to Eq. 7.19. The largest generalised mean and the smallest generalised mean of each main criterion could then be selected constituting the FPIS (A^+) and the FNIS (A^-). Now, the difference distances of each of the alternatives (d_k^+ and d_k^-) can be calculated as in Eqs. 7.20 and 7.21. Finally, combining the different distances, the relative closeness index for each alternative green initiative can be obtained. The results are presented in Table 7.8, together with the corresponding rankings based on the index values.

The results derived for the proposed fuzzy hierarchical TOPSIS approach show that A_2, implementing green raw material in 6 months, has the highest relative

Table 7.2 Weights of assessment criteria and sub-criteria with respect to the case scenario

Criteria	Criteria weights (w_{c_i})	Sub-criteria	Sub-criteria weights ($w_{c_{ij}}$)	Final weights (W_{ij})
C_1 manufacturing	0.285	C_{11} processes	0.269	0.077
		C_{12} technical capability	0.121	0.034
		C_{13} innovation capability	0.193	0.055
		C_{14} production capacity	0.417	0.119
C_2 purchasing	0.163	C_{21} materials	0.423	0.069
		C_{22} suppliers	0.227	0.037
		C_{23} inventory level	0.123	0.020
		C_{24} assurance of supply	0.227	0.037
C_3 logistics	0.184	C_{31} inbound logistics	0.110	0.020
		C_{32} outbound Logistics	0.230	0.042
		C_{33} packaging	0.302	0.056
		C_{34} shipment accuracy	0.358	0.066
C_4 marketing	0.368	C_{41} saleability	0.372	0.137
		C_{42} growth	0.237	0.087
		C_{43} marketability	0.278	0.102
		C_{44} customer service	0.113	0.042

Table 7.3 Linguistic classification of performance evaluation of green initiatives and their corresponding triangular fuzzy numbers

Rating level	A qualitative explanation of the effect of green initiatives on operations performance	Triangular fuzzy numbers (TFN)
1	Definitely poor	(0, 1, 2)
2	Very poor	(1, 2, 3)
3	Poor	(2, 3, 4)
4	Medium poor	(3, 4, 5)
5	Fair	(4, 5, 6)
6	Medium good	(5, 6, 7)
7	Good	(6, 7, 8)
8	Very good	(7, 8, 9)
9	Absolutely good	(8, 9, 10)

closeness index, which should be recommended among the three alternative time windows. This is due to the fact that there are potential gaps in capability and resources in its supply chain in order to successfully implement green raw material now. Marketing-wise, the case company will generate more business opportunities if green new material can be implemented now since few competitors have already launched a similar green initiative. The implementation will not only improve the company's environmental performance but also enhance the brand image. However, manufacturing-wise, the company is less prepared in terms of manufacturing processes, production capacity and technical and innovation capabilities in implementing green new material at moment. Such a movement requires alterations in their internal and external operations and, in result, may compromise the

Table 7.4 Subjective cognition results of decision makers' evaluation

	A_1	A_2	A_3
C_{11}	(2, 3, 4)	(4, 5, 6)	(6, 7, 8)
C_{12}	(3, 4, 5)	(5, 6, 7)	(7, 8, 9)
C_{13}	(4, 5, 6)	(5, 6, 7)	(7, 8, 9)
C_{14}	(3, 4, 5)	(6, 7, 8)	(7, 8, 9)
C_{21}	(5, 6, 7)	(6, 7, 8)	(6, 7, 8)
C_{22}	(3, 4, 5)	(5, 6, 7)	(7, 8, 9)
C_{23}	(4, 5, 6)	(5, 6, 7)	(5, 6, 7)
C_{24}	(5, 6, 7)	(6, 7, 8)	(5, 6, 7)
C_{31}	(4, 5, 6)	(5, 6, 7)	(6, 7, 8)
C_{32}	(5, 6, 7)	(6, 7, 8)	(7, 8, 9)
C_{33}	(6, 7, 8)	(6, 7, 8)	(7, 8, 9)
C_{34}	(4, 5, 6)	(5, 6, 7)	(6, 7, 8)
C_{41}	(7, 8, 9)	(7, 8, 9)	(5, 6, 7)
C_{42}	(7, 8, 9)	(6, 7, 8)	(4, 5, 6)
C_{43}	(8, 9, 10)	(7, 8, 9)	(5, 6, 7)
C_{44}	(6, 7, 8)	(6, 7, 8)	(5, 6, 7)

Table 7.5 Normalised fuzzy decision-making matrix

	A_1	A_2	A_3
C_{11}	(0.2, 0.3, 0.4)	(0.4, 0.5, 0.6)	(0.6, 0.7, 0.8)
C_{12}	(0.3, 0.4, 0.5)	(0.5, 0.6, 0.7)	(0.7, 0.8, 0.9)
C_{13}	(0.4, 0.5, 0.6)	(0.5, 0.6, 0.7)	(0.7, 0.8, 0.9)
C_{14}	(0.3, 0.4, 0.5)	(0.6, 0.7, 0.8)	(0.7, 0.8, 0.9)
C_{21}	(0.5, 0.6, 0.7)	(0.6, 0.7, 0.8)	(0.6, 0.7, 0.8)
C_{22}	(0.3, 0.4, 0.5)	(0.5, 0.6, 0.7)	(0.7, 0.8, 0.9)
C_{23}	(0.4, 0.5, 0.6)	(0.5, 0.6, 0.7)	(0.5, 0.6, 0.7)
C_{24}	(0.5, 0.6, 0.7)	(0.6, 0.7, 0.8)	(0.5, 0.6, 0.7)
C_{31}	(0.4, 0.5, 0.6)	(0.5, 0.6, 0.7)	(0.6, 0.7, 0.8)
C_{32}	(0.5, 0.6, 0.7)	(0.6, 0.7, 0.8)	(0.7, 0.8, 0.9)
C_{33}	(0.6, 0.7, 0.8)	(0.6, 0.7, 0.8)	(0.7, 0.8, 0.9)
C_{34}	(0.4, 0.5, 0.6)	(0.5, 0.6, 0.7)	(0.6, 0.7, 0.8)
C_{41}	(0.7, 0.8, 0.9)	(0.7, 0.8, 0.9)	(0.5, 0.6, 0.7)
C_{42}	(0.7, 0.8, 0.9)	(0.6, 0.7, 0.8)	(0.4, 0.5, 0.6)
C_{43}	(0.8, 0.9, 1.0)	(0.7, 0.8, 0.9)	(0.5, 0.6, 0.7)
C_{44}	(0.6, 0.7, 0.8)	(0.6, 0.7, 0.8)	(0.5, 0.6, 0.7)

operations performance. In fact, the company will be better positioned from the manufacturing perspective if implementing in 12-month time. The ideal solution is to implement in 6-month time by which the company will still have the marketing advantages over its rival competitors while its operational resources are better prepared than now. This is also reflected in the further analysis of weighted performance ratings of three implementation time windows with respect to individual sub-criteria. The analysis result is described in Fig. 7.2. It does not indicate the important operational areas for implementing green initiatives but also highlight

Table 7.6 Weighted normalised fuzzy decision-making matrix

	A_1	A_2	A_3
C_{11}	(0.015, 0.023, 0.031)	(0.031, 0.038, 0.046)	(0.046, 0.054, 0.061)
C_{12}	(0.010, 0.014, 0.017)	(0.017, 0.021, 0.024)	(0.024, 0.028, 0.031)
C_{13}	(0.022, 0.028, 0.033)	(0.028, 0.033, 0.039)	(0.039, 0.044, 0.050)
C_{14}	(0.036, 0.048, 0.059)	(0.071, 0.083, 0.095)	(0.083, 0.095, 0.107)
C_{21}	(0.034, 0.041, 0.048)	(0.041, 0.048, 0.055)	(0.041, 0.048, 0.055)
C_{22}	(0.011, 0.015, 0.019)	(0.019, 0.022, 0.026)	(0.026, 0.030, 0.033)
C_{23}	(0.008, 0.010, 0.012)	(0.010, 0.012, 0.014)	(0.010, 0.012, 0.014)
C_{24}	(0.019, 0.022, 0.026)	(0.022, 0.026, 0.030)	(0.019, 0.022, 0.026)
C_{31}	(0.008, 0.010, 0.012)	(0.010, 0.012, 0.014)	(0.012, 0.014, 0.016)
C_{32}	(0.021, 0.025, 0.030)	(0.025, 0.030, 0.034)	(0.030, 0.034, 0.038)
C_{33}	(0.033, 0.039, 0.044)	(0.033, 0.039, 0.044)	(0.039, 0.044, 0.050)
C_{34}	(0.026, 0.033, 0.040)	(0.033, 0.040, 0.046)	(0.040, 0.046, 0.053)
C_{41}	(0.096, 0.110, 0.123)	(0.096, 0.110, 0.123)	(0.068, 0.082, 0.096)
C_{42}	(0.061, 0.070, 0.078)	(0.052, 0.061, 0.070)	(0.035, 0.044, 0.052)
C_{43}	(0.082, 0.092, 0.102)	(0.072, 0.082, 0.092)	(0.051, 0.061, 0.072)
C_{44}	(0.025, 0.029, 0.033)	(0.025, 0.029, 0.033)	(0.021, 0.025, 0.029)

Table 7.7 The final weighted normalised fuzzy decision matrix

	A_1	A_2	A_3
C_1	(0.083, 0.112, 0.140)	(0.147, 0.175, 0.204)	(0.192, 0.220, 0.249)
C_2	(0.072, 0.088, 0.105)	(0.092, 0.108, 0.125)	(0.096, 0.112, 0.128)
C_3	(0.089,0.107, 0.126)	(0.102, 0.120, 0.139)	(0.120, 0.139, 0.157)
C_4	(0.264, 0.300, 0.337)	(0.245, 0.282, 0.318)	(0.175, 0.212, 0.249)

Table 7.8 The relative closeness index of alternatives along with the final ranking

	d^+	d^-	$\tilde{C}_k$	Ranking
A_1	0.182	0.088	0.326	3
A_2	0.067	0.205	0.753	1
A_3	0.069	0.163	0.702	2

the areas that the company is less prepared to handle the new requirements brought by the new GSCM initiative. Therefore, necessary actions should be deployed to address these issues before the green initiative can be fully implemented.

This study demonstrated that GSCM is not limited to the green technical aspects, but also on the non-environmental criteria. The managers are able to capture a fairly complete picture of the context of GSCM implementation through the assessment process. The proposed approach is useful for reviewing GSCM development, which can lead to improving productivity and sustaining the competitive advantages. The proposed hierarchical fuzzy TOPSIS approach provides a practical decision support tool for GSCM implementation since it seeks to take explicit account of multiple criteria in aiding the decision making, and compares

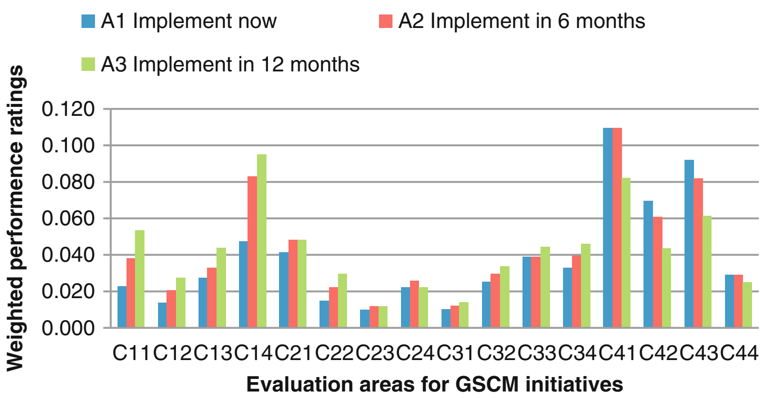


Fig. 7.2 Weighted performance ratings of alternative implementation time windows with respect to individual sub-criteria

and ranks GSCM alternatives in indicator basis and as a system. The constructed hierarchical model can be used for identifying improvement areas when implementing GSCM initiatives within the firm's operational conditions. Although the case study concerned a fashion retail chain is presented in the chapter, the proposed approach can also be used by firms in other industry sectors as it can be easily modified and refined by set relevant criteria to their firm in order to apply it.

7.6 Conclusions

The implementation of a new green initiative could generate a competitive edge for a company. It is also a risky process involving uncertainty. In order to reduce these risks and uncertainties, companies need to evaluate their new green initiatives carefully and assess the improvement areas when implementing green initiatives. This study proposed a fuzzy hierarchical TOPSIS approach to support such an assessment in order to achieve sustainable economic and environmental performance. The hierarchical TOPSIS has demonstrated the superiority of the hierarchical structure of AHP and easiness of implementation of TOPSIS. The fuzzy TOPSIS method is applied in order to solve the problem of decision making in fuzzy environmental segmentation. The proposed method successfully extends the TOPSIS method by applying both linguistic variables and a fuzzy aggregation method which effectively avoids vague and imprecise judgments. From a practical point of view, the illustrative example of the fashion retail chain helps the researchers and practitioners to understand the importance of conducting appropriate risk assessment when implementing GSCM initiatives.

References

Azevedo, S. G., Carvalho, H., & Machado, V. C. (2011). The influence of green practices on supply chain performance: a case study approach. *Transportation Research Part E, 47*, 850–871.

Bacallan, J. J. (2000). Greening the supply chain. *Business and Environment, 6*(5), 11–12.

Bao, Q., Ruan, D., Shen, Y., Hermans, E., & Janssens, D. (2012). Improved hierarchical fuzzy TOPSIS for road safety performance evaluation. *Knowledge-Based Systems, 32*, 84–98.

Boran, F. E., Genc, S., Kurt, M., & Akay, D. (2009). A multi-criteria intuitionistic fuzzy group decision making for selection of supplier with TOPSIS method. *Expert System with Applications, 36*(8), 11363–11368.

Bottani, E., & Rizzi, A. (2006). A fuzzy TOPSIS methodology to support outsourcing of logistics services. *Supply Chain Management: An International Journal, 11*(4), 294–308.

Büyüközkan, G., & Çifçi, G. (2012). A novel hybrid MCDM approach based on fuzzy DEMATEL, fuzzy ANP and fuzzy TOPSIS to evaluate green suppliers. *Expert Systems with Applications, 39*, 3000–3011.

Chamodrakas, I., Alexopoulou, N., & Martakos, D. (2009). Customer evaluation for order acceptance using a novel class of fuzzy methods based on TOPSIS. *Expert Systems with Applications, 36*(4), 7409–7415.

Chan, F. T. S., & Chan, H. K. (2010). An AHP model for selection of suppliers in the fast changing fashion market. *International Journal of Advanced Manufacturing Technology, 51*(9–12), 1195–1207.

Chan, F. T. S., Chan, H. K., Lau, H. C. W., & Ip, R. W. L. (2006). Benchmarking logistics performance of the postal industry—a double AHP approach. *Benchmarking: An International Journal, 13*(6), 636–661.

Chang, C.-W., Wu, C.-R., Lin, C.-T., & Chen, H.-C. (2007). An application of AHP and sensitivity analysis for selecting the best slicing machine. *Computers and Industrial Engineering, 52*(2), 296–307.

Chen, Y. M., & Huang, P.-N. (2007). Bi-negotiation integrated AHP in suppliers selection. *International Journal of Operations and Production Management, 27*(11), 1254–1274.

Chen, C. T., Linb, C. T., & Huang, S. F. (2005). A fuzzy approach for supplier evaluation and selection in supply chain management. *International Journal of Production Economics, 102*(2), 289–301.

Dağdeviren, D. (2008). Decision making in equipment selection: An integrated approach with AHP and PROMETHEE. *Journal of Intelligent Manufacturing, 19*(4), 397–406.

Ertuğrul, İ., & Karakaşoğlu, N. (2008). Comparison of fuzzy AHP and fuzzy TOPSIS methods for facility location selection. *International Journal of Advanced Manufacturing Technology, 39*(7–8), 783–795.

Gao, Y., Liu, Z., Hu, D., Zhang, L., & Gu, G. (2010). Selection of green product design scheme based on multi-attribute decision-making method. *International Journal of Sustainable Engineering, 3*(4), 277–291.

Holt, D., & Ghobadian, A. (2009). An empirical study of green supply chain management practices amongst UK manufacturers. *Journal of Manufacturing Technology Management, 20*(7), 933–956.

Hwang, C. L., & Yoon, K. (1981). *Multiple attributes decision making methods and applications*. Berlin: Springer.

Kahraman, C., Büyüközkan, G., & Ateş, N. Y. (2007). A two phase multi-attribute decision-making approach for new product introduction. *Information Sciences, 177*, 1567–1582.

Kelemenis, A., & Askounis, D. (2010). A new TOPSIS-based multi-criteria approach to personnel selection. *Expert Systems with Applications, 37*(7), 4999–5008.

Kelemenis, A., Eragzakis, A., & Askounis, D. (2011). Support managers' selection using an extension of fuzzy TOPSIS. *Expert Systems with Applications, 38*(3), 2774–2782.

Korpela, J., Lehmusvaara, A., & Nisonen, J. (2007). Warehouse operator selection by combining AHP and DEA methodologies. *International Journal of Production Economics, 108*(1–2), 135–142.

Krohling, R. A., & Campanharo, V. C. (2011). Fuzzy TOPSIS for group decision making: A case study for accidents with oil spill in the sea. *Expert System with Applications, 38*(4), 4190–4197.

Lee, Y., & Kozar, K. A. (2006). Investigating the effect of website quality on e-business success: An analytic hierarchy process (AHP) approach. *Decision Support Systems, 42*(3), 1383–1401.

Li, T. (2010). Applying TRIZ and AHP to develop innovative design for automated assembly systems. *International Journal of Advanced Manufacturing Technology, 46*, 301–313.

Lu, L. Y. Y., Wu, C. H., & Kuo, T.-C. (2007). Environmental principles applicable to green supplier evaluation by using multi-objective decision analysis. *International Journal of Production Research, 45*(18–19), 4317–4331.

Ng, C. Y., & Chuah, K. B. (2010). Evaluation of eco design alternatives using fuzzy AHP methodology. *Design Principles and Practices: An International Journal, 4*(1), 1–14.

Peattie, K. (2001). Golden goose or wild goose? The hunt for the green consumer. *Business Strategy and the Environment, 10*(4), 187–199.

Ramanathan, R. (2007). Supplier selection problem: integrating DEA with the approaches of total cost of ownership and AHP. *Supply Chain Management: An International Journal, 12*(4), 258–261.

Rao, P., & Holt, D. (2005). Do green supply chains lead to competitiveness and economic performance? *International Journal of Operation and Production Management, 25*(9), 898–916.

Roghanian, E., Rahimi, J., & Ansari, A. (2010). Comparison of first aggregation and last aggregation in fuzzy group TOPSIS. *Applied Mathematical Modelling, 34*(12), 3754–3766.

Saaty, T. L. (1980). *The analytic hierarchy process*. New York: McGraw-Hill.

Saaty, T. L. (1996). *Decision making with dependence and feedback: The analytical hierarchy process*. Pittsburgh: RWS.

Sarkis, J. (2003). A strategic decision framework for green supply chain management. *Journal of Cleaner Production, 11*(4), 397–409.

Sarminento, R., & Thomas, A. (2010). Identifying improvement areas when implementing green initiatives using a multitier AHP approach. *Benchmarking: An International Journal, 17*(3), 452–463.

Shang, K. C., Lu, C. S., & Li, S. (2010). A taxonomy of green supply chain management capability among electronic-related manufacturing firms in Taiwan. *Journal of Environmental Management, 91*, 1218–1226.

Sharma, S., & Agrawal, N. (2009). Selection of a pull production control policy under different demand situations for a manufacturing system by AHP-algorithm. *Computers and Operations Research, 36*(5), 1622–1632.

Srivastava, S. K. (2007). Green supply-chain management: A state-of-the-art literature review. *International Journal of Management Review, 9*(1), 53–80.

Vachon, S. (2007). Green supply chain practices and the selection of environmental technologies. *International Journal of Production Research, 45*(18), 4357–4379.

Wang, Y. M., & Elhag, T. M. S. (2006). Fuzzy TOPSIS method based on alpha level sets with an application to bridge risk assessment. *Expert Systems with Applications, 31*(2), 309–319.

Wang, X., Chan, H. K., Yee, W. Y., & Diaz-Rainey, I. (2012). A two-stage Fuzzy-AHP model for risk assessment of implementing green initiatives in the fashion supply chain. *International Journal of Production Economics, 135*(2), 595–606.

Yan, W., Chen, C.-H., Huang, Y., & Mi, W. (2008). An integration of bidding-oriented product conceptualization and supply chain formation. *Computers in Industry, 59*(2–3), 128–144.

Yang, C., Liu, T., Kao, C., & Wang, H. (2010). Integrating AHP and DELPHI methods to construct a green product assessment hierarchy for early stage of product design and development. *International Journal of Operations Research, 7*(3), 35–43.

Yong, D. (2006). Plant location selection based on fuzzy TOPSIS. *International Journal of Advanced Manufacturing Technology, 28*, 839–844.

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control, 8*(3), 338–353.

Zhu, Q., & Sarkis, J. (2004). Relationships between operational practices and performance among early adopters of green supply chain management practices in Chinese manufacturing enterprises. *Journal of Operations Management, 22*(3), 265–289.

Zhu, Q., Sarkis, J., & Lai, K. (2007). Initiatives and outcomes of green supply chain management implementation by Chinese manufacturers. *Journal of Environmental Management, 85*(1), 179–189.

Zhu, Q., Sarkis, J., & Lai, K. (2008). Green supply chain management implications for ''closing the loop''. *Transportation Research Part E: Logistics and Transportation Review, 44*(1), 1–18.

Chapter 8
Fuzzy-ANP Approach for Environmental Risk Assessment of Product Designs

8.1 Introduction

Analytical hierarchy process (AHP) has been widely used to solve many complicated (MCDM) problems, as discussed in the previous chapters. However, one limitation of AHP is the assumption of independence among various factors. The dynamic nature of many MCDM problems determines that factors considered in the decision problem are often not independent. The decision will mostly affect the performance of not just one, but other factors. The dynamic characteristics and complexity of the problem environment would require intensive and robust analysis in the decision making process. To address this issue, the ANP is used to take critical factors and their interdependencies into consideration. Nevertheless, ANP does not allow for uncertainty among factors. In fact, the uncertainty associated with the problem, or the lack of environmental data, is the main challenge to many MCDM. Thereby, fuzzy logic, which can be employed to deal with uncertain parameters and information, is introduced in the pairwise comparison of ANP to make up for this deficiency in conventional ANP.

AHP does not explicitly consider the interactions within the various factors/clusters, and the criteria considered are usually not independent because of the dynamic nature of the problems. To overcome the disadvantages of the previously proposed AHP models, ANP is often used to solve the problem of dependence among alternatives or criteria. The ANP approach is capable of handling interdependence among criteria by obtaining their composite weights through the development of a supermatrix. The supermatrix is a partitioned matrix, where each submatrix is composed of a set of relationships between two clusters in a network structure. The arrows represent the inter-dependence among the life cycle phases and associated criteria. The inter-dependencies are taken into account and in this way the effects of phases/criteria on each other are analysed. In order to solve the supermatrix, firstly, each of the columns may either be normalised by dividing each weight in the column by the sum of that column. In this way, the blocks in each column of the supermatrix are weighted, which is known as the weighted supermatrix. The final weights are then obtained from the limit matrix, in which the constant values of each value are determined by taking the necessary limit of the

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weighted supermatrix. In addition to this, the final weights can be calculated using matrix operations. Matrix operations are easy to follow and often employed in order to convey how dependencies are worked out (Dağdeviren and Yüksel 2010).

This chapter presents a dynamic approach that integrates fuzzy logic and ANP for conducting environmental risk assessment in order to select environmental sustainable product designs. An illustrative case example is provided as an operational guideline for how to apply it to the life cycle assessment of eco-designs. This is in contrast to the FAHP approach in Chap. 5. The results show that the proposed fuzzy ANP approach is a viable and highly capable methodology and can be used as an effective tool for the evaluation of environmentally sustainable product designs.

8.2 Using FANP and Fuzzy AHP for Green Design Evaluation

In this section, we propose a dynamic approach for the evaluation of eco-designs. First of all, with reference to the EuP directive as discussed in Chap. 5, the evaluation framework is developed which decomposes a complex decision problem into a network structure. After that, fuzzy AHP is employed to acquire the comparative ratings of alternative designs when conducting the environmental impact assessment. Then Fuzzy ANP is used to determine weights of product life cycle phases and main criteria within each phase through pairwise comparison. Finally, the aggregated evaluation is carried out and the best green design can be selected.

8.2.1 An Evaluation Framework for Eco-Designs

The selection of eco-designs requires a systematic approach to integrate environmental considerations into new product development. It is essential to break down this complex problem into more manageable sub-problems. As illustrated in Fig. 8.1, the evaluation framework is composed of four stages. The first stage, the overall goal, is the selection of the best eco-design. The second stage includes the product life cycle phases to be considered in the evaluation. According to the EuP directive (European Council 2005), 'Life cycle' means the consecutive and interlinked stages of an EuP from raw material use to final disposal. It is recommended that the analysis should be broken down into the following six phases:

- L_1. Raw material selection and use
- L_2. Manufacturing
- L_3. Packaging, transport, and distribution
- L_4. Installation and maintenance

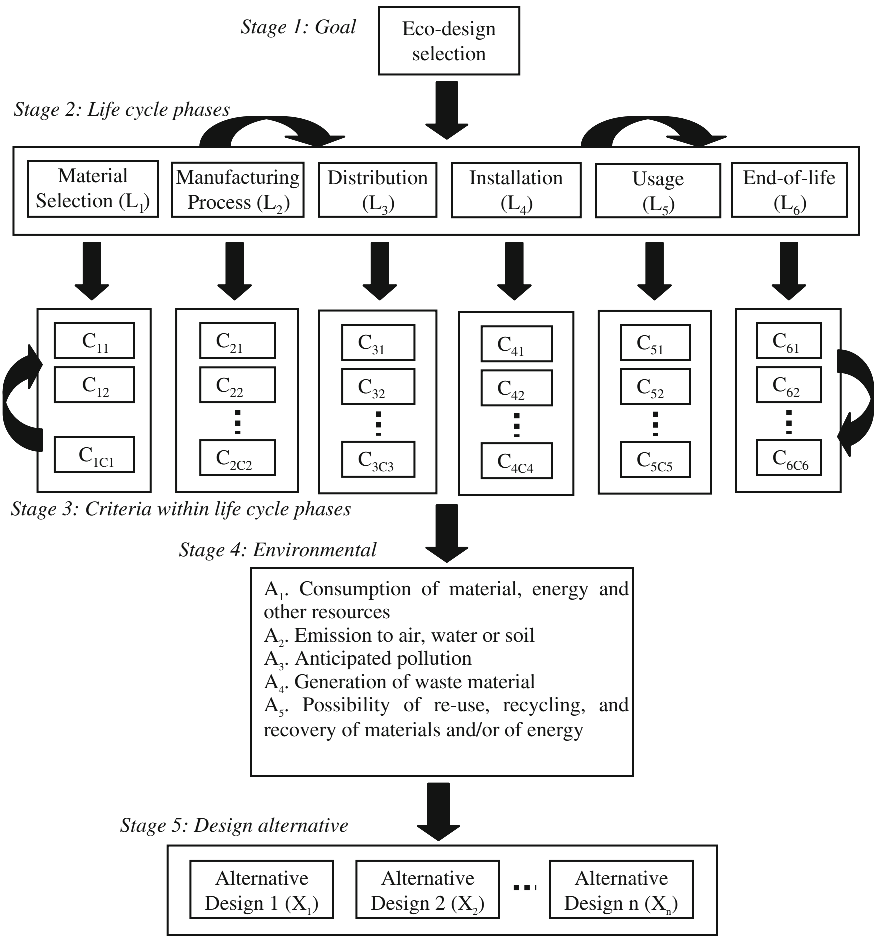

Fig. 8.1 Framework for the evaluation of eco-designs

- L_5. Usage
- L_6. End-of-life (i.e., the state of an EuP having reached the end of its first use until its final disposal)

However, the number of phases for evaluation is not necessary to be restricted to six as proposed above as some products may not involve all 6 phases.

One of the key issues in the evaluation of eco-designs is that of determining which criteria to use in order to assess their environmental performance. At stage three, it is recommended that all the main criteria under each life cycle phase should be identified. For example, in the 'Material Selection' phase, the main types of raw material such as plastics, metals or electronic components used, need to be recorded as evaluation criteria. Details have been listed in Chap. 5 and hence they are not repeated here. The criteria of the third stage are connected to their associated life cycle phases with a single directional arrow. The arrows in the third stage represent the interdependencies among the criteria. For example, the selection of raw material type may have an effect on the way that a product is manufactured. The interdependencies among criteria in this stage are taken into account and the effects of the criteria on each other are analysed in Sect. 8.2.3.

At stage four, for all the criteria identified throughout the entire life cycle phases, the impact assessment can be carried out by grouping the environmental output of alternative product designs (X_n). This output is categorised into 5 assessment attributes at the fourth level according to the requirement of the EuP directive:

- A_1. Consumption of material, energy and other resources
- A_2. Emission to air, water or soil
- A_3. Anticipated pollution
- A_4. Generation of waste material
- A_5. Possibility of re-use, recycling, and recovery of materials and/or of energy

At stage five, the product design alternatives (X_n) are listed at the bottom of the hierarchical network. The next question is how to evaluate a new design with different options on different criteria and it will be discussed in the following sections.

8.2.2 Use Fuzzy AHP for Environmental Risk Assessment

The LCA helps to establish links between the environmental impacts, operation and economics of the process. However, one major challenge of LCA is to assess the potential environmental impact associated with a product by compiling an inventory of relevant inputs and outputs. The evaluation of the potential environmental impacts requires substantial data from the manufacturer and scientific evidences. In fact, many organizations, especially small and medium enterprises (SMEs), do not have sufficient resources to carry out a systematic LCA due to a lack of information or expertise when coming to the selection of alternative product designs. In addition, it is difficult to compare different factors due to the lack of adequate information. Fuzzy set theory has been proven to have advantages within vague, imprecise and uncertain contexts. Fuzzy AHP is adopted in this chapter to rank the level of relevant environmental risk of design options. Readers can refer to Chap. 5 for the detail of fuzzy AHP. The triangular fuzzy numbers are used as a pairwise comparison scale for deriving the impact ratings of different design alternatives. To ensure the accuracy of the method, the consistency measure is also performed to screen out inconsistency of responses. Since triangular fuzzy numbers are used, it has to be defuzzified into a crisp number to compute the consistency index (CI). The central value of the triangular fuzzy number is used here since the central value corresponds to the centroid of the triangular area because of the symmetry of the triangular number.

8.2.3 Use Fuzzy ANP to Estimate Weights for Life Cycle Phases and Criteria

Using the fuzzy AHP method discussed in Chap. 5, environmental impact assessment can be conducted and ratings of environmental risks for each criterion with respect to the different designs can be obtained. Nonetheless, selecting the best green design is still a challenging task due to the conflicting nature of the objectives. For example, while material selection has a significant effect on the economic cost, energy consumption during usage could be the most important factor that affects the consumers purchasing decision. Therefore it is necessary to know how important one life cycle phase or criterion is over another for a particular product. In other words, the weights between main phases and associated criteria have to be determined for the evaluation.

The fuzzy AHP method is useful to rank how important one factor is over another in the evaluation. Nevertheless, there is also a limitation since the basic assumption of AHP is the condition of functional independence of decision levels and the criteria in each level. The decision making problem in the study involves interaction between life cycle phases and various criteria within those different life cycle phases, as illustrated in Fig. 1. For example, 'Material Selection' phase may have an impact in other phases such as "Manufacturing Process" or "Usage". In order to determine the relationship of the degree of interdependence, here, the ANP, is used to address the relative importance of the evaluation criteria. Saaty (1996) suggested the use of AHP to solve the problem of independence among criteria, and the use of ANP to solve the problem of dependence among criteria. The value of ANP lies in its ability to easily represent the decision making problem which involves many complicated relationships. Not only does it enable the pairwise comparisons of life cycle phases, but it also provides the decision maker to independently compare all the interconnected criteria.

Due to the dynamic characteristics of LCA, we explore the appropriateness of ANP to allow for the explicit consideration of interactions in the decision making process. In this study, the matrix operations of Saaty and Takizawa (1986) are used as they are easy-to-understand in the calculation of the weights of life cycle phases and criteria by fuzzy ANP. The fuzzy ANP process starts with pairwise comparisons of life cycle phases, with respect to their relative importance towards the goal, using the fuzzy AHP described in Chap. 5. Similar, pairwise comparisons of the criteria in each life cycle phase are conducted with respect to their relative importance towards their associated phases. By using triangular fuzzy numbers again, the relative strength of each pair of phases/criteria and the preferences of the decision maker in the same hierarchy are indicated. Once the pairwise comparisons are completed, the local weight vectors, w_1 and w_2, are computed for life cycle phases and associated criteria respectively. In order to control the result of the method, the consistency ratio for each of the matrices is calculated to ensure that it is less than 0.10. If there is no interrelationship between various criteria in each life cycle phase or across phases, the relative importance weights for the criteria can be calculated. The next step is to resolve the effects of the interdependence that exists among life cycle phases and the evaluation criteria. The decision makers examine the effects of all the phases on each other by using pairwise comparison. Various pairwise comparison matrices, which identity the relative impacts of interrelationships between phases, are formed for each of the phase. The normalised principal eigenvectors for these matrices are calculated and shown as column component in interdependence weight matrix of life cycle phases A, where zeros are assigned to the eigenvector weights of the phases from which a given phase is given. The same process is repeated for the criteria in each life cycle phase and the interdependence weight matrix of criteria B is structured. Now the interdependence weights of the phases and criteria can be obtained by synthesising the results from previous two steps as follows:

$$W_l = Aw_1^T, \text{ and } W_{lc} = Bw_2^T. \tag{8.1}$$

Along with the comparative environmental ratings $R_{lc}(X_i)$ of alternative designs relating to the criteria, the calculated interdependence weights, W_l and W_{lc} are then used for the aggregated evaluation of eco-designs. This will be illustrated in Sect. 8.2.4 (Step 4).

8.2.4 FANP Approach for Green Design Evaluation

Here, both fuzzy AHP and ANP are employed as an innovative decision support model for the evaluation of eco-designs over the entire product life cycle. Making the final decision requires a systematic approach to incorporate all the elements (see Table 8.1) in the evaluation framework into consideration. A step by step approach for the green design selection process, considering all environmental issues from cradle to grave, is shown in the flowchart in Fig. 8.2.

Step 1: Similar to conventional LCA, the proposed approach starts with defining the problem under study which is the selection of best green design from alternative designs. An expert group comprising the product designers, the engineers, and the plant manager needs to be formed for the evaluation process. A system analysis is conducted through analysing the main phases of the product life cycle (e.g. raw material selection and use; manufacturing; distribution; installation and maintenance, usage; and end-of-life) and the main criteria are then identified in each phase. Relevant data such as the bill of material, manufacturing processes, packaging, means of transportation, and recycling practices need to be collected to support the identification process. After that, the hierarchical network for the selection of eco-designs can be constructed, as illustrated in Table 8.1.

Table 8.1 The structure framework of LCA based green design selection

Overall objective	Life cycle phase	Criteria	W_l	W_{lc}	R_{lc}	Alternative designs (Xi)
Aggregative green design index (AERI)	L_1		W_1			X_1
		C_{11}		W_{11}	$R_{11}(X_i)$	X_2
		C_{12}		W_{12}	$R_{12}(X_i)$	…
		…				X_n
		C_{1c_1}		W_{1c_1}	$R_{1C_1}(X_i)$	
	L_2		W_2			
		C_{21}		W_{21}	$R_{21}(X_i)$	
		C_{22}		W_{22}	$R_{22}(X_i)$	
		…				
		C_{2c_2}		W_{2c_2}	$R_{2C_2}(X_i)$	
	L_3		W_3			
		C_{31}		W_{31}	$R_{31}(X_i)$	
		C_{32}		W_{32}	$R_{32}(X_i)$	
		…				
		C_{3c_3}		W_{3c_3}	$R_{3C_3}(X_i)$	
	L_4		W_4			
		C_{41}		W_{41}	$R_{41}(X_i)$	
		C_{42}		W_{42}	$R_{42}(X_i)$	
		…				
		C_{4c_4}		W_{4c_4}	$R_{4C_4}(X_i)$	
	L_5		W_5			
		C_{51}		W_{51}	$R_{51}(X_i)$	
		C_{52}		W_{52}	$R_{52}(X_i)$	
		…				
		C_{5c_5}		W_{5c_5}	$R_{5C_5}(X_i)$	
	L_6		W_6			
		C_{61}		W_{61}	$R_{61}(Xi)$	
		C_{62}		W_{62}	$R_{62}(X_i)$	
		…				
		C_{6c_6}		W_{6c_6}	$R_{6C_6}(X_i)$	

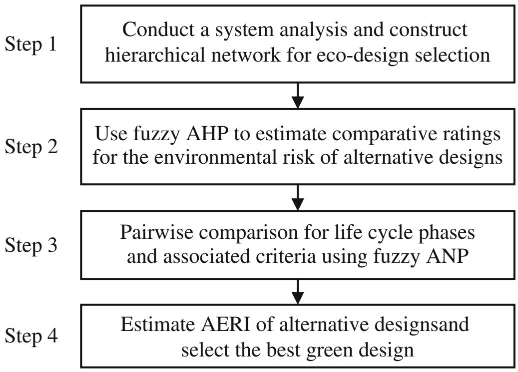

Fig. 8.2 Procedures of the proposed approach

Step 2: This step proceeds with the collection of relevant data for the environmental risk assessment. Unlike a conventional LCA where a systematic assessment can only be carried out with sufficient information, expert opinions will be collected in the proposed approach if scientific evidence is not available. The fuzzy AHP described in Chap. 5 is utilised to estimate comparative ratings for the environmental performance of alternative designs against each criterion.

Step 3: The ANP is applied to reflect the interdependence that exists between the criteria within the decision hierarchical network. Experts' opinion is required through paired comparison analysis. The different degrees of influence are expressed with nine linguistic terms and the equivalent fuzzy membership functions for linguistic values. The Fuzzy AHP is also used here to calculate the weights. The interdependent weights of the life cycle phases and evaluation criteria are then obtained by fuzzy ANP as discussed in Sect. 8.2.3

Step 4: In the final stage of the evaluation, the alternative designs are ranked with the aggregated environmental risk index (AERI) through aggregated evaluation. An AERI considers all the ratings of environmental risks for the identified criteria throughout the life cycle phases and the importance weights between different criteria and life cycle phases in the estimation.

$$\mathrm{AERI} = \sum_{l=1}^{6} W_l \sum_{c=1}^{c_l} W_{lc} R_{lc}(X_i). \tag{8.2}$$

This index is useful in evaluating different product designs and the one with the lowest AEI value implies that the associated design should be selected.

8.3 Case Study

The case study discussed here is concerned with a manufacturing company selecting the best design for one of its electronic products. The company wants to take into account all the possible important criteria which can have a negative impact on the environment throughout its product life cycle. Therefore, an LCA was conducted for an electronic personal product. Details of the case and the LCA results were reported in Yung et al. (2009, 2011). In this study, the authors make reference to the case to demonstrate how the proposed model can facilitate and simplify new product development from green design perspective.

Step 1: The evaluation starts with analysing the product life cycle to decide the number of phases required for evaluation. Since the electronic product used in this case study is a battery-driven product, it does not require phase 4, installation and maintenance. Therefore, only five life cycle phases were defined in the selection framework. Like most multiple-criteria decision making processes, one challenge of the proposed approach is to choose the criteria against which alternatives will be evaluated. With reference to the case (Yung et al. 2009, 2011), the key criteria under each phase can thus be identified. The hierarchy of the LCA based green design selection was constructed as shown in Table 8.2 (only selected criteria are shown here for demonstration purpose). In contrast, if an LCA of a product has not been developed before, some background information has to be collected in order to construct a similar hierarchical structure as shown in Fig. 8.1 and Table 8.2.

Step 2: After structuring the hierarchical network, an environmental risk assessment was conducted through detailed evaluation of different designs for every criterion at each life cycle phase. The fuzzy AHP method was used to assign comparative ratings of environmental risks to the different alternative designs being assessed. Here, the criterion C_{11}, plastics, is used

Table 8.2 An example of hierarchy structure for LCA based green design evaluation

Life cycle phases	Criteria	Assessment attributes	Alternative designs
L_1. Material selection	C_{11}. Plastics	A_1. Consumption of material, energy and other resources	Design 1 (X_1) Design 2 (X_2) Design 3 (X_3)
	C_{12}. Electronic component	A_2. Emission to air, water or soil	Design 4 (X_4)
	C_{13}. Metal	A_3. Anticipated pollution	
		A_4. Generation of waste material	
L_2. Manufacturing	C_{21}. Solder paste painting		
	C_{22}. SMD pick and place component	A_5. Possibility of re-use, recycling, and recovery of materials and/or of energy	
	C_{23}. Re-flow soldering		
	C_{24}. PAD cleaning		
	C_{25}. DIE sticking		
	C_{26}. Wire bonding		
	C_{27}. Packing		
L_3. Distribution	C_{31}. Packaging		
	C_{32}. Transportation		
L_4. Usage	C_{41}. Energy consumption		
	C_{42}. Waste		
	C_{43}. Residue		
L_5. End-of-life	C_{51}. Reuse		
	C_{52}. Remanufacture		
	C_{53}. Recycling		
	C_{54}. Toxic material		
	C_{55}. Landfill for non-toxic Material		

Table 8.3 The fuzzy evaluation of impact assessment A1 with respect to criterion C_{11}

$C_{11}\_A_1$	Design 1	Design 2	Design 3	Design 4
Design 1	(1, 1, 1)	(2/5, 1/2, 2/3)	(5/2, 3, 7/2)	(3/2, 2, 5/2)
Design 2	(3/2, 2, 5/2)	(1, 1, 1)	(7/2, 4, 9/2)	(5/2, 2, 7/2)
Design 3	(2/7, 1/3, 2/5)	(2/9,1/4, 2/7)	(1, 1, 1)	(2/5, 1/2, 2/3)
Design 4	(2/5, 1/2, 2/3)	(2/7, 1/2, 2/5)	(3/2, 2, 5/2)	(1, 1, 1)

as an example to assess the consumption of material, energy and other resources among the four design alternatives. First, the fuzzy evaluation matrix of alternative designs was constructed by the pairwise comparison of the four different designs with respect to the assessment category A1 using triangular fuzzy numbers, which is shown in Table 8.3.

The next step (Step 3) is to calculate the fuzzy geometric mean ($\tilde{r}_i$) and fuzzy weights ($\tilde{w}_i$) of all life cycle phases. To use Eq. 5.4 to obtain the fuzzy weights of dimensions for owners group, that is:

$$\begin{aligned}\tilde{r}_1 &= (\tilde{a}_{11} \otimes \tilde{a}_{12} \otimes \tilde{a}_{13} \otimes \tilde{a}_{14})^{1/4} \\ &= \left(\left(1 \times \frac{2}{5} \times \frac{1}{2} \times \frac{2}{3}\right)^{\frac{1}{4}}, \left(1 \times \frac{1}{2} \times 3 \times 2\right)^{\frac{1}{4}}, \left(1 \times \frac{2}{3} \times \frac{7}{2} \times \frac{5}{2}\right)^{\frac{1}{4}} \right) \\ &= (1.107, 1.316, 1.554).\end{aligned}$$

Similarly, we can obtain the remaining $\tilde{r}_i$, that is,

$$\begin{aligned}\tilde{r}_2 &= (1.903, 2.213, 2.505) \\ \tilde{r}_3 &= (0.399, 0.452, 0.525) \\ \tilde{r}_4 &= (0.643, 0.760, 0.904).\end{aligned}$$

For the risk rating of each dimension, they can be calculated by Eq. 5.5 as follow,

$$\begin{aligned}\tilde{R}_1 &= \tilde{r}_1 \otimes (\tilde{r}_1 \oplus \tilde{r}_2 \oplus \tilde{r}_3 \oplus \tilde{r}_4)^{-1} \\ &= (1.107, 1.316, 1.554) \otimes (1/(1.107 + \cdots + 0.643), 1/(1.316 + \cdots + 0.760), 1/(1.554 + \cdots + 0.904)) \\ &= (0.202, 0.278, 0.383).\end{aligned}$$

Likewise, the remaining ratings of alternative design options can be obtained and the results are displayed in Table 8.4.

Table 8.4 Fuzzy weights for different life cycle phases

	L	M	U
$\tilde{R}_1$	0.202	0.278	0.383
$\tilde{R}_2$	0.347	0.467	0.618
$\tilde{R}_3$	0.073	0.095	0.130
$\tilde{R}_4$	0.117	0.160	0.223

Table 8.5 Non-fuzzy ratings for alternative design options

	Non-fuzzy weights	Normalised weights
R_1	0.288	0.279
R_2	0.477	0.463
R_3	0.099	0.096
R_4	0.167	0.162

Using the COA method (Eq. 5.6), the non-fuzzy value of the f risk ratings for each design option can be calculated. To take the Design 1 as an example, the calculation process is as follows:

$$\begin{aligned} w_1 &= \frac{[(Uw_i - Lw_i) + (Mw_i - Lw_i)]}{3} + Lw_i \\ &= \frac{(0.383 - 0.202) + (0.278 - 0.202)}{3} + 0.202 \\ &= 0.288. \end{aligned}$$

Table 8.5 shows the non-fuzzy risk ratings of alternative design options and their normalised value.

Now, for Criterion C_{11}, the environmental risk ratings of different designs with respect to the remaining four assessment attributes were determined by following the same procedure discussed above. Using the same approach, the environmental risk ratings of alternative designs with respect to the five assessment attributes can be conducted for all the criteria identified in the product life cycle. The summary of environmental risk assessment results, with respect to the criteria in all life cycle phases, is displayed in Table 8.6.

Step 3: After the environmental assessment, the importance weights of each life cycle phase and its associated criteria were estimated using the Fuzzy ANP approach. The assessment starts with a pairwise comparison among the main life cycle phases. Assuming there is no interaction between them, the comparative weights are then determined by the fuzzy AHP method discussed above. The fuzzy evaluation matrix and the comparative weights of each life cycle phase are shown in Table 8.7.

Next, interdependent weights of the life cycle phases are calculated and the dependencies among the phases are considered. Dependencies among the phases are determined by analysing the impact of each phase on every other phase using pairwise comparison. On the basis of a group study by an expert team, the dependencies between life cycle phases for this case study are determined and shown in Fig. 8.3. The dependencies among all phases are then defined via pairwise comparison matrices. Five pairwise comparison matrices are formed for L_1, L_2, L_3, L_4 and L_5 phases. The resulting relative importance weights of these matrices are calculated. The results are displayed in Table 8.8, separately for each phase. “0” values presented in Table 8.8 mean that there is no dependence between two phases. The numerical values show the degree of relative impact between two factors.

Table 8.6 Summary of environmental risk ratings with respect to criteria in all life cycle phases

		Design 1	Design 2	Design 3	Design 4			Design 1	Design 2	Design 3	Design 4
C_{11}	A_1	0.279	0.463	0.096	0.162	C_{31}	A_1	0.131	0.265	0.193	0.411
	A_2	0.117	0.389	0.389	0.105		A_2	0.199	0.260	0.209	0.324
	A_3	0.214	0.549	0.132	0.105		A_3	0.204	0.262	0.247	0.324
	A_4	0.200	0.553	0.144	0.105		A_4	0.201	0.264	0.226	0.275
	A_5	0.214	0.132	0.549	0.105		A_5	0.184	0.262	0.211	0.342
C_{12}	A_1	0.205	0.401	0.293	0.102	C_{32}	A_1	0.150	0.271	0.197	0.382
	A_2	0.322	0.291	0.266	0.101		A_2	0.178	0.256	0.193	0.314
	A_3	0.196	0.389	0.269	0.101		A_3	0.197	0.250	0.221	0.314
	A_4	0.232	0.370	0.232	0.109		A_4	0.207	0.269	0.237	0.320
	A_5	0.293	0.293	0.212	0.150		A_5	0.178	0.256	0.193	0.334
C_{13}	A_1	0.250	0.490	0.104	0.155	C_{41}	A_1	0.169	0.331	0.331	0.169
	A_2	0.403	0.212	0.212	0.122		A_2	0.185	0.382	0.291	0.361
	A_3	0.212	0.408	0.269	0.122		A_3	0.212	0.277	0.223	0.361
	A_4	0.223	0.341	0.330	0.097		A_4	0.239	0.304	0.240	0.336
	A_5	0.345	0.311	0.285	0.161		A_5	0.194	0.330	0.210	0.324
C_{21}	A_1	0.194	0.382	0.308	0.115	C_{42}	A_1	0.213	0.338	0.280	0.169
	A_2	0.222	0.419	0.235	0.110		A_2	0.193	0.275	0.187	0.353
	A_3	0.234	0.372	0.234	0.110		A_3	0.193	0.275	0.187	0.353
	A_4	0.200	0.312	0.365	0.101		A_4	0.230	0.307	0.232	0.328
	A_5	0.298	0.298	0.216	0.159		A_5	0.190	0.319	0.218	0.313
C_{22}	A_1	0.221	0.245	0.277	0.257	C_{43}	A_1	0.170	0.353	0.239	0.239
	A_2	0.221	0.245	0.290	0.254		A_2	0.188	0.359	0.242	0.261
	A_3	0.218	0.261	0.241	0.254		A_3	0.173	0.361	0.248	0.261
	A_4	0.224	0.232	0.281	0.291		A_4	0.204	0.266	0.214	0.347
	A_5	0.221	0.275	0.276	0.230		A_5	0.194	0.280	0.240	0.299
C_{23}	A_1	0.127	0.425	0.294	0.154	C_{51}	A_1	0.173	0.266	0.245	0.316
	A_2	0.292	0.319	0.256	0.102		A_2	0.188	0.348	0.235	0.236
	A_3	0.199	0.395	0.273	0.102		A_3	0.194	0.381	0.197	0.236
	A_4	0.298	0.298	0.216	0.152		A_4	0.225	0.251	0.237	0.320
	A_5	0.296	0.296	0.139	0.230		A_5	0.181	0.258	0.208	0.336
C_{24}	A_1	0.186	0.308	0.408	0.098	C_{52}	A_1	0.151	0.310	0.199	0.340
	A_2	0.335	0.279	0.261	0.144		A_2	0.194	0.240	0.194	0.238
	A_3	0.199	0.378	0.278	0.144		A_3	0.195	0.357	0.206	0.238
	A_4	0.251	0.356	0.233	0.145		A_4	0.213	0.278	0.288	0.213
	A_5	0.265	0.314	0.207	0.229		A_5	0.183	0.260	0.209	0.339
C_{25}	A_1	0.155	0.303	0.290	0.252	C_{53}	A_1	0.190	0.301	0.134	0.375
	A_2	0.261	0.153	0.133	0.132		A_2	0.180	0.307	0.195	0.338
	A_3	0.192	0.382	0.269	0.132		A_3	0.249	0.240	0.231	0.338
	A_4	0.233	0.337	0.233	0.167		A_4	0.232	0.270	0.227	0.308
	A_5	0.300	0.300	0.218	0.160		A_5	0.177	0.256	0.192	0.334
C_{26}	A_1	0.347	0.240	0.240	0.172	C_{54}	A_1	0.151	0.310	0.199	0.340
	A_2	0.342	0.198	0.261	0.172		A_2	0.194	0.240	0.194	0.231

(continued)

Table 8.6 (continued)

		Design 1	Design 2	Design 3	Design 4			Design 1	Design 2	Design 3	Design 4
	A_3	0.206	0.370	0.269	0.172		A_3	0.199	0.364	0.210	0.231
	A_4	0.243	0.353	0.243	0.182		A_4	0.205	0.267	0.276	0.254
	A_5	0.306	0.306	0.221	0.156		A_5	0.183	0.260	0.209	0.339
C_{27}	A_1	0.155	0.303	0.290	0.252	C_{55}	A_1	0.170	0.262	0.241	0.326
	A_2	0.261	0.153	0.133	0.132		A_2	0.186	0.345	0.233	0.232
	A_3	0.192	0.382	0.269	0.132		A_3	0.200	0.393	0.203	0.232
	A_4	0.233	0.337	0.233	0.167		A_4	0.228	0.254	0.240	0.323
	A_5	0.300	0.300	0.218	0.160		A_5	0.183	0.261	0.210	0.340

Table 8.7 The fuzzy evaluation of comparative weights of life cycle phases

Life cycle phases	L_1	L_2	L_3	L_4	L_5	Weights
L_1	(1, 1, 1)	(5/4, 17/9, 5/2)	(19/6, 23/6, 13/3)	(19/7, 10/3, 4)	(19/6, 13/3, 21/4)	0.403
L_2	(2/5, 1/2, 4/5)	(1, 1, 1)	(16/7, 10/3, 4)	(17/9, 5/2, 22/7)	(2, 10/3, 13/3)	0.276
L_3	(1/4, 1/4, 1/3)	(1/4, 1/3, 3/7)	(1, 1, 1)	(1/3, 4/9, 5/8)	(5/8, 5/4, 17/9)	0.089
L_4	(1/4, 2/7, 3/8)	(1/3, 2/5, 1/2)	(8/5, 9/4, 26/9)	(1, 1, 1)	(9/5, 5/2, 19/6)	0.150
L_5	(1/5, 1/4, 1/3)	(1/4, 1/3, 1/2)	(1/2, 4/5, 8/5)	(1/3, 2/5, 5/9)	(1, 1, 1)	0.082

The relative importance of the criteria on the basis of inner dependence can be calculated by using the data provided in Tables 8.7 and 8.8 as follows:

$$W_L = \begin{bmatrix} L_1 \\ L_2 \\ L_3 \\ L_4 \\ L_5 \end{bmatrix} = \begin{bmatrix} 0.231 & 0.445 & 0.342 & 0.273 & 0.196 \\ 0.307 & 0.555 & 0.412 & 0.403 & 0.254 \\ 0 & 0 & 0.246 & 0 & 0.184 \\ 0 & 0 & 0 & 0.324 & 0.199 \\ 0.430 & 0 & 0 & 0 & 0.167 \end{bmatrix} \times \begin{bmatrix} 0.402 \\ 0.276 \\ 0.089 \\ 0.150 \\ 0.082 \end{bmatrix} = \begin{bmatrix} 0.303 \\ 0.395 \\ 0.037 \\ 0.065 \\ 0.187 \end{bmatrix}.$$

According to the calculation results, there are significant differences between the weights obtained for interdependent life cycle phases and the results obtained in Table 8.7 when dependencies are not considered.

Using the same procedure, the weights of criteria in each life cycle phase are calculated. The detail of fuzzy evaluation matrices and comparative weights of criteria with respect of its life cycle phases are displayed in the Tables 8.9, 8.10, 8.11, 8.12 and 8.13. Since there is no impact between criteria within both "Material Selection" and "End of Life" phases, the local weights of the criteria with respect of their associated phases are estimated through the fuzzy AHP, as

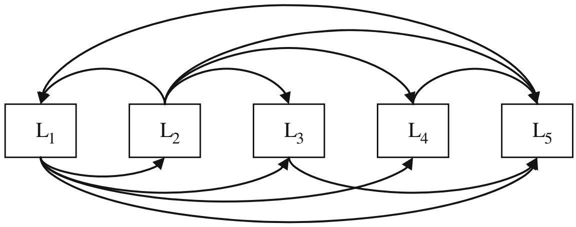

Fig. 8.3 Inner dependence among life cycle phases

Table 8.8 Degree of relative impact for life cycle phases

Life cycle phases	L_1	L_2	L_3	L_4	L_5
L_1	0.231	0.445	0.342	0.273	0.196
L_2	0.307	0.555	0.412	0.403	0.254
L_3	0	0	0.246	0	0.184
L_4	0	0	0	0.324	0.199
L_5	0.430	0	0	0	0.167

Table 8.9 Fuzzy evaluation of comparative weights of criteria in life cycle phase L_1

L_1	C_{11}	C_{12}	C_{13}	Weights
C_{11}	(1, 1, 1)	(1, 3/2, 2)	(1, 2, 3)	0.447
C_{12}	(1/2, 2/3, 1/1)	(1, 1, 1)	(1, 3/2, 2)	0.317
C_{13}	(1/3, 1/2, 1)	(1/2, 2/3, 1)	(1, 1, 1)	0.236

Table 8.10 Fuzzy evaluation of comparative weights of criteria in life cycle phase L_2

L_2	C_{21}	C_{22}	C_{23}	C_{24}	C_{25}	C_{26}	C_{27}	Independent weights	Weights
C_{21}	0.684	0.353	0	0	0	0	0	0.136	0.163
C_{22}	0	0.647	0.427	0	0.348	0	0	0.198	0.275
C_{23}	0	0	0.573	0.415	0.000	0.400	0	0.240	0.221
C_{24}	0.316	0	0	0.585	0.419	0	0	0.076	0.141
C_{25}	0	0	0	0	0.233	0.362	0.378	0.129	0.111
C_{26}	0	0	0	0	0	0.237	0.408	0.129	0.068
C_{27}	0	0	0	0	0	0	0.214	0.092	0.020

shown in Tables 8.9 and 8.13. The overall weights information for each element in the hierarchical network is summarised in Table 8.14. At the same time, the consistency ratio of each judgement is calculated and checked to ensure that it is lower than or equal to 0.1.

Table 8.11 Fuzzy evaluation of comparative weights of criteria in life cycle phase L_3

L_3	C_{31}	C_{32}	Independent weights	Weights
C_{31}	0.415	0	0.434	0.180
C_{32}	0.585	1	0.566	0.820

Table 8.12 Fuzzy evaluation of comparative weights of criteria in life cycle phase L_4

L_4	C_1	C_{42}	C_{43}	Independent weights	Weights
C_{41}	1	0.684	0	0.226	0.535
C_{42}	0	0.316	0.415	0.451	0.276
C_{43}	0	0	0.585	0.322	0.188

Table 8.13 Fuzzy evaluation of comparative weights of criteria in life cycle phase L_5

L_5	C_{51}	C_{52}	C_{53}	C_{54}	C_{55}	Weights
C_{51}	(1, 1, 1)	(1, 3/2, 2)	(1/2, 2/3, 1)	(1, 3/2,2)	(1/2, 2/3, 1)	0.197
C_{52}	(1/2, 2/3, 1/1)	(1, 1, 1)	(2/5, 1/2, 2/3)	(1, 1, 1)	(1/2, 2/3, 1)	0.145
C_{53}	(1, 3/2, 2)	(3/2, 2, 5/2)	(1, 1, 1)	(3/2, 2, 5/2)	(1, 3/2, 2)	0.295
C_{54}	(1/2, 2/3, 1)	(1, 1, 1)	(2/5, 1/2, 2/3)	(1, 1, 1)	(1, 1, 3/2)	0.159
C_{55}	(1, 3/2, 2)	(1, 3/2, 2)	(1/2, 2/3, 1)	(2/3, 1, 1)	(1, 1, 1)	0.204

Step 4: The aggregative environmental risk index (AERI) of each design can then be calculated through Eq. 8.2. By aggregating environmental impact ratings of each assessment attribute with respect to all criteria and comparative weights between the criteria and life cycle phases, the lowest value of AERI suggests the best green design that the manufacturing company should select. The results are illustrated in Table 8.15, in which the Design 1 has the lowest AERI.

Table 8.14 Summary of weights of life cycle phases and its associated criteria

Life cycle phase	W_l	Criteria	W_{lc}
L_1	0.303	C_{11}	0.447
		C_{12}	0.317
		C_{13}	0.236
L_2	0.395	C_{21}	0.163
		C_{22}	0.275
		C_{23}	0.221
		C_{24}	0.141
		C_{25}	0.111
		C_{26}	0.068
		C_{27}	0.020
L_3	0.037	C_{31}	0.180
		C_{32}	0.820
L_4	0.065	C_{41}	0.535
		C_{42}	0.276
		C_{43}	0.188
L_5	0.187	C_{51}	0.197
		C_{52}	0.145
		C_{53}	0.295
		C_{54}	0.159
		C_{55}	0.204

Table 8.15 The AEI results of four alternative designs

Life cycle phases	L_1	L_2	L_3	L_4	L_5	AEI
Weights	0.303	0.395	0.037	0.065	0.187	
Design 1	1.191	1.181	0.911	0.990	0.974	2.086
Design 2	1.901	1.543	1.304	1.590	1.449	2.973
Design 3	1.272	1.286	1.049	1.220	1.072	2.271
Design 4	0.593	0.890	1.665	1.513	1.512	2.390

8.4 Results and Discussion

The proposed approach provides a more efficient way to assess the environmental performance throughout the entire product life cycle for alternative designs compared to the conventional LCA approach. The AERI values displayed in the Table 8.15 give a clear indication that Design 1 has the lowest overall environmental risk and should be selected. However, a full LCA may be needed if the final two design options exhibiting similar AERI values. Nevertheless, the proposed approach helps the designers to screen out less feasible design options. As a result, it saves the resource and time required to conduct full LCA for all of the design options. In addition, the proposed approach also shows the environmental risk of each design with respect to the life cycle phases, as illustrated in Fig. 8.4. The results reflect the relative importance of each product life cycle phase for improving the environmental performance of product designs. For example, "Material Selection" and "Manufacturing Process" in this case are the two most important stages, since decisions made in these stages could have serious environmental consequences in the later stages of the product life cycle. Although Design 1 has a similar or even worse environmental performance in other life cycle stages comparing to other designs, it stands out among the alternative designs because of relatively better performance in the "Material Selection" and "Manufacturing Process" phases. Such an analysis helps companies to identify the

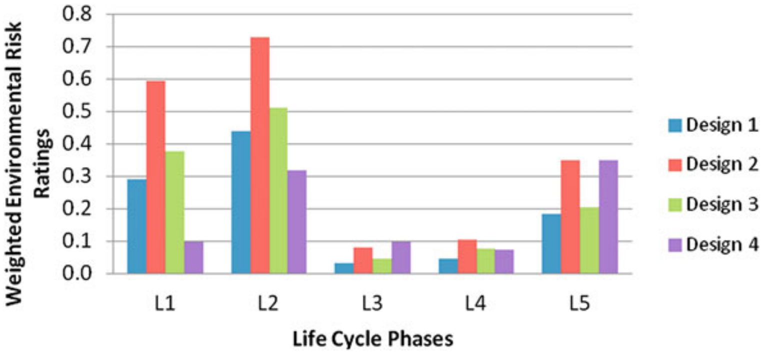

Fig. 8.4 Environmental performance of each design with respect to the life cycle phases

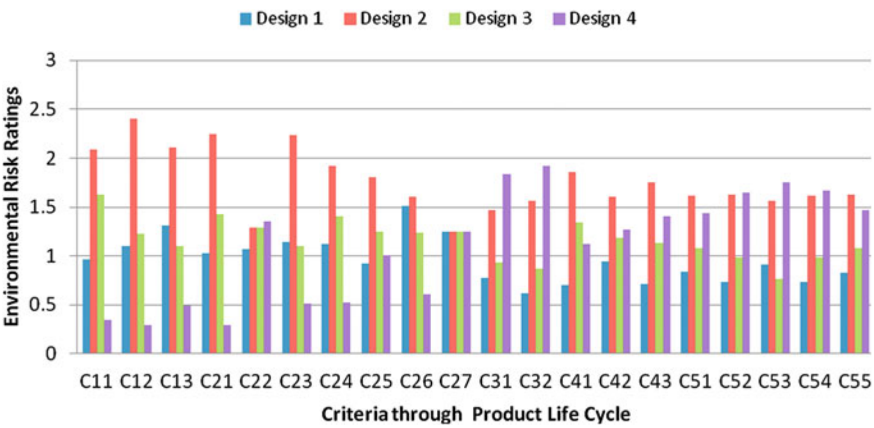

Fig. 8.5 Environmental performance of each design with respect to the criteria

life cycle phases that have the most significant negative environmental effect, and therefore, extra resources can be deployed for more rigorous assessment.

Even with the lowest AEI value, Design 1 could have a relative higher environmental risk at certain life cycle phases compared to other design alternatives. In order to make further improvement, analysis is conducted to examine how individual criteria throughout entire product life cycle contribute to the overall performance. The results are illustrated in Fig. 8.5, where environmental performance of each design with respect the criteria are displayed. As shown in Fig. 8.5, Design 4, which has the second highest AEI values, have lower risk than Design 1 in C_{11}, C_{12}, C_{13} of the "Material Selection" phase and a few criteria in the "Manufacturing" phases. In order to make improvement in these criteria for the Design 1, some of Design 4's specifications are adopted. However, better environmental performance in the above criteria is the result of the decision made in the material selection phase. The designers have to accept a compromise that such changes will lead to higher risking ratings in both C_{31} (Packaging), C_{32} (Transportation) and C_{53} (Recycling) since the proportion of raw materials used is modified. This is demonstrated in Fig. 8.6, in which the comparison of the environmental performance between Design 1 and its modified design is described.

It is somewhat easier to make an improvement decision if such design modifications will not lead to a compromise in the performance of other criteria. However, often the design change in one criterion could have a knock on effect on other criteria because of the interrelationship between the criteria throughout the product life cycles, as discussed in this case scenario. Therefore, it is important to look at the weighted environmental performance of each design with respect to the criteria. As shown in Fig. 8.7, although Design 4 has a better performance in some criteria, the advantages in those criteria can be ignored when the weighted factors are considered. Such an analysis enables companies to focus on the factors that have most significant negative effect on the environment. This will facilitate

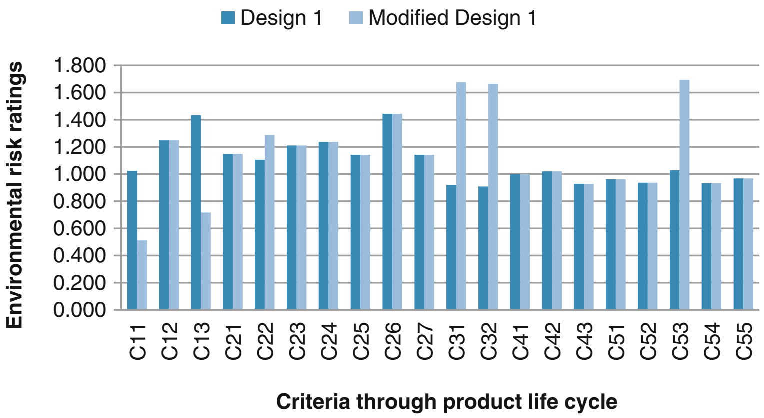

Fig. 8.6 Comparison between design 1 and its modified design

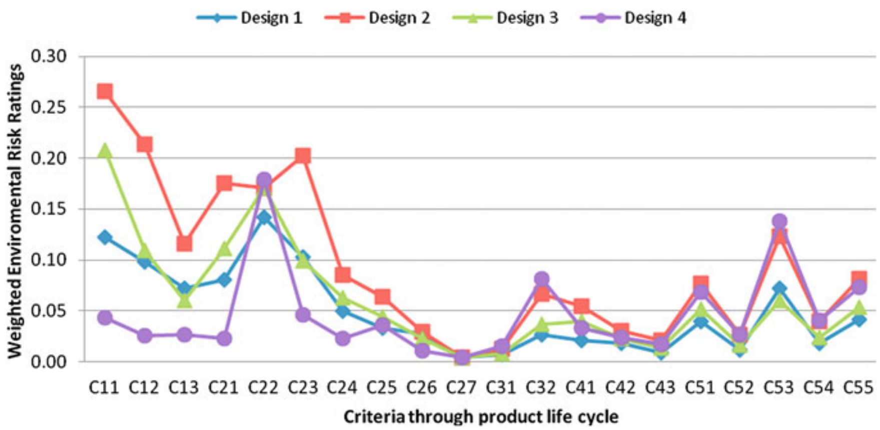

Fig. 8.7 Weighted environmental performance of each design with respect to the criteria

incorporating environment considerations in the product design and lead to consistent sustainable new product development.

8.5 Conclusions

Green design is becoming increasingly important for manufacturing companies and will determine the sustainability of a company in the long term. However, green design requires the consideration of environmental aspects, at all stages of the product life cycle, within the product development process. The dynamic nature of a product life cycle means that the decision model for evaluating eco-designs should reflect the interaction and relationship among the life cycle phases and criteria. In this chapter, a comprehensive decision support model for the evaluation of eco-designs is developed using the concept of life cycle assessment (LCA) and fuzzy ANP approach. The novelty of the model lies in the fact that an analytical tool enables the specific environmental preferences concerning the product to be taken into consideration in making the design choice. It offers a more precise and accurate analysis by integrating interdependent relationships within product life cycle phases and among a set of criteria.

Despite various advantages of the proposed approach outlined in the chapter, there are some limitations which can lead to further research opportunities. For instance, although the proposed approach has been demonstrated by a case study of a electronics manufacturer, further investigation is needed in the future, including the involvement of additional specialists, to refine fuzzy rules and the use of statistics instead of experts' judgments to define the dependence among environmental factors. In addition, many MCDM approaches have been proposed for green design selection, such as AHP, ANP, fuzzy set theory, case-based reasoning (CBR), and their hybrids. However, there is little research that systematically compares these approaches with respect to environmental risk assessment based green design selection or evaluation. Future work could be undertaken to conduct an extensive analysis to examine any inadequacy of the approaches and provide recommendation for improvements. Moreover, while this research only focuses on the environmental risk assessment, it is also crucial to corporate economic and social factors in order to achieve the ultimate in sustainable new product development. Therefore, one further avenue for future research would be to integrate the economic, social and environmental factors into the development of a multi-objective treatment of design evaluation.

References

Dağdeviren, M., & Yüksel, İ. (2010). A fuzzy analytic network process (ANP) model for measurement of the sectoral competition level. *Expert System with Application, 37*, 1005–1014.

European Council. (2005). Directive 2005/32/EC of the European Parliament of the council of 6 July 2005 establishing a framework for the settings of ecodesign requirements for energy-using products and amending Council Directive 92/42/EEC and Directive 96/57/EC and 2000/55/EC of the European Parliament and of the Council. *Official Journal of the European Union*, L191, *48*, 29058.

Saaty, T. L., & Takizawa, M. (1986). Dependence and independence: From linear hierarchies to nonlinear networks. *European Journal of Operational Research, 26*, 229–237.

Saaty, T. L. (1996). *The analytic network process*. Pittsburgh: RWS Publications.

Yung, W. K. C., Chan, H. K., Wong, D. C. W., So, J. H. T., Choi, A. C. K., & Yue, T. M. (2009). Life cycle assessment of two personal electronic products—a note with respect to the energy-using product directive. *International Journal of Advanced Manufacturing Technology, 42*(3–4), 415–419.

Yung, K. C., Chan, H. K., So, H. T., Wong, W. C., Choi, C. K., & Yue, T. M. (2011). A life-cycle assessment for eco-redesign of a consumer electronic product. *Journal of Engineering Design, 22*(2), 69–85.

Chapter 9
Conclusions and Future Research Directions

9.1 Conclusions

In this book, the authors have made use of several real-life case studies to demonstrate how hierarchical approach (more specifically AHP and ANP) can be coupled with fuzzy logic in multi-criteria decision-making (MCDM) risk assessment–related problems. In summary, they are supplier selection of a manufacturing organisation, selection of eco-design options, risk management of a food supply chain and risk evaluation of green supply chain implementation. This is summarised in Table 9.1.

The merit of fuzzy AHP is to evaluate the criteria or sub-criteria using fuzzy numbers instead of precise numbers. This can incorporate the uncertainty that is encountered in real-life environment. Compared to conventional MCDM approach, especially traditional AHP, the fuzzy AHP approaches employed in this book provide practical solutions, which are simple and less demanding upon the computational power and time needed to make a decision. While the use of the model does not involve cumbersome mathematical operations, the fuzzy AHP models are tractable enough to capture the vagueness of uncertainty and vulnerability and provide the efficiency and flexibility to incorporate the knowledge of decision makers. Many of the cases are computed with the help of Excel spreadsheet only.

Fuzzy AHP is not without shortcomings despite its usefulness. One major limitation of the models presented in this book is that decision makers have to make subjective assessments of pairwise comparisons (even if fuzzy variables are considered) and the relative weightings of the criteria and sub-criteria. In fact, that is highly dependent on the knowledge, expertise and communication skills of the decision makers. In addition, sufficient information, even if uncertain, is still required to be able to analyse the problems and to identify main criteria within each of the problems. Therefore, next section presents future research directions pinpointing various limitations of the fuzzy AHP methods.

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Table 9.1 Summary of the case studies

Chapter	Case	Method	Characteristics (pros and cons)
4	Supplier selection	Two-stage fuzzy AHP	Simple, but not as powerful as the other tools. This is simply because fuzzy calculation and AHP are separated
5	Selection of eco-design options	Fuzzy AHP	Standard approach and popular. The approach is well documented but is complicated in terms of pairwise comparisons
6	Risk management of food supply	Fuzzy extent AHP	Less complicated in terms of comparisons and hence computational effort. But is more complex in mathematical terms and cannot make full use of the fuzzy comparisons. However, this is applicable to multi-tier hierarchical models
7	Risk evaluation of green supply chain implementation	Fuzzy hierarchical TOPSIS	Simper than fuzzy extent AHP mathematically. Fuzzy hierarchical TOPSIS benefits both from the superiority of the hierarchical structure of AHP and easiness of implementation of TOPSIS in a fuzzy environment
8	Selection of eco-design options	Fuzzy extent ANP	Can include dependency of the criteria and sub-criteria. However, it is the most sophisticated method mathematically among the other presented in this book

9.2 Future Research Directions

The applications in this book can help verify that the fuzzy-based AHP approaches can take uncertainty or vague information into consideration. Having said that there is still a big room for making improvement. There are many areas that AHP and fuzzy in general can further advance the knowledge in the MCDM field. Some are general problems associated with the fuzzy AHP methods, while the others are specific to the models. The major concern is mainly pinpointing the shortcomings of various fuzzy AHP approaches. Some of them are summarised as follows:

- Although fuzzy logic is well known for handling uncertain or vague parameter, there is still a lack of mathematical formulation to verify that fuzzy AHP can improve the solution from standard AHP. Saaty (2006), "the father of the AHP", and later in another paper (Saaty and Tran 2007) argued that there is no need to incorporate fuzzy logic in AHP as the pairwise comparisons in AHP are "fuzzy" enough. Therefore, mathematical proof or sensitivity analysis on the merits of using fuzzy logic in AHP is desired. If the mathematical formulation of fuzzy AHP can be derived such that under which situations we should or should not employ fuzzy AHP can be revealed, the usefulness of fuzzy logic with AHP can be spelt out explicitly. Currently, researchers try to blend the two methods and aim to utilise the benefits of both methods, which is not incorrect. However, such approach is without a solid theoretical ground. In other words, the quality of the solutions obtained from fuzzy AHP may not be good enough in view of the additional computational effort involved (Raharjo et al. 2008). It may be just as good as the solutions obtained from the regular AHP without fuzzy modelling. As a matter of fact, the authors of this book attempted to analyse slight disturbance on the standard AHP and a simple approximate solution leads to a similar results using fuzzy AHP (Wang et al. 2013).

- One of the shortcomings of using AHP or its fuzzy versions is the subjectivity in the pairwise comparison. In the literature, some researchers have proposed using data envelopment analysis (DEA) to tackle this shortcoming. DEA is nonparametric multi-input–multi-output analysis (Charnes et al. 1978). DEA is also linked to MCDM and hence would be able to be linked to AHP (Doyle and Green 1993; Stewart 1996). The objective of DEA is to determine the weightings of the inputs and outputs in order to determine whether a set of solutions is efficient or inefficient in Pareto-optimal terms. Obviously, DEA does not consider ranking as in AHP. Therefore, a two-step approach was proposed by Sinuany-Stern et al. (2000), so the weightings of an AHP hierarchy can be obtained in the first step using DEA by considering every two criteria, and then they are applied to standard AHP ranking for selecting the best option. Since then, various applications utilising both AHP and DEA have been developed (e.g. Chen 2002; Yang and Kuo 2003; Feng et al. 2004; Ahmad et al. 2006; Ramanathan 2007; Wang et al. 2008; Tseng and Lee 2009). Nevertheless, combining fuzzy AHP and DEA is under-explored and is potentially a big area for research.
- As mentioned above, one of the shortcomings of AHP or fuzzy AHP is the subjectivity in pairwise comparisons to obtain the weightings of the criteria and sub-criteria. Artificial neural network (ANN) is another possible approach to overcome this pitfall. Like DEA, ANN is also a multi-input–multi-output modelling tool. To be precise, ANN is not a decision-making tool but this is a perfect match to "train" any decision-making tools in order to get rid of the aforementioned subjectivity to aid decision making. This is because ANN is an algorithm to "train" the logic behind an application and is widely used in applications like voice or pattern recognition in various applications (e.g. Ramalingam et al. 2006). ANN is also widely used in MCDM problems (e.g. Malakooti and Raman 2000; Chen and Lin 2003). ANN can be employed with fuzzy AHP in two ways. The first is to use it in post-pairwise comparisons to rank alternative. Once the weightings of the criteria and sub-criteria can be found using standard fuzzy AHP approach, the ANN can be applied to find the "actual" relationship between the outputs from the fuzzy AHP and the known outcomes. In other words, the ANN is used to verify the results and to predict the results in future applications without going through the pairwise comparisons. This has been applied, for example, in selecting stores location (Kuo et al. 2002), machine tool selection (Taha and Rostam 2011). Alternatively, ANN can even be used to represent the hierarchical structure in order to construct the reciprocal matrix in standard AHP (Stam et al. 1996). In such a case, the elements in the matrix

(i.e. the pairwise comparisons) are obtained after the ANN training processes. In other words, subjectivity in determining the elements can be reduced by referencing to the actual output (i.e. decisions to make based on previous experience). Recently, this has been applied even to determine the missing judgement in the pairwise comparisons (Hu and Tsai 2006; Gomez-Ruiz et al. 2010).

- Another difficulty of using AHP to solve complex decision problems is to identify all associated decision criteria for a hierarchy model. Although comprehensive literature review is often used to identify the decision criteria, it is also questioned whether those identified criteria are relevant to the decision problem. This can be addressed by the Delphi method developed by Dalkey and Helmer (1963). It is a technique to obtain the most reliable consensus of a group of experts through a series of intensive questionnaires using controlled opinion feedback. Since its launch in 1963 at RAND Corporation, the Delphi method has been widely applied in many management areas. Although it is a flexible technique that has been successfully used to explore new concepts, the traditional Delphi method has also suffered from low convergence expert opinions and high execution cost due to iterative process of collecting and modifying experts' judgement (Joshi et al. 2011). In addition, there is also a possibility that opinion organisers may filter our particular expert options (Kuo and Chen 2008). One of the approaches to tackle the shortfalls is the incorporation of fuzzy set theory with Delphi method. Murry et al. (1985) integrated the traditional Delphi method and the fuzzy theory to improve the vagueness and ambiguity of Delphi method. Hsu and Yang (2000) use triangular fuzzy number to encompass expert opinions and establish the fuzzy Delphi method. Their method does not only encompass all the expert opinions in one investigation but also has the advantage of simplicity, which provides a better outcome of criteria selection. Overall, fuzzy Delphi is a more efficient and cost-effective approach which incorporates every expert opinion into consideration to achieve the consensus of group decisions (Guo and Chen 2008).

Based on the above, it can be observed that there is still big room to further extend fuzzy AHP analysis. Although AHP or fuzzy AHP is a useful method for MCDM problems, it has difficulty in many aspects so coupling with other methods for solving MCDM risk assessment problems is definitely a research direction in this area for researchers. The authors hope that readers can find interests in this area and can further advance research along this direction.

References

Ahmad, N., Berg, D., & Simons, G. R. (2006). The integration of analytical hierarchy process and data envelopment analysis in a multi-criteria decision-making problem. *International Journal of Information Technology and Decision Making, 5*(2), 263–276.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research, 2*(6), 429–444.

Chen, T. Y. (2002). Measuring firm performance with DEA and prior information in Taiwan's banks. *Applied Economics Letters, 9*(3), 1041–1051.

Chen, J., & Lin, S. (2003). An interactive neural network-based approach for solving multiple criteria decision-making problems. *Decision Support Systems, 36*(2), 137–146.

Dalkey, N., & Helmer, O. (1963). An experimental application of the Delphi method to the use of experts. *Management Science, 9*(3), 458–467.

Doyle, J. R., & Green, R. H. (1993). Data envelopment analysis and multiple criteria decision making. *Omega, 21*(6), 713–715.

Feng, Y. J., Lu, H., & Bi, K. (2004). An AHP/DEA method for measurement of the efficiency of R&D management activities in universities. *International Transactions in Operational Research, 11*(2), 181–191.

Gomez-Ruiz, J. A., Karanik, M., & Peláez, J. I. (2010). Estimation of missing judgments in AHP pairwise matrices using a neural network-based model. *Applied Mathematics and Computation, 216*(10), 2959–2975.

Hsu, T. H., & Yang, T. H. (2000). Application of fuzzy analytic hierarchy process in the selection of advertising media. *Journal of Management and Systems, 7*(1), 19–39.

Hu, Y.-C., & Tsai, J.-F. (2006). Backpropagation multi-layer perceptron for incomplete pairwise comparison matrices in analytic hierarchy process. *Applied Mathematics and Computation, 180*(1), 53–62.

Joshi, R., Banwet, D. K., & Shankar, R. (2011). A Delphi-AHP-TOPSIS based benchmarking framework for performance improvement of a cold chain. *Expert Systems with Applications, 38*(8), 10170–10182.

Kuo, Y.-F., & Chen, P.-C. (2008). Constructing performance appraisal indicators for mobility of the service industries using Fuzzy Delphi Method. *Expert Systems with Applications, 35*(4), 1930–1939.

Kuo, R. J., Chi, S. C., & Kao, S. S. (2002). A decision support system for selecting convenience store location through integration of fuzzy AHP and artificial neural network. *Computers in Industry, 47*(2), 199–214.

Malakooti, B., & Raman, V. (2000). Clustering and selection of multiple criteria alternatives using unsupervised and supervised neural networks. *Journal of Intelligent Manufacturing, 11*(5), 435–451.

Murry, T. J., Pipino, L. L., & Gigch, J. P. (1985). A pilot study of fuzzy set modification of Delphi. *Human Systems Management, 5*(1), 611–623.

Raharjo, H., Brombacher, A. C., & Xie, M. (2008). Dealing with subjectivity in early product design phase: A systematic approach to exploit quality function deployment potentials. *Computers and Industrial Engineering, 55*(1), 253–278.

Ramalingam, V., Palaniappan, B., Panchanatham, N., & Palanivel, S. (2006). Measuring advertisement effectiveness—a neural network approach. *Expert Systems with Applications, 31*(1), 159–163.

Ramanathan, R. (2007). Supplier selection problem: integrating DEA with the approaches of total cost of ownership and AHP. *Supply Chain Management: An International Journal, 12*(4), 258–261.

Saaty, T. L. (2006). There is no mathematical validity for using fuzzy number crunching in the analytic hierarchy process. *Journal of Systems Science and Systems Engineering, 15*(4), 457–464.

Saaty, T. L., & Tran, L. T. (2007). On the invalidity of fuzzifying numerical judgments in the analytic hierarchy process. *Mathematical and Computer Modelling, 46*(7–8), 962–975.

Sinuany-Stern, Z., Mehrez, A., & Hadad, Y. (2000). An AHP/DEA methodology for ranking decision making units. *International Transactions in Operational Research, 7*(2), 109–124.

Stam, A., Sun, M., & Haines, M. (1996). Artificial neural network representations for hierarchical preference structures. *Computers and Operations Research, 23*(12), 1191–1201.

Stewart, T. J. (1996). Relationships between data envelopment analysis and multicriteria decision analysis. *The Journal of the Operational Research Society, 47*(5), 654–665.

Taha, Z., & Rostam, S. (2011). A fuzzy AHP-ANN-based decision support system for machine tool selection in a flexible manufacturing cell. *International Journal of Advanced Manufacturing Technology, 57*(5–8), 719–733.

Tseng, Y. F., & Lee, T. Z. (2009). Comparing appropriate decision support of human resource practices on organizational performance with DEA/AHP model. *Expert Systems with Applications, 36*(3), 6548–6558.

Wang, Y. M., Liu, J., & Elhag, T. M. S. (2008). An integrated AHP–DEA methodology for bridge risk assessment. *Computers and Industrial Engineering, 54*(3), 513–525.

Wang, X., Chan, H. K., Lee, C. K. M., & Li, D. (2013). A hierarchical model for eco-design of consumer electronic products. *Technological and Economic Development of Economy* (in press).

Yang, T., & Kuo, C. (2003). A hierarchical AHP/DEA methodology for the facilities layout design problem. *European Journal of Operational Research, 147*(1), 128–136.

Appendix A
Introduction to Life-Cycle Assessment (LCA)

This appendix briefly reviews the life-cycle assessment (LCA) concepts, which link to eco-design closely, and its recent development. Eco-design is getting important in the past decade, partly due to legislative pressure (Maxwell and van der Vorst 2003). It "covers any design activity which aims at improving the environmental performance of a product" (Hauschild et al. 2004). In other words, it is the process of taking environmental impacts into design considerations. Undoubtedly, a proper tool should be employed for assessing environmental impacts with respect to the requirements of eco-design. LCA is a scientific approach that can be utilised to analyse the environmental impacts of a product in all phases of its life cycle, so that the so-called "cradle-to-grave" analysis can be achieved (e.g., Eberle et al. 2007). Figure A.1 illustrates this concept.

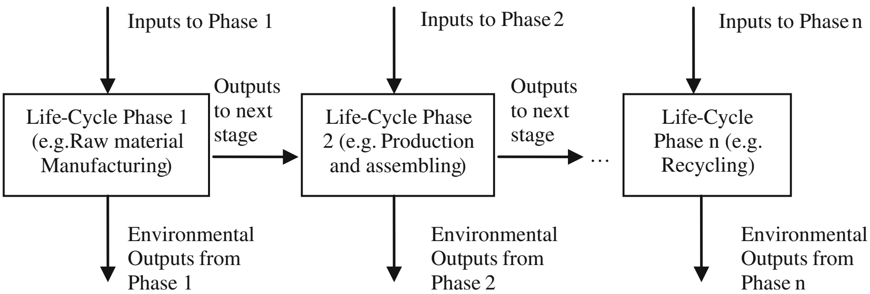

Fig. A.1 A basic LCA

LCA has been gaining increasing concerns in recent years (Park and Seo 2004). It is one of the most effective concepts for a life cycle related assessment of products and services (Bovea and Galardo 2006). Energy and material flow of a product along its life cycle can be investigate and evaluated (Nissen 1995). More specifically, this is a "methodology for assessing the environmental impacts and resource consumption associated with the existence of products throughout their life cycle" (Westkämper et al. 2001). LCA can facilitate the quantification of environmental impacts throughout the product's life cycle (Nielsen and Wenzel 2002;

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Del Borghi et al. 2007). It is of vital importance to adopt this kind of philosophy as early as possible in any product development cycle (Kobayashi 2006). A typical procedure to carry out LCA is to:

1. Calculate the life cycle inventory and then to interpret the results. The inputs for calculating the life cycle inventory is all materials and resources consumption throughout a product's life cycle.
2. Then, a list of environmental aspects with respect to the inputs can be generated as output. These quantitative data are called life cycle inventory.
3. The profile of the product from the eco-design point of view can then be concluded by categorising the life cycle inventory, and then aggregating the results to form the output (i.e., interpretation of the results). Normally, some tools are needed to convert the inputs to life cycle inventory, and then to the output.

Applications of LCA are abundant in the literature. Below are some examples. Lenau and Bey (2001) made use of LCA and developed an indicator method to interpret the LCA results in order to illustrate the rough environmental evaluations of three examples, namely, a vacuum cleaner, two sweaters and a passenger car. They concluded that simple method has to be used in the early stages of product development. Czaplicka (2003) analysed the design of a conveyor belt from the eco-design point of view. LCA was employed to evaluate the environmental impacts of a traditional conveyor belt, and appropriate redesign options (e.g., using different materials). Czaplicka (2003) advocates using LCA as a tool for establishing ecological policy. Bovea and Vidal (2004) also applied LCA for materials selection problem in a case study regarding eco-design of wood-based furniture.

Another line of research is to interpret the LCA results in monetary terms. Senthil et al. (2003) attempted to convert the LCA results into life cycle cost so that comparisons among alternatives could be done easier by economic evaluation. The rationale behind this is to assign a cost value to each environmental impact, and then to calculate the overall life cycle cost of a product. They illustrated the method by two case studies regarding packaging materials. However, it is not always easy to link the environmental impacts to appropriate cost items. Even if the environmental impacts can be represented by monetary terms, their effects may not be so accurate by using a simple additive system for evaluation. In this regards, a weighting system or even some other multi-criterion decision making methods may need but how to determine the importance (i.e., the set of weightings) would be a crucial problem to be tackled.

One of the shortcomings of conducting LCA is the requirement of extensive data collection and hence simplification of LCA may need (Nissen 1995; Lenau and Bey 2001; Hauschild et al. 2005; Hur et al. 2005).

Appendix B
Pairwise Comparisons of the Example in Chapter 3

This appendix lists all the pairwire comparisons for the example in Sect. 3.4 of Chap. 3. Please refer to Fig. 3.2 for the symbols used in the following tables. Tables B.1, B.2, B.3, B.4, B.5, B.6 summarise the pairwise comparisons between different criteria and sub-criteria.

Table B.1 Pairwise comparisons of the main criteria – the five life-cycle phases

	LC_1	LC	LC_3	LC_4	LC_5
LC_1	1	3	9	6	9
LC_2	1/3	1	9	4	9
LC_3	1/9	1/9	1	5	1/5
LC_4	1/6	1/4	1/5	1	1/9
LC_5	1/9	1/9	5	9	1

CR = 0.09

Table B.2 Pairwise comparisons of the sub-criteria of LC_1

	LC_{11}	LC_{12}	LC_{13}	LC_{14}	LC_{15}
LC_{11}	1	1/5	1/3	2	1/7
LC_{12}	5	1	5	7	1/3
LC_{13}	3	1/5	1	5	1/5
LC_{14}	1/2	1/7	1/5	1	1/9
LC_{15}	7	3	5	9	1

CR = 0.07

Table B.3 Pairwise comparisons of the sub-criteria of LC_2

	LC_{21}	LC_{22}	LC_{23}	LC_{24}	LC_{25}
LC_{21}	1	2	1/4	1/6	1/8
LC_{22}	1/2	1	1/6	1/8	1/9
LC_{23}	4	6	1	5	1/5
LC_{24}	6	8	1/5	1	1/9
LC_{25}	8	9	5	9	1

CR = 0.09

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Table B.4 Pairwise comparisons of the sub-criteria of LC_3

	LC_{31}	LC_{32}	LC_{33}
LC_{31}	1	1/3	1/5
LC_{32}	3	1	1/3
LC_{33}	5	3	1

CR = 0.04

Table B.5 Pairwise comparisons of the sub-criteria of LC_4

	LC_{31}	LC_{32}
LC_{31}	1	7
LC_{32}	1/7	1

CR = 0.00

Table B.6 Pairwise comparisons of the sub-criteria of LC_5

	LC_{51}	LC_{52}	LC_{53}
LC_{51}	1	1/5	1/3
LC_{52}	5	1	3
LC_{53}	3	1/3	1

CR = 0.04

Tables B.7, B.8, B.9, B.10, B.11, B.12, B.13, B.14, B.15, B.16, B.17, B.18, B.19, B.20, B.21, B.22, B.23, B.24 summarise the pairwise comparisons for different criteria and sub-criteria with respect to the five environmental assessments.

Table B.7 Pairwise comparisons of the sub-criteria of LC_{11}

	EA_1	EA_2	EA_3	EA_4	EA_5
EA_1	1	1/5	1/7	1/3	1/9
EA_2	5	1	1/3	3	1/6
EA_3	7	3	1	5	2
EA_4	3	1/3	1/5	1	1/3
EA_5	9	6	1/2	3	1

CR = 0.09

Table B.8 Pairwise comparisons of the sub-criteria of LC_{12}

	EA_1	EA_2	EA_3	EA_4	EA_5
EA_1	1	1/7	1/9	1/6	1/7
EA_2	7	1	1/4	2	1
EA_3	9	4	1	7	3
EA_4	6	1/2	1/7	1	1/5
EA_5	7	1	1/3	5	1

CR = 0.08

Table B.9 Pairwise comparisons of the sub-criteria of LC_{13}

	EA_1	EA_2	EA_3	EA_4	EA_5
EA_1	1	3	5	7	1/3
EA_2	1/3	1	3	5	1/5
EA_3	1/5	1/3	1	3	1/7
EA_4	1/7	1/5	1/3	1	1/9
EA_5	3	5	7	9	1

CR = 0.05

Table B.10 Pairwise comparisons of the sub-criteria of LC_{14}

	EA_1	EA_2	EA_3	EA_4	EA_5
EA_1	1	1/5	1/3	1/7	3
EA_2	5	1	3	1/3	7
EA_3	3	1/3	1	1/3	5
EA_4	7	3	3	1	9
EA_5	1/3	1/7	1/5	1/9	1

CR = 0.05

Table B.11 Pairwise comparisons of the sub-criteria of LC_{15}

	EA_1	EA_2	EA_3	EA_4	EA_5
EA_1	1	1/3	1/5	1/9	3
EA_2	3	1	1/3	1/7	5
EA_3	5	3	1	1/5	7
EA_4	9	7	5	1	9
EA_5	1/3	1/5	1/7	1/9	1

CR = 0.08

Table B.12 Pairwise comparisons of the sub-criteria of LC_{21}

	EA_1	EA_2	EA_3	EA_4	EA_5
EA_1	1	7	7	3	9
EA_2	1/7	1	1	1/5	3
EA_3	1/7	1	1	1/5	3
EA_4	1/3	5	5	1	5
EA_5	1/9	1/3	1/3	1/5	1

CR = 0.05

Table B.13 Pairwise comparisons of the sub-criteria of LC_{22}

	EA_1	EA_2	EA_3	EA_4	EA_5
EA_1	1	7	7	5	9
EA_2	1/7	1	1	1/3	5
EA_3	1/7	1	1	1/3	5
EA_4	1/5	3	3	1	7
EA_5	1/9	1/5	1/5	1/7	1

CR = 0.07

Table B.14 Pairwise comparisons of the sub-criteria of LC_{23}

	EA_1	EA_2	EA_3	EA_4	EA_5
EA_1	1	1/7	1/7	1/3	5
EA_2	7	1	1	5	9
EA_3	7	1	1	5	9
EA_4	3	1/5	1/5	1	3
EA_5	1/5	1/9	1/9	1/3	1

CR = 0.08

Table B.15 Pairwise comparisons of the sub-criteria of LC_{24}

	EA_1	EA_2	EA_3	EA_4	EA_5
EA_1	1	7	7	5	3
EA_2	1/7	1	1	1/3	1
EA_3	1/7	1	1	1/3	1
EA_4	1/5	3	3	1	3
EA_5	1/3	1	1	1/3	1

CR = 0.05

Table B.16 Pairwise comparisons of the sub-criteria of LC_{25}

	EA_1	EA_2	EA_3	EA_4	EA_5
EA_1	1	6	6	4	2
EA_2	1/6	1	1	1/3	1
EA_3	1/6	1	1	1/3	1
EA_4	1/4	3	3	1	3
EA_5	1/2	1	1	1/3	1

CR = 0.06

Table B.17 Pairwise comparisons of the sub-criteria of LC_{31}

	EA_1	EA_2	EA_3	EA_4	EA_5
EA_1	1	5	5	3	1
EA_2	1/5	1	1	1/3	1/6
EA_3	1/5	1	1	1/3	1/6
EA_4	1/3	3	3	1	1/3
EA_5	1	6	6	3	1

CR = 0.01

Table B.18 Pairwise comparisons of the sub-criteria of LC_{32}

	EA_1	EA_2	EA_3	EA_4	EA_5
EA_1	1	3	5	7	1
EA_2	1/3	1	3	5	1/3
EA_3	1/5	1/3	1	3	1/5
EA_4	1/7	1/5	1/3	1	1/7
EA_5	1	3	5	7	1

$CR = 0.03$

Table B.19 Pairwise comparisons of the sub-criteria of LC_{33}

	EA_1	EA_2	EA_3	EA_4	EA_5
EA_1	1	5	3	7	9
EA_2	1/5	1	1/3	3	7
EA_3	1/3	3	1	5	5
EA_4	1/7	1/3	1/5	1	3
EA_5	1/9	1/7	1/5	1/3	1

$CR = 0.07$

Table B.20 Pairwise comparisons of the sub-criteria of LC_{41}

	EA_1	EA_2	EA_3	EA_4	EA_5
EA_1	1	7	7	8	9
EA_2	1/7	1	3	3	5
EA_3	1/7	1/3	1	3	5
EA_4	1/8	1/3	1/3	1	2
EA_5	1/9	1/5	1/5	1/2	1

$CR = 0.06$

Table B.21 Pairwise comparisons of the sub-criteria of LC_{42}

	EA_1	EA_2	EA_3	EA_4	EA_5
EA_1	1	7	7	8	9
EA_2	1/7	1	3	3	5
EA_3	1/7	1/3	1	3	5
EA_4	1/8	1/3	1/3	1	2
EA_5	1/9	1/5	1/5	1/2	1

$CR = 0.06$

Table B.22 Pairwise comparisons of the sub-criteria of LC_{51}

	EA_1	EA_2	EA_3	EA_4	EA_5
EA_1	1	5	5	7	1
EA_2	1/5	1	1	3	1/5
EA_3	1/5	1	1	3	1/5
EA_4	1/7	1/3	1/3	1	1/7
EA_5	1	5	5	7	1

$CR = 0.02$

Table B.23 Pairwise comparisons of the sub-criteria of LC_{52}

	EA_1	EA_2	EA_3	EA_4	EA_5
EA_1	1	7	7	5	1
EA_2	1/7	1	1	3	1/5
EA_3	1/7	1	1	3	1/5
EA_4	1/5	1/3	1/3	1	1/7
EA_5	1	5	5	7	1

CR = 0.05

Table B.24 Pairwise comparisons of the sub-criteria of LC_{53}

	EA_1	EA_2	EA_3	EA_4	EA_5
EA_1	1	7	7	6	1
EA_2	1/7	1	1	2	1/5
EA_3	1/7	1	1	2	1/5
EA_4	1/6	1/2	1/2	1	1/6
EA_5	1	1/5	5	6	1

CR = 0.02

References

Abdi, M. R. (2009). Fuzzy multi-criteria decision model for evaluating reconfigurable machines. *International Journal of Production Economics, 117*(1), 1–15.

Bovea, M. D., & Vidal, R. (2004). Materials selection for sustainable product design: a case study of wood based furniture eco-design. *Materials and Design, 25*(2), 111–116.

Bovea, M. D., & Gallardo, A. (2006). The influence of impact assessment methods on materials selection for eco-design. *Materials and Design, 27*(3), 209–215.

Czaplicka, K. (2003). Eco-design of non-metallic layer composites with respect to conveyor. *Materials and Design, 24*(2), 111–120.

Del Borghi, A., Binaghi, L., Del Borghi, M., & Gallo, M. (2007). The application of the environmental product declaration to waste disposal in a sanitary landfill—Four case studies. *International Journal of Life Cycle Assessment, 12*(1), 40–49.

Eberle, U., Lange, A., Dewaele, J., & Schowanek, D. (2007). LCA study and environmental benefits for low temperature disinfection process in commercial laundry. *International Journal of Life Cycle Assessment, 12*(2), 127–138.

Hauschild, M., Jeswiet, J. & Alting, L. (2005). from life cycle assessment to sustainable production: status and perspectives. *CIRP Annals*, *54*(2), Session "A".

Hur, T., Lee, J., Ryu, J., & Kwon, E. (2005). Simplified LCA and matrix methods in identifying the environmental aspects of a product system. *Journal of Environmental Management, 75*(3), 229–237.

Kobayashi, H. (2006). A systematic approach to eco-innovative product design based on life cycle planning. *Advanced Engineering Informatics, 20*(2), 113–125.

Lenau, T., & Bey, N. (2001). Design of environmentally friendly products using indicators. *Proceedings of the Institution of Mechanical Engineers Part B: Journal of Engineering Manufacture, 215*(5), 637–645.

Maxwell, D., & van der Vorst, R. (2003). Developing sustainable products and services. *Journal of Cleaner Production, 11*(8), 883–895.

Nielsen, P. H., & Wenzel, H. (2002). Integration of environmental aspects in product development: a stepwise procedure based on quantitative life cycle assessment. *Journal of Cleaner Production, 10*(3), 247–257.

Nissen, U. (1995). A methodology for the development of cleaner products. *Journal of Cleaner Production, 3*(1–2), 83–87.

Park, J.-H., & Seo, K.-K. (2004). Incorporating life-cycle cost into early product development. *Proceedings of the Institution of Mechanical Engineers Part B: Journal of Engineering Manufacture, 218*(9), 1059–1066.

Senthil, K. D., Ong, S. K., Nee, A. Y. C., & Tan, R. B. H. (2003). A proposed tool to integrate environmental and economical assessments of products. *Environmental Impact Assessment Review, 23*(1), 51–72.

Westkämper, E., Alting, L., & Arndt, G. (2001). Life cycle management and assessment: approaches and visions towards sustainable manufacturing. *Proceedings of the Institution of Mechanical Engineers Part B: Journal of Engineering Manufacture, 215*(5), 599–626.