ANALYZING AND MANAGING FLEXIBILITY IN ENGINEERING SYSTEMS DESIGN BASED ON DECISION RULES AND STOCHASTIC PROGRAMMING: APPLICATIONS IN WASTE-TO-ENERGY SYSTEMS

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Declaration

I hereby declare that this thesis is my original work and it has been written by me in its entirety. I have duly acknowledged all the sources of information which have been used in the thesis.

This thesis has also not been submitted for any degree in any university previously.

Xie Qihui

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Summary

This thesis introduces an approach to analyze and manage flexibility in engineering systems design based on decision rules and stochastic programming. The approach differs from standard real options analysis (ROA) relying on dynamic programming in that it parameterizes the decision variables used to design and manage the flexible system in operations. Decision rules are based on heuristics triggering mechanisms that are used by decision makers (DMs) to determine the appropriate timing to exercise the flexibility. They can be treated similarly as and combined with physical design variables, and optimal values can be determined using multistage stochastic programming techniques. The proposed decision rule approach is first formulated as a generic stochastic programming model. The model is then instantiated through applications in waste-to-energy systems (WTE) as demonstration. Results show that the proposed approach recognizes the value associated with flexibility in a similar amount as standard ROA. In addition, the form of the solution provides intuitive guidelines to DMs for exercising the flexibility in operations. Furthermore, the demonstration shows that the method is suitable for analyzing complex systems and problems when multiple uncertainty sources and different flexibility strategies are considered simultaneously. Finally, a framework is developed to guide designers to apply the decision rule approach throughout the design process.

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List of Abbreviations

AD	Anaerobic digester
ADP	Approximated dynamic programming
CCA	Contingent-claims analysis
DM	Decision maker
DSM	Design Structure Matrix
ENPV	Expected net present value
GBM	Geometric Brownian motion
MILP	Mixed integer linear program
MSRF	Multi-storey recycling facility
NPV	Net present value
ROA	Real options analysis
SAA	Sample average approximation
WTE	Waste-to-energy

Chapter 1 – Introduction

1.1 Background

The design of complex engineering systems – such as real estate development projects, airports, bridges, power plants, telecommunication, and waste-to-energy (WTE) systems – is challenging because engineering systems typically have a long lifespan and operate in an uncertain environment. The lifecycle performance of engineering systems is affected inevitably by such uncertainty. Flexibility in engineering systems design, also referred as the concept of real options – "the right, but not obligation to change a system in the face of uncertainty" (Trigeorgis, 1996), provides a way to handle uncertainty in the face of changing conditions (Fricke & Schulz, 2005). It helps improve the lifecycle performance of engineering systems by reducing exposure to downside risks (i.e. acting like an insurance policy) and enabling the system to capture upside opportunities (i.e. like a call option on a stock). Attributable to these characteristics, flexibility has been demonstrated in many industry case studies to help improve expected lifecycle performance by 10% to 30% compared to standard design and project evaluation approaches (Cardin, 2014; de Neufville & Scholtes, 2011).

The case of the SYSAV WTE plant in Malmö, Sweden provides a real-world example of how flexibility works in large scale engineering systems. The SYSAV WTE plant is the most energy efficient plant in Sweden, as well as being one of the advanced plants in the world. It had two boilers with a capacity of 200,000 tonnes of waste per year when it began operation in 1973

(Friotherm, 2006). As the demand on waste incineration increased, it was extended by a new Unit 3 in 2003 and a new Unit 4 in 2008. Now the facility has a total capacity of 630,000 tonnes of waste per year and is one of the largest of its kind in Europe (Poulsen, 2008). The flexibility to expand capacity has improved the performance of the SYSAV WTE plant through two ways. On the one hand, it enabled the facility to start with small capacity to save on initial capital cost. Also, the capacity expansion flexibility enabled the system to expand to satisfy the increasing demand, when the amount of solid waste had increased dramatically.

Real options analysis (ROA) is a systematic approach that relies on financial options theory to assess the value of flexibility in irreversible investments in real physical assets operating under uncertainty (Mun, 2006). Classical ROA approaches are based on the Black-Sholes financial options-pricing model that emerges from solving a system of stochastic partial differential equations and using dynamic programming (Black & Scholes, 1973; Dixit & Pindyck, 1994). A simplification of the financial options model was introduced by Cox, Ross, and Rubinstein (1979), who proposed a binomial lattice as a discrete-time approximation of the Black-Scholes options pricing model. The binomial lattice approach has been widely used in capital budgeting and strategic decision making because it explicitly accounts for the value of flexibility (Trigeorgis, 1996).

There are several challenges when applying the standard ROA in an applied engineering setting. First, previous studies on ROA generally focus on how to value flexibility. Determining the optimal time to exercise the flexibility, however, may be challenging in practice. For instance in binomial lattice analysis, one needs to determine the current stage and state in the lattice by fitting past historical data. From that state, future evolution of the uncertainty driver is projected, a backward induction process must be applied up to the decision point based on a pre-defined recursive formula, and decision makers (DMs) must choose an exercise policy based on the highest expected reward. In addition, the wide adoption of ROA techniques has been challenged in practice, partly because it relies on advanced mathematical concepts that may not be intuitive to DMs in practice (Engel & Browning, 2008). Furthermore, the analysis of a flexible system considering two or more independent but intertwined uncertainty drivers and flexibility strategies can be challenging. The analysis requires the development of a multinomial lattice if two or more uncertainty drivers analyzed (Antikarov & Copeland, 2001). The curse of dimensionality arising in the dynamic programming analysis may make it difficult for applying such approaches when more complex systems and problems are considered (Nembhard, Shi, & Aktan, 2005). Another challenge is that standard ROA relies on assumptions that apply well to finance, but not necessarily in an engineering setting. For example, the path independence assumption crucial to path recombination and computational savings may not hold (T. Wang & de Neufville, 2005). Because of path dependencies inherent to complex engineering systems, system value after an up-down movement may not be the same as that after a down-up movement because the decision sequences and resulting physical artifacts may differ.

Recent efforts have focused on developing practical approaches for assessing the value of flexibility in an engineering setting, to help designers and DMs implement it, and to manage it in operations. The work on flexibility in engineering design aims to do that just by relaxing and/or modifying some of the underlying assumptions behind standard ROA, to better suit the needs of industrial and systems engineers. The emphasis is rather to enable rank ordering of different design alternatives (e.g. rigid vs. flexible design), based on their expected lifecycle performance. A main challenge, however, is how to actually extract the value of flexibility in operations. After flexibility has been embedded in the system design, its value may be lost when the system is implemented for various reasons. A major reason for this to happen is that decision makers (DMs) simply may not know when and how to exercise the flexibility. Ambiguity and vagueness may crop up in decision making process, so that opportunities of exercising the flexibility are missed (Janney & Dess, 2004). For example, in the garage design problem in de Neufville, Scholtes, and Wang (2006), it is shown that a flexible design (phased design with the flexibility to expand capacity) produces much greater expected net present value (ENPV) ($5.12 million) as compared to the best alternative fixed design ($2.94 million). However, in reality the flexibility was never exercised because the new owners were unaware of the flexibility embedded nor how to exercise it in an optimal manner.

1.2 Motivation

The motivation for this study is twofold. First, there is a need to provide intuitive guidance to DMs on when and how to exercise the flexibility in operations. This is important because a well-designed engineering system can reach better lifecycle performance only if it is implemented following an optimal or best design strategy, in a stochastic sense. As uncertainty evolves over time, it may be challenging to make decisions on when to exercise flexibility so as to achieve better performance – especially when many stakeholders and thousands of design variables are involved.

Second, it is difficult to access the value of flexibility in large scale engineering system projects. These systems typically face multiple uncertainty sources (e.g. market prices and demand, amount of natural resources, regulations, technology, etc.). In addition, several flexibility strategies may be implemented simultaneously to extract additional value from uncertainty. How to analyze and manage different flexibilities concurrently in the face of multiple sources of uncertainty can be a challenging task.

1.3 Purpose of study

The main purpose of this study is to propose a new approach to analyze and manage flexibility in engineering systems based on heuristics-based decision rules and multistage stochastic programming. This approach contrasts and compares to standard ROA by emulating directly the decision making process, and parameterizing its characteristics as well as the physical design variables. A decision rule is a heuristics-based triggering mechanisms used by DMs to determine when it is appropriate to exercise a given flexibility. Some conditional-go decision rules can be thought of as conditional "*If-Then-Else*" programming statements, planning for a particular flexible action if certain conditions about the main uncertainty drivers are met. A multistage stochastic programming model is proposed to find stochastically optimal decision rules and physical design variables to implement and manage the flexible system in operations. Such approach is in line with Simon's view (1972) that human decision agents may tend to rely on heuristic rules to achieve stated satisfactory level of performance when operating under complex and uncertain environments. A typical solution using the proposed approach consists of two parts. One part contains the physical system design variable(s) describing the initial physical state of the system. The other part contains the decision rule(s) guiding decision-making dynamically based on available information at the decision points, and as uncertainty unfolds.

1.4 Expected contributions

The main contributions of this thesis can be summarized into three parts. The first part is a new approach for analyzing and managing flexibility in engineering systems design. The approach differs from standard ROA used in flexibility valuation based on dynamic programming by parameterizing the decision variables used to design and manage the flexible system in operations. This approach not only recognizes the inherent value stemming from flexibility, it also provides solutions with intuitive guidance on how to manage the flexibility in operations. In addition, this new approach lends itself naturally to analyze complex systems embedded with multiple flexibility strategies and facing multiple uncertainty sources (of course, the systems must be able to be modelled as multistage integer linear programs).

The second part is a framework to apply the proposed decision rule approach in design practice. The framework addresses the idea of design for implementation by focusing on generating decision rules throughout the design phase. With this framework, designers can start with a baseline design and generate a valuable flexible design that is practical to implement in operations by exploiting the concept of decision rules.

The third part is applications of the proposed approach in designs of three WTE systems. Numerical studies on three different WTE systems are carried out to demonstrate the application of the decision rule approach and the framework. Throughout these case studies, managerial insights are provided to improve the design and management of these real projects.

1.5 Thesis content summary

The remainder of this thesis is organized as follows:

Chapter 2 provides a literature review of theories and methodologies of real options and flexibility in engineering systems, stochastic programming, decision rules, and WTE systems. Research gaps are identified after the review.

Chapter 3 introduces the generic formulation of the proposed approach. The details of the multistage stochastic programming model and formulations of three types of decision rules are described. In particular, the solution algorithm for the multistage stochastic programming model is described in details.

Chapter 4 presents how the generic model introduced in Chapter 3 can be instantiated to model simple flexibilities. First, six managerial flexibilities are modeled by following simple project examples. Then, a case study on the design of a WTE systems using anaerobic digester (AD) technology is carried out to demonstrate the application of the proposed approach in real systems.

Chapter 5 demonstrates the ability of the proposed approach to analyze complex systems with compound flexibilities and multiple uncertainty sources. A complex engineering system – hybrid WTE system – with two flexibility strategies and two uncertainty sources is analyzed to exhibit this advantage of the proposed approach.

Chapter 6 proposes a framework to apply the decision rule approach in design practice. The framework is summarized in six-step procedures. Comparison between the proposed framework and a standard real options analysis approach is made to show the difference. A third case study – design of multi-storey recycling facility – is conducted to demonstrate how to apply the framework in design practice.

Finally, Chapter 7 summarizes this thesis, and discusses the applications and limitations of the proposed approach. It ends with giving insights on future reach opportunities.

Chapter 2 – Literature Review

This chapter aims to provide an up-to-date review of existing works and identify the research gaps addressed in this thesis. Flexibility is associated with the concept of a real option, which provides the “right, but not the obligation, to change a system as uncertainty unfolds” (Trigeorgis, 1996). Three commonly used ROA approaches are introduced in Section 2.1: Black-Scholes model, multiplicative lattice approaches, and simulation-based approaches. The strengths and weaknesses of each approach are discussed. Section 2.2 discusses the challenges of applying existing ROA approaches in analyzing flexibility in engineering systems design. In Section 2.3, stochastic programming and decision rules are introduced as potential solutions to address the identified challenges faced by existing ROA approaches. In Section 2.4, the application domain – the WTE systems – is introduced and the research gaps related to them are identified. Finally, the research gaps and research opportunities based on the review are summarized at the end of this chapter.

2.1 Real options analysis

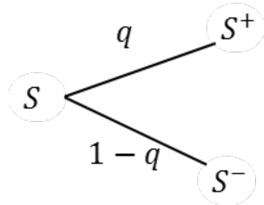
ROA is a systematic approach that relies on financial options theory to assess the value of flexibility in irreversible investments in real physical assets operating under uncertainty (Mun, 2006). Classical ROA approaches are based on the Black-Sholes options-pricing model that has emerged from solving a system of stochastic partial differential equations and using dynamic programming (Black & Scholes, 1973; Dixit & Pindyck, 1994). A simplification of the financial options model was introduced by Cox et al. (1979), who proposed a binomial lattice as a discrete-time approximation of the Black-Scholes options-pricing model. With the rapid development of computer technologies, simulation models have become easily available to assess the value of real options that are otherwise difficult to value by partial differential equations or lattice approaches. This section will introduce these three approaches and identify their challenges in practice.

2.1.1 The Black-Scholes model

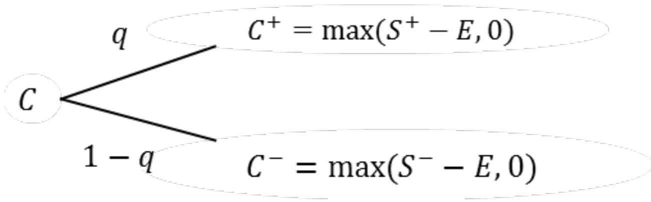
Classical ROA approaches stem from the Black-Sholes financial options-pricing model that has emerged from solving a system of stochastic partial differential equations (Black & Scholes, 1973). There are two basic types of financial options: calls and puts. A call option is the right to buy a specific asset by paying a pre-specified exercise price on or before a specified time; a put option is the right for the holder to sell the underlying asset to receive the exercise price. If the option can be exercised at any time up to the expiration date, it is called an American option; if only on the expiration date, a European option. The underlying assets to options include the common stock, stock indexes, bonds, commodities, foreign currencies, corporate liabilities, and so on.

The basic idea to evaluate options is to construct a replicating portfolio composed of N shares of the underlying asset (e.g. the common stock) and \$$B$ of riskless bond that will exactly replicate the future payouts of the option. According to the law of one price, to prevent risk-free arbitrage profits, the option and this equivalent portfolio must have exactly the same price (or value). Thus, the value of the option can be determined by calculating the cost of its equivalent replicating portfolio.

Suppose the price of the underlying stock (current price being S) will either rise up to S^+ or deline to S^+, with probabilities q and $1-q$, respectively, i.e.

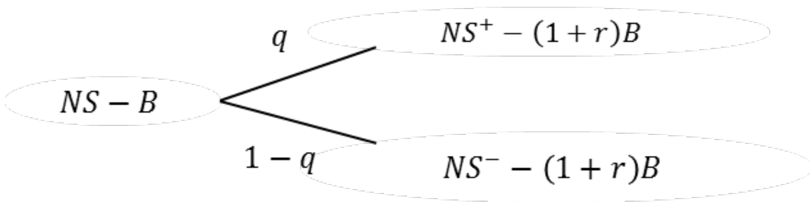


The value of the option, C, is contingent on the price of the underlying stock. Denote the exercise price as E,



where C^+ and C^- are the values of the call option at the end of the period if the stock price rises or declines, respectively.

The net out-of-pocket cost of the equivalent replicating portfolio for this call option is $NS - B$. Let r be the risk-free interest rate. The value of this portfolio over the next period will accordingly be



To satisfy the law of one price, the portfolio should have the same payouts in each state at the end of the period as the option, i.e.

$$NS - B = C \tag{2.1}$$

$$NS^{+} - (1+r)B = C^{+} \tag{2.2}$$

$$NS^{-} - (1+r)B = C^{-} \tag{2.3}$$

Solving these equations yields

$$N = \frac{C^{+} - C^{-}}{S^{+} - S^{-}} \tag{2.4}$$

$$B = \frac{S^{-}C^{+} - S^{+}C^{-}}{(S^{+} - S^{-})(1+r)} \tag{2.5}$$

$$C = \frac{pC^{+} + (1-p)C^{-}}{1+r} \tag{2.6}$$

where

$$p \equiv \frac{(1+r) - S^{-}}{S^{+} - S^{-}} \tag{2.7}$$

is the risk-neutral probability.

Standard option valuation typically relies on four basic assumptions as below:

S1: Frictionless markets which mean that: 1) there are no transaction costs or taxes; 2) there are no restrictions on short sales, and full use of proceeds is allowed; 3) all shares of all securities are infinitely divisible; and 4) borrowing and lending are unrestricted.

S2: The risk-free interest rate is constant over the life of the option.

S3: No dividends paying for the underlying asset over the life of the option.

S4: The stock prices follow a stochastic diffusion Wiener process, i.e.:

$$\frac{dS}{S} = \alpha\, dt + \sigma\, dz \tag{2.8}$$

where α is the instantaneous expected return on the stock, σ is the instantaneous standard deviation of stock returns, and dz is the differential of a standard Wiener process.

Black and Scholes (1973) introduced the Black-Sholes partial differential equation to solve the continuous application of the dynamic portfolio replication strategy under assumptions S1 to S4.

In the equivalent replicating portfolio represented by (2.1), its limit is $N = \partial C/\partial S$. As the Wiener processes underlying S and C are the same, the Wiener-process can be eliminated in an infinitely short period of time, dt. According to Ito's lemma,

$$dC = \frac{\partial C}{\partial t} dt + \frac{\partial C}{\partial S} dS + \frac{1}{2}\frac{\partial^2 C}{\partial S^2}\sigma^2 S^2 dt \tag{2.9}$$

From $dC = N\, dS - dB$ and $N = \partial C/\partial S$,

$$dC = \frac{\partial C}{\partial S} dS - dB \tag{2.10}$$

Equating the above two expressions for dC results in

$$dB = \left(-\frac{\partial C}{\partial t} - \frac{1}{2}\frac{\partial^2 C}{\partial S^2}\sigma^2 S^2\right)dt \tag{2.11}$$

Since the portfolio must be riskless under the assumption of no arbitrage, hence,

$$dB = Br\, dt = \left(\frac{\partial C}{\partial S}dS - C\right)r\, dt \tag{2.12}$$

Equating the two expressions for dB in (2.11) and (2.12) and denoting partial derivatives using subscripts, the following partial differential equation is obtained:

$$\frac{1}{2}\sigma^2 S^2 C_{SS} + rSC_S - C_\tau - rC = 0 \tag{2.13}$$

subject to the terminal condition

$$C = \max(S - E, 0) \tag{2.14}$$

and boundary conditions

$$C = 0 \text{ when } S = 0 \tag{2.15}$$

$$C \to S\ as\ S \to \infty \tag{2.16}$$

Solving the partial differential equation subject to the terminal condition and the boundary conditions results in the famous Black-Sholes formula for the prices at time zero:

$$C(S, \tau; E) = SN(d_1) - Ee^{-r\tau}N(d_2) \tag{2.17}$$

where

$$d_1 = \frac{\ln\left(\frac{S}{E}\right) + (r + \frac{1}{2}\sigma^2)\tau}{\sigma\sqrt{\tau}}$$

$$d_2 = d_1 - \sigma\sqrt{\tau}$$

where $N(\cdot)$ is the cumulative standard normal destitution function.

The Black-Sholes formula represents the continuous application of the replicating portfolio hedge. The number of shares of the stock held in the portfolio is given by $N(d_1)$, and the amount of riskless bond borrowed is given by $Ee^{-r\tau}N(d_2)$.

As real options are likened to financial options, the options-pricing model has been applied to assess the value of real options in many studies. Myers (1984) first suggested using the options-pricing method to value investments with operating options. Many studies have applied the classic options-pricing theory to assess the value of real options by identifying a twin security which is traded in the financial markets (Mason & Merton, 1985). McDonald and Siegel (1985) applied options-pricing techniques to study the investment problem of a firm given the option to shut down or change the production level. Grenadier and Weiss (1997) developed a model of the optimal investment strategy in technological innovations based on options pricing.

Applications of the Black-Scholes model on real options rely on satisfying the basic assumptions S1 to S4. For many real options, however, these assumptions are hard to be satisfied. First of all, the underlying project or system upon which the real options are built does not have a market price. Secondly, the no-arbitrage condition is usually unrealistic for real options; it is difficult to find equivalent replicating portfolios for real options. Lastly, the assumption based on the stochastic diffusion Wiener process is not suitable for many real options. Collectively, these challenges limit wide application of the Black-Scholes model in ROA.

2.1.2 Lattice approaches

As a discrete-time approximation of the Black-Scholes options-pricing model, the binomial lattice model introduced by Cox et al. (1979) won more popularity in ROA due to its simplicity. In the binomial lattice model, the stochastic process of the value of the underlying asset is approximated using a multiplicative binomial lattice. It assumes that the value of the underlying asset, S, may either increase at a rate u with a probability q or decrease to dS with a probability $1 - q$, such that $d = 1/u$. By assuming path independence, the lattice nodes recombine so that the number of possible outcomes is significantly reduced. The movement of the value of the underlying asset can be described in Figure 2-1.

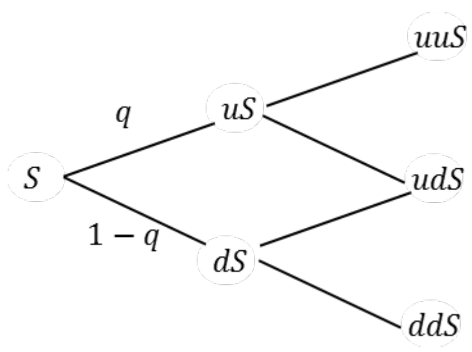


Figure 2-1: The evolution of uncertainty in the binomial lattice

The value of the option represented by Equation (2.6) still holds after denoting $S^{+} \equiv uS$ and $S^{-} \equiv dS$. The evaluation procedure can be extended to multiple time periods. With the total number of periods denoted as T, and as the number of upward movements as n, the price of the option will be:

$$C = \frac{\sum_{n=0}^{T} \frac{T!}{n!\,(T-n)!} p^n (1-p)^{T-n} \max(u^n d^{T-n} S - E, 0)}{(1+r)^T} \tag{2.18}$$

It is noteworthy that the risk-neutral probability p is used in Formula (2.17), which is defined by Equation (2.7). The relationship between the up and down movements in a binomial lattice and the standard deviation of the rate of return on the underlying asset can be described as:

$$u = e^{\sqrt{T/n}}$$

The binomial formula can approximate the continuous time form by dividing its life time, T, into increasingly small intervals, until n approaches infinity. It has been proved that, in the limit, the binomial model approaches the Black-Scholes model (Cox et al., 1979).

The binomial lattice approach has been widely used in various application fields. Luenberger (1997) applied the binomial lattice method to value the investment of a gold mine. Antikarov and Copeland (2001) provided a detailed guide on how to apply the binomial lattice approach to value real projects. The binomial lattice approach has also been used by de Neufville (2008) in evaluating the flexibility to abandon a mine pit subject to copper price uncertainty.

Variants of the binomial lattice methods have also been proposed for ROA. Kamrad and Ritchken (1991) developed a multinomial lattice procedure to value real options with multiple sources of uncertainty. As shown in Figure 2-2, a lattice with two sources of uncertainty consists of five possible movements emerging from each node, each with a probability of occurrence. As there is no recombination in the multinomial lattice, the number of nodes increases exponentially with the number of time periods. This constitutes the main challenge for the multinomial lattice method – the curse of dimensionality.

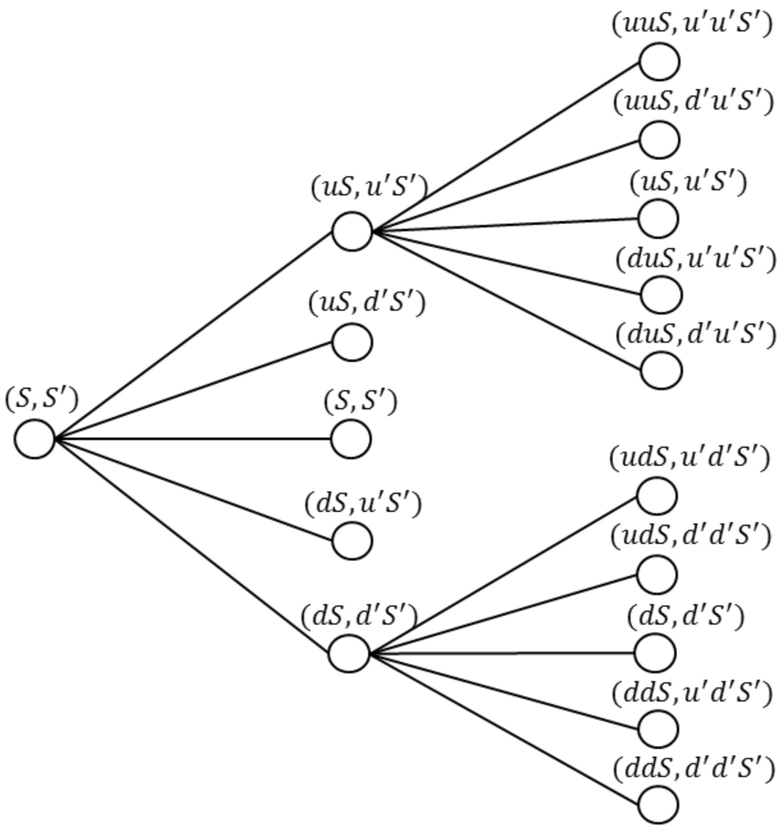


Figure 2-2: A multinomial lattice with two uncertainty sources

The lattice approaches provide some guidance on how to value flexibility and when to exercise it in operations. One challenge in practice, however, is the determination of the optimal timing to exercise flexibility. For instance, one needs to determine the current stage and state in the lattice by fitting past historical data. From there, future evolution of the uncertainty driver is projected, a backward induction must be applied up to the decision point based on a pre-defined recursive formula, and DMs must choose an exercise policy based on the highest expected reward. Another challenge is that the lattice approaches rely on assumptions that apply well to finance, but not necessarily to an engineering setting. For example, the path-independence assumption crucial to path recombination and computational savings may not hold (T. Wang & de Neufville, 2005). Because of path dependencies inherent to complex engineering systems, system value after an up-down movement may not be the same as after a down-up movement because the decision sequences and resulting physical artifacts may differ. Furthermore, when two or more uncertainty drivers and flexibility strategies are involved a complex flexible system, even multinomial lattices may become impractical due to the curse of dimensionality (Nembhard et al., 2005).

2.1.3 Simulation-based approach

With the rapid development of computer technologies, simulation models have become easily available to assess the value of real options that otherwise are difficult to value by using partial differential equations or lattice approaches. In simulation models, the stochastic process of uncertainty sources is modeled by generating a sizeable number of scenarios using Monte Carlo simulation. Decision rules are usually embedded in these models to facilitate the decisions on the exercise of options. Moel and Tufano (2000) applied the simulation method to value the real options inherent in the Antamina Mine in Peru. Juan, Olmos, Pérez, and Casasus (2001) developed a simulation based model to evaluate the value of options in a harbor investment project. Another application has been seen in simulation model built by de Neufville et al. (2006) using spreadsheet to assess the value of options to expand the capacity of a parking garage under demand uncertainty.

The use of the simulation-based approach is meritorious in that it enables the handling of complex systems in contrast to approaches based on the options-pricing theory i.e. the Black-Scholes model and binomial lattice approach; the difference is that the former does not require as strict assumptions as the latter. One key challenge, however, is the ability to specify the stochastic process so that the model simulates the system accurately. Another challenge concerns the computational efficiency; for a system is too complex or a payoff function that is expensive to compute, it may be time-consuming to acquire the required accuracy.

2.2 Flexibility in engineering systems

In the context of engineering, flexibility is an important system attribute that enables engineering systems to change easily in the face of uncertainty (Fricke & Schulz, 2005). Over the last decade, ROA approaches have been adapted to suit the needs of flexibility analysis in engineering design. All the aforesaid approaches, however, have limitations for practical applications. The Black-Sholes model requires the establishment of partial differential equations, which may not be intuitive to DMs in practice. In the Black-Sholes model and lattice-based approaches, all the decisions on flexibility exercise are determined as outcomes of the model; there are no generic decision rules to guide managers as uncertainty resolves throughout the project lifecycle.

Exercising the real option is typically based on a process inspired from the Bellman's recursive formula, which may not fully capture the actual decision-making process in reality (Bellman, 1952). Although the simulation-based approach explicitly employs decision rules, there is currently no systematic approach to determine the most value-enhancing decision-rule parameters.

2.3 Stochastic programming and decision rules

Stochastic programming is a method for modeling optimization problems that involve uncertainty. In stochastic programming models, some parameters are uncertain but their probability distributions are known or can be estimated. The goal of the model is to find some feasible policy for all possible data instances that maximize the expectation of the objective function. When some of the decision variables involved in a stochastic programming model are restricted to take integer values whereas other decision variables takes continuous values, the model is called a mixed-integer stochastic programming model. Mixed-integer programming is very useful for formulating discrete optimization problems, especially in simulating decision-making process. Ahmed, King, and Parija (2003) used a stochastic mixed-integer programming model to solve a capacity expansion problem. Tao Wang (2005) proposed stochastic mixed-integer programming for ROA to address the problem of path-dependency that constrains classical ROA approaches.

As pointed out by Birge and Louveaux (2011), there are few general efficient methods to solve stochastic mixed-integer programming problems. Certain techniques are available to solve problems with special properties, such as decomposition methods, simple integer recourse, and sampling average approximation, etc. The concept of decision rules has also been applied to approximate and solve stochastic programming models (Georghiou, Wiesemann, & Kuhn, 2015; Kuhn, Parpas, & Rustem, 2008).

A decision rule, or implementable policy, is a function which maps the observations of uncertainty data to decisions (Shapiro, Dentcheva, & Ruszczyński, 2009). Garstka and Wets (1974) surveyed different types of decision rules in stochastic programming. Four classes of decision rules are identified and studied via case examples: zero-order, linear, safety-first and conditional-go decision rules. The authors opined that difficulties might arise in restricting the class of acceptable rules to those specific functional forms to derive optimal rules, unless for some highly-structured problems. Nevertheless, any approximation of the optimal rule by a certain class of decision rules would yield quantitative bounds that have significant theoretical and practical implications.

Even for some intractable problems, a good approximation to an optimal solution can be obtained by searching for specific classes of decision rules. This is a utilitarian view in the paradigm investigating how to enable flexibility in design and management of engineering systems. Due to the complexity of the systems and uncertain environment, the design problems are usually of a substantial size and cannot be solved easily. By formulating the problem using decision rules, it is possible to obtain a good approximation to the optimal solution typically found using standard ROA techniques. In addition, generic decision rules have an advantage in that they are practical and intuitive for DMs to use in operations. They can be modeled explicitly to emulate the decision-making process in a firm or organization.

As such, this thesis recognizes the importance of decision rules as a way to assess the value of flexibility in design and management of complex systems. Against this backdrop, a systematic approach based on stochastic programming is proposed to find stochastically optimal decision rules that guide dynamic decision-making based on available information, as uncertainties are resolved.

2.4 Waste-to-energy systems design

The case application studies rely on the design and deployment of WTE technologies in an urban setting. Municipal solid waste management is becoming a predicament in the sustainable development of megacities. In the face of increasing waste and limited landfill sites, WTE technologies, which generate energy in the form of electricity and/or heat from waste, are garnering high favor due to their capacity to recover energy while efficiently disposing of waste. Various WTE technologies are promising in terms of offering electricity, heat and transport fuels (Münster & Lund, 2010). Thus far, the literature on WTE systems has mainly focused on system optimization and evaluation; consideration has not been dedicated to the strategic management process of designing and deploying capacity in WTE systems. In particular, little research has been taken to analyze WTE systems from the perspective of flexibility. This thesis targets the issue of how to manage the decision making process during the implementation of such flexible systems by applying the proposed approach based decision rules.

Three different types of WTE systems are studied as demonstrations in this thesis. An upcoming AD plant that treats food waste in Singapore is first considered in Section 4.3. This case study is inspired by Hu and Cardin (2015), who have considered embedding flexibility into the system design as a mechanism to deal pro-actively with uncertainties. Upon analysis of the uncertainty and interdependency of the system elements in an AD plant, two system elements related to capacity are identified as valuable opportunities for embedding flexibility. Therefore, in this case study, it is assumed that the AD plant is designed with flexibility to expand the capacity as needed. This case study demonstrates how the decision rule approach can be used to analyze the flexibility to expand capacity. Results are compared to that of standard ROA.

The design of a hybrid WTE system with AD and gasification technologies is analyzed in the second case study in Section 5.2. This is an advanced facility with improved efficiency of waste treatment using a combination of those two WTE technologies. In such a complex system, two sources of uncertainty (i.e. the amount of food waste and other organic waste) and two flexibility strategies (i.e. capacity expansion of AD and capacity adjustment for the gasifier) are considered simultaneously. This case study shows that the proposed approach can be extended to analyze complex systems when multiple uncertainty sources and flexibility strategies are considered simultaneously.

Finally, the design of a multi-storey recycling facility (MSRF) is elucidated to demonstrate the application of the generic framework proposed in Chapter 6. MSRF is a first-of-its-kind facility planned by Singapore as a solution to reduce land-take while creating more space for essential activities undertaken by the waste management industry (NEA, 2014b). An MSRF facility is envisaged to be a multi-story, multi-tenanted pilot facility processing different waste streams that could share common facilities and services such as weighbridges and a vehicle-parking depot. It achieves land-saving by hosting recycling activities for different types of wastes on different stories.

2.5 Research questions

Previous sections review existing ROA approaches and discuss their application in the analysis of flexibility in engineering systems. The review identifies several inadequacies in using existing ROA approaches in an engineering context. To address these challenges, an approach based on stochastic programming and decision rules is recognized as a potential solution to analyze flexibility in engineering systems design. The concept of decision rules, however, has not been systematically studied in this area. Motivated by these research gaps, this thesis aims to develop an efficient approach to analyze and manage flexibility in engineering systems. More specifically, the research objectives can be summarized via the five research questions as below:

1. *How to provide intuitive guidance for DMs to operate the systems in practice, besides assessing the value of flexibility in engineering systems?*

This thesis introduces the concept of decision rules in the design process to generate results that are readily applicable for decision making in operations. Decision rules provide practical guidance on when it is appropriate to and how to exercise the flexibility. They are intuitive for DMs to follow in operations because they enable emulating directly the decision making process in reality. As such, decision rules can be either normative or prescriptive (i.e. what they should be) or descriptive (i.e. what they are currently). The hypothesis is that with clearly specified decision rules, DMs are less likely to fall into escalation of commitment, so that the theoretical value of flexibility can be fully extracted in operations.

2. *How to analyze flexibility exploiting the idea of decision rules?*

As decision rules can be characterized by decision variables whose "stochastically optimal values" can be approximated, the problem of searching for optimal decision rules fits well into a stochastic programing framework. Therefore, the hypothesis is that the concept of decision rules in flexibility analysis can be formulated using multistage stochastic programming models.

3. *How to solve the stochastic programming model with decision rules?*

The multistage stochastic programming models are usually of large size, but many of them have a specific structure, which is suitable to be solved by applying some decomposition methods. Various decomposition methods are available in the literature on stochastic programming. The hypothesis is that the proposed models can be solved by applying some decomposition techniques. In particular, it is postulated that a Lagrangian decomposition approach can be used as a solution algorithm.

4. *How to guide designers to apply the decision rule approach during the design process?*

A framework is necessary to guide designers on how to apply the proposed decision rule approach. The framework should explain all necessary procedures to address the concept of decision rules throughout the design phase. The hypothesis is that with this framework, designers can start with a baseline design and generate a valuable flexible design that is practical to operate by exploiting the concept of decision rules.

5. *How to validate the efficiency and effectiveness of the proposed approach?*

Numerical studies can be used to demonstrate the efficiency and effectiveness of the proposed approach. First, case examples from Trigeorgis (1996) will be used to demonstrate the ability of the proposed approach to model different types of flexibility. Then, case studies on three different WTE systems will be conducted to demonstrate the efficiency and effectiveness of the proposed approach by comparing with standard ROA approaches. The hypothesis is that these case studies will show that the proposed approach is able to analyze different types of flexibility efficiently.

2.6 Summary

This chapter reviews existing ROA approaches and discusses their application in the analysis of flexibility in engineering systems. The review identifies several inadequacies of applying existing ROA approaches in an engineering context. Stochastic programming and decision rules are recognized as a potential solution to address the challenges faced by existing ROA approaches. WTE systems are selected as a meaningful application domain as they are important for sustainable development of megacities while little research has been undertaken to analyze them from the perspective of flexibility. Based on the review, research opportunities are identified and research objectives are summarized as five concise questions. The rest of this thesis will introduce the proposed approach by addressing the five research questions.

Chapter 3 – A Generic Stochastic Programming Model with Decision Rules

3.1 Introduction

In the previous chapter, relevant research works were briefly introduced and their limitations were identified. The main research gap addressed in this thesis is the inadequacy of an approach in, firstly, providing intuitive guidance to DMs on when and how to exercise the flexibility in operations and, secondly assessing the value of flexibility in large scale engineering system projects. To address these research opportunities, this thesis proposes an approach based on decision rules and multistage stochastic programming to assess the value of flexibility and to determine the best design and exercise strategies in operations.

In this chapter, a generic multistage stochastic programming model using decision rules is introduced. Three types of decisions rules that can be applied easily to the management of flexibility in engineering systems are introduced by generic formulations. An algorithm based on Lagrangian decomposition is proposed to solve the multistage stochastic programming model. Instantiations of the generic model are introduced in subsequent chapters using simple examples and real-case studies on WTE systems.

3.2 Model formulation

Let $\boldsymbol{\xi} = (\boldsymbol{\xi}_1, \dots, \boldsymbol{\xi}_T)$ be a scenario of uncertainty, where $\boldsymbol{\xi}_t$ is the uncertainty to be observed in period $t \in \mathcal{T} = \{1,2,\dots,T\}$. Note that $\boldsymbol{\xi}_t$ is a vector so that it can represent multiple sources of uncertainty. Denote Ω as the set of all possible uncertainty scenarios. Suppose the total number of scenarios is very large or even infinite. As a common approach, the sample average approximation (SAA) method is applied to reduce the number of scenarios to a manageable size: it is assumed that a sample $\boldsymbol{\xi}^1, \dots \boldsymbol{\xi}^K$ of K scenarios, with the corresponding probabilities $p^k \geq 0, \sum_{k=1}^{K} p^k = 1$, is generated using Monte Carlo simulation to approximate the problem. Figure 3-1 illustrates the sequence of events over the finite planning horizon. There is no operation at the beginning of planning horizon, time 0, which represents present time. The DM must make a decision $\boldsymbol{x}_t$ at the beginning of period t from a set of feasible decisions X_t when $t \geq 1$. Note that $\boldsymbol{x}_t$ is a vector, which means it can consider several flexibility strategies simultaneously. Let $X \subseteq X_1 \times \cdots \times X_T$ denote the set of all feasible decisions sequence $\boldsymbol{x}$, where $\boldsymbol{x} = (\boldsymbol{x}_1, \dots, \boldsymbol{x}_T)$. A decision rule, or implementable policy, δ, is a function which maps each scenario of uncertainty $\boldsymbol{\xi}$ in Ω to a sequence of decisions $\boldsymbol{x}$ in X (i.e., $\delta: \Omega \rightarrow X$). Let $\mathcal{D}$ denote the set of all mappings from Ω to X. The form of δ varies in different problems, a vector of parameters $\boldsymbol{\theta}$ is used to characterize it. So the decision rule can be represented as $\delta_{\boldsymbol{\theta}}$.

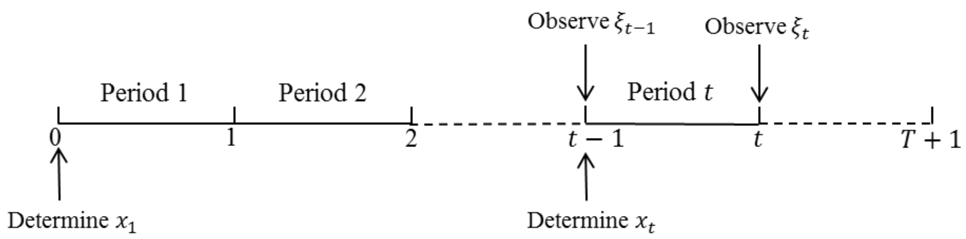


Figure 3-1: Planning horizon and sequence of events

It is assumed that the DM's choices are nonanticipative in that the choice of decision $\boldsymbol{x}_t$ at the beginning of period t only depends on the information available up to the beginning of period t. In the multistage setting, the uncertain data $\boldsymbol{\xi}_1, \dots, \boldsymbol{\xi}_T$ is revealed gradually over time. Let notation $\boldsymbol{\xi}_{[t]} := (\boldsymbol{\xi}_1, \dots, \boldsymbol{\xi}_{t-1})$ denote the history of the uncertainty realization up to the beginning of period t. The nonanticipativity constraint requires that the decision x_t depends only on the uncertain data process $\boldsymbol{\xi}_{[t]}$. In other words, if the revealed uncertainty data up to the beginning of period t in two scenarios is the same, then the decision made at the beginning of period t should be exactly the same, no matter how different they will be in the following periods. Exploiting this requirement, $\delta_{\boldsymbol{\theta}}(\boldsymbol{\xi})$ can be represented as $\delta_{\boldsymbol{\theta}}(\boldsymbol{\xi}) = \left(\delta_{\boldsymbol{\theta}}(\boldsymbol{\xi}_{[1]}), \dots, \delta_{\boldsymbol{\theta}}(\boldsymbol{\xi}_{[T]})\right)$, where $\delta_{\boldsymbol{\theta}}(\boldsymbol{\xi}_{[t]})$ is the decision made at the beginning of period t.

The DM's goal is to select a feasible decision rule to maximize total expected profit. The profits are determined by a sequence of profit functions $\left(r_1(\delta_{\boldsymbol{\theta}}(\boldsymbol{\xi}_{[1]}), \boldsymbol{\xi}_1), \dots, r_T(\delta_{\boldsymbol{\theta}}(\boldsymbol{\xi}_{[T]}), \boldsymbol{\xi}_T)\right)$ where the profit in period t depends on the decision $\boldsymbol{x}_t$ and the revealed uncertain data $\boldsymbol{\xi}_t$ in period t. Let

$\mathrm{r}(\delta_{\boldsymbol{\theta}}(\boldsymbol{\xi}),\boldsymbol{\xi}) = \sum_{t=1}^{T}\left(\frac{1}{1+\pi}\right)^{t} r_t\left(\delta_{\boldsymbol{\theta}}\left(\boldsymbol{\xi}_{[t]}\right),\boldsymbol{\xi}_t\right)$ denote the total profit. The problem of choosing an optimal decision rule is then:

$$\max_{\delta_{\boldsymbol{\theta}}}\left\{\boldsymbol{E}[\mathrm{r}(\delta_{\boldsymbol{\theta}}(\boldsymbol{\xi}),\boldsymbol{\xi})] = \sum_{k=1}^{K} p^k \sum_{t=1}^{T} r_t\left(\delta_{\boldsymbol{\theta}}\left(\boldsymbol{\xi}_{[t]}^{k}\right),\xi_t^k\right)\right\} \tag{3.1}$$

$$\text{s.t.}\, \delta_{\boldsymbol{\theta}}\left(\boldsymbol{\xi}_{[t]}^{k}\right) \in X_t, \forall k, t \tag{3.2}$$

$$\delta_{\boldsymbol{\theta}}\left(\boldsymbol{\xi}_{[t]}^{k}\right) = \delta_{\boldsymbol{\theta}}\left(\boldsymbol{\xi}_{[t]}^{k'}\right), \ \text{if}\, \boldsymbol{\xi}_{[t]}^{k} = \boldsymbol{\xi}_{[t]}^{k'}, \forall k, k', t \tag{3.3}$$

$$\delta_{\boldsymbol{\theta}} \in \Delta \subseteq \mathcal{D} \tag{3.4}$$

where Δ is a subset of $\mathcal{D}$, the variables with superscript k correspond to the variables in scenario k.

It is worthy to mention that though expected net present value (ENPV) is used here as objective function in the model, the objective function is not necessary to be restricted to be ENPV only. The objective function can be extended to other types of objectives for engineering systems with different characteristics or DMs with different risk profile. Examples of extensions could be mean-variance, where both the return and risk are taken into consideration (Gülpınar, Rustem, & Settergren, 2003), and Conditional Value-at-Risk, which is a widely accepted risk measure (Schultz & Tiedemann, 2006). In this thesis, it is assumed that the decision maker is risk neutral and ENPV is used as the objective.

If this model can be solved to the optimum, then an optimal decision rule δ^* can be obtained, under which the DM will do best by choosing $\delta_{\boldsymbol{\theta}}{}^{*}(\xi)$ to attain the maximum expected total profit as uncertainty $\boldsymbol{\xi}$ unfolds. However, even with the SAA method, the problem may be very large. In the case of $\Delta = \mathcal{D}$, to obtain an analytical formulation of δ^* might be extremely difficult. In the design of flexible engineering systems, one is usually interested in certain types of flexibilities embedded in the system, which will lead to some particular patterns of decision rules. Therefore, to obtain the closed form solution to the decision rule problem, Δ can be restricted to a class of mappings, which is a subset of $\mathcal{D}$.

By restricting Δ to be a proper subset of $\mathcal{D}$, it is possible to solve such problem which is generally intractable computationally. Several forms of decision rules are introduced in Section 3.3. The choice of decision rule form is based on the characteristics of the specific problem.

As can be seen from the formulations, the decision rule approach is flexible to model engineering design problems. From the perspective of modeling, there are two important features. The first one is that the decision rule approach can readily handle multiple uncertainty sources. In model (3.1)-(3.4), the uncertainty is represented as a vector $\boldsymbol{\xi}$. Thus the number of uncertainty sources corresponds to the number of elements in $\boldsymbol{\xi}$. As can be seen in the formulations, the number of elements in $\boldsymbol{\xi}$ does not change the structure of the problem. Furthermore, the complexity of the model is determined by the number of decision variables and the number of constraints, neither of which will be significantly increased as the number of elements in $\boldsymbol{\xi}$ increases. In fact, as the uncertainty is represented using $\boldsymbol{K}$ scenarios, the problem can be decomposes into $\boldsymbol{K}$ small problems which are easy to solve. Therefore, increasing from single uncertainty source to multiple uncertainty sources will not significantly increase the complexity of the modeling and analysis. It is also straightforward to consider multiple flexibility strategies simultaneously. This can be seen by the fact that $\boldsymbol{x}_t$ is a vector of decisions, with each element representing a decision regarding a given flexibility strategy. This formulation also lends itself naturally to Lagrangian decomposition, and can handle a considerable number of scenarios efficiently. The model needs to be scaled up to handle several flexibilities simultaneously, while the computational difficulty does not increase intractably. In Chapter 4, this thesis introduces modeling of different types of flexibilities using the proposed model. A simple WTE system is used as demonstration application. Chapter 5 then demonstrates scalability of the approach to more complex systems with multiple flexibility strategies and multiple uncertainty drivers.

3.3 Decision rules

In this section, three generic types of decision rules that can be applied easily to the management of flexibility in engineering systems are introduced. Decision rules specific to a given system may be generated using systematic concept generation processes, and typically rely on the designer's creativity and expertise with the system (Cardin et al., 2013). Decision rules can be created by considering generic real option strategies (e.g. capacity expansion, abandonment, switching, phasing capacity deployment, deferring investment, etc.) combined with design enablers (which physically enable the exercise of the decision rule) (Cardin, 2014). Thus many decision rules exist and can be explored, depending on the system of interest, the uncertainty it faces, and its purpose or mission. This is an active topic of ongoing research.

3.3.1 Conditional-go decision rule

With conditional-go decision rules, the decision at each time stage is made according to an estimate of future conditions, based on past information. The rule is usually expressed as "*if the uncertainty realizations in the past satisfy a certain set of criteria, then exercise the flexibility, else do nothing*." There are various ways to formulate the conditional-go decision rules. Binary variables are usually introduced to facilitate this. A common formulation of the conditional go rule useful in the proposed stochastic programming setting is as below:

$$\boldsymbol{e}_t = \mathbf{1}(g(\boldsymbol{\xi}_{[t]}) \in \boldsymbol{\phi}_t) \tag{3.5}$$

where $\boldsymbol{e}_t$ is a vector of binary variables, each element of $\boldsymbol{e}_t$ representing the decision to exercise or not a flexibility: if it is equal to 1, then the flexibility is exercised; if equal to 0, it is not exercised. $\mathbf{1}(\cdot)$ is an indicator function. $g(\boldsymbol{\xi}_{[t]})$ is a function of $\boldsymbol{\xi}_{[t]}$, and can be an estimate of future conditions based on $\boldsymbol{\xi}_{[t]}$. $\boldsymbol{\phi}_t$ is the criteria to be satisfied in order to exercise the flexibility at time t. The Big-M method is very useful in the formulation of the indicator function.

Because of the use of binary variables, a problem relying on conditional-go decision rules can often be formulated as a mixed integer linear program (MILP). The class of conditional-go decision rules is a compromise between precision and computational difficulty. While it cannot necessarily find a global optimum, it is often helpful to find good enough approximations. The form of the solution is useful in the management of flexibility in practice, since it emulates a system operator's decision making process – and simplifies it greatly.

To make a connection with standard ROA, the formulation of Bellman's equation in the binomial lattice can be thought conceptually as a conditional-go decision rule. The decision rule can be described as "if the expected value of the up and down movement in the next stage is higher when exercising the option, then exercise the option, if not, keep the system in the same state." Such decision rule is applied recursively in the backward induction process, starting from the last stage (e.g. last time period) until time zero, or the exercise time. Such decision rule is hard-coded in the binomial lattice approach. Thus, there is less freedom to implement different types of decision rules, and decision rules that emulate directly the system operator's decision making process.

3.3.2 Constant decision rule

If the decision to be made at time stage t, $\delta_t(\cdot)$, is independent of the observations of the uncertainty data up to stage t, $\boldsymbol{\xi}_{[t]}$, then the decision rule belongs to a class called constant decision rules. This is a special case of a multistage problem: the problem of determining a decision rule function degenerates to determining a single sequence of decisions to be made at each stage. Thus it actually enables the DM to collapse a multistage problem into a two-stage problem. Only one linear program is required to solve to determine the options to be chosen at each stage. In this way, the computation cost can be reduced dramatically.

$$\max_{\boldsymbol{x}} \left\{ \sum_{k=1}^{K} p^k \sum_{t=1}^{T} r_t\left(\boldsymbol{x}_t, \boldsymbol{\xi}_t^k\right) \right\} \tag{3.6}$$

$$\text{s.t. } \boldsymbol{x}_t \in X_t, \forall k, t \tag{3.7}$$

The shortcoming of this class of decision rules is that it does not fully follow a rational process because it forces the DM to make decisions for all time stages before realizing any of the uncertainties. However, in some cases, it can provide an insurance policy against the worst possible outcomes.

3.3.3 Linear decision rule

Linear decision rules are a class of decision rules $\delta_t(\cdot)$ that are linearly dependent on the observed uncertainty data $\boldsymbol{\xi}_{[t]}$. They can be expressed as $\delta_t\left(\boldsymbol{\xi}_{[t]}\right) = L_t \boldsymbol{\xi}_{[t]}$, for some matrix L_t with proper dimensions. Substituting these linear decision rules to problem (3.1) – (3.4) yields the following approximate problem:

$$\max_{L} \left\{ \sum_{k=1}^{K} p^k \sum_{t=1}^{T} r_t\left(L_t \boldsymbol{\xi}_{[t]}^k, \boldsymbol{\xi}_t^k\right) \right\} \tag{3.8}$$

$$\text{s.t. } L_t \boldsymbol{\xi}_{[t]}^k \in X_t, \forall k, t \tag{3.9}$$

By using linear decision rules, the size of the original stochastic programming problem grows only moderately with the number of time stages. Therefore, the original problem can be converted to a finite linear program that is amenable to numerical solution. The form of the solution is also easy to use in operations, since it is a linear combination of the observed uncertainty realizations.

3.4 Solution procedure - Lagrangian decomposition

An important challenge in multistage stochastic programming is the large dimension that makes most problems NP-hard to solve. Even if the problem can be simplified into a deterministic structure by assuming the finiteness of Ω, the computational effort still increases significantly with the number of scenarios. However, in order to obtain a good approximation for the uncertainty, a large number of scenarios are usually needed. In the cases where integer decision variables are involved, the problem will become computationally intractable. To overcome this difficulty, decomposition is an effective approach.

It can be observed that the structure of problem (3.1) – (3.4) is convenient to be split into K small subproblems, one for each scenario. And the optimal value of problem (3.1) – (3.4) is equal to the weighted sum with weights p^k, of the optimal value of the subproblems. However, it is the nonanticipativity requirement that links the decision sequences associated with different scenarios. The nonanticipativity constraints (3.3) can be expressed by ensuring the equality of the parameters $\boldsymbol{\theta}$ in each scenario, i.e.

$$\boldsymbol{\theta}^1 = \cdots = \boldsymbol{\theta}^K \tag{3.10}$$

where $\boldsymbol{\theta}^k$ is a replication of the decision rule parameters in scenario $\boldsymbol{\xi}^k$. Another way to write the nonanticipativity is to require that

$$\boldsymbol{\theta}^k = \overline{\boldsymbol{\theta}}, \qquad 1 \leq k \leq K \tag{3.11}$$

where $\overline{\boldsymbol{\theta}} = \sum_{k=1}^{K} p^k \boldsymbol{\theta}^k$ is the average of $\boldsymbol{\theta}^k$ over its K replications.

The size of the original problem grows exponentially in the number of scenarios. If the coupling constraints can be relaxed, the problem can be decomposed into K subproblems such that each scenario can be solved independently. Lagrangian relaxation is applied to the coupling constraints by allowing the DM to follow different decision rules in different scenarios; however, violations of the decision rule coupling constraints are penalized with Lagrange multipliers in the objective function.

By assigning Lagrange multipliers $\boldsymbol{\lambda} = (\lambda^1, \dots, \lambda^K)$ to these coupling constraints, the following Lagrangian is obtained

$$L(\delta_{\boldsymbol{\theta}}, \boldsymbol{\lambda}) := \sum_{k=1}^{K} p^k r(\delta_{\boldsymbol{\theta}}(\boldsymbol{\xi}^k), \boldsymbol{\xi}^k) + \sum_{k=1}^{K} \lambda^k (\boldsymbol{\theta}^k - \overline{\boldsymbol{\theta}}) \tag{3.12}$$

The dualization of problem (3.1) – (3.4) with respect to the coupling constraints can be expressed as the following problem:

$$Z^{LD} = \min_{\boldsymbol{\lambda}} \left\{ D(\boldsymbol{\lambda}) := \max_{\theta} L(\delta_{\theta}, \boldsymbol{\lambda}) \right\} \quad s.t. \text{ (3.2) and (3.4)} \tag{3.13}$$

By general duality theory, the optimal value of problem (3.13) is greater than or equal to the optimal value of problem (3.1) – (3.4). Therefore, an upper bound of problem (3.1) – (3.4) is obtained by solving problem (3.13). The form of $D(\boldsymbol{\lambda})$ makes it suitable to be decomposed into K scenario subproblems:

$$\max_{\boldsymbol{\theta}^k} \left(r\left(\delta_{\boldsymbol{\theta}^k}(\boldsymbol{\xi}^k), \boldsymbol{\xi}^k\right) + \left(\lambda^k - \frac{\sum_{k=1}^{K} \lambda^k}{K} \right) \boldsymbol{\theta}^k \right), \quad \forall k \tag{3.14}$$

The subproblems are generally of small size in comparison to problem (3.13), so they can be solved efficiently by applying parallel computation techniques.

$D(\boldsymbol{\lambda})$ can be obtained by summing up the optimums of the subproblems with weights p^k.

Theoretically, if all the constraints are convex and all the variables are continuous, the optimum of Z^{LD} will be equal to the optimum of the original problem (3.1) – (3.4). However, a duality gap may exist due to the existence of integer decision variables. This means that the optimum of Z^{LD} will be strictly larger than the optimum of problem (3.1) – (3.4). Therefore, the aim is to obtain a good upper bound on problem (3.1) – (3.4) by solving Z^{LD}.

A tight upper bound Z^{LD} can be obtained by using a subgradient method to vary $\boldsymbol{\lambda}$. Given an initial value $\boldsymbol{\lambda}_0$, a sequence of multiplier values $\boldsymbol{\lambda}_i$ is generated by the following rule

$$\lambda^k{}_{i+1} = \lambda^k{}_i + t_i\left(\boldsymbol{\theta}_i^k - \overline{\boldsymbol{\theta}}_i\right) \tag{3.15}$$

where $\boldsymbol{\theta}_i^k$ and $\overline{\boldsymbol{\theta}}_i$ are optimal solutions to $D(\lambda)$ with the multipliers set to $\lambda^k{}_i$ and t_i is a scalar step size in the i^{th} iteration. For the choice of step size t_i, the most commonly used strategy is adopted (Fisher, 2004):

$$t_i = \frac{\rho_i(D(\boldsymbol{\lambda}_i) - D^*)}{\left\|\boldsymbol{\theta}_i - \overline{\boldsymbol{\theta}}_i\right\|^2} \tag{3.16}$$

where D^* is the value of the best known feasible solution to problem (3.1) – (3.4), $D(\boldsymbol{\lambda}_i)$ is the optimal solution to the Lagrangian relaxation with multipliers set to $\boldsymbol{\lambda}_i$ and the scalar ρ_i is chosen between 0 and 2 and its value is halved whenever $D(\boldsymbol{\lambda}_i)$ fails to decrease in a fixed number of iterations.

A heuristic method can be used to generate feasible solutions to Z^{LD}, which are lower bounds. This method should be designed based on the characteristics of the problem. For example, in the application of the AD plant problem described in Section 4.2, the heuristic method used is: set the maximum capacity x_M as the maximum value of x_M^k among the K subproblems; set the initial capacity ε, and other two decision rule variables α, β as the average value of ε^k, α^k and β^k respectively.

The gap between the upper bound and lower bound determines the quality of the solution. Because solving the dual to optimality is not guaranteed, the search is terminated when the gap is lower than a certain value or after a predetermined number of iterations.

3.5 Summary

This chapter proposes a generic multistage stochastic programming model to explicitly consider decision rules in the analysis of flexibility in the design of engineering systems. Three types of decisions rules are introduced using generic formulations. An algorithm based on Lagrangian decomposition is introduced to solve the multistage stochastic programming model.

Chapter 4 – Modeling Simple Flexibilities

4.1 Introduction

This chapter demonstrates how the generic model proposed in Chapter 3 can be applied to model flexibilities in engineering systems. First, six types of managerial flexibilities are formulated by using simple examples from Trigeorgis (1996). Subsequently, a case study on a WTE system using AD technology is conducted as demonstration to apply the proposed approach in a real-world engineering system problem.

4.2 Simple examples of flexibility

Trigeorgis (1996) utilized a generic example to show how contingent-claims analysis (CCA) could be used to evaluate the value of operating real options (flexibility). In this section, the sample example is analyzed using the proposed decision rule approach to demonstrate its capability to model these flexibilities. The results are compared to those of CCA presented by Trigeorgis (1996). Throughout the formulations of these simple flexibilities, conditional-go rules are applied as it emulates the decision making process of CCA.

Suppose that a firm has an opportunity to invest $I_0 = \$104$ million (all equity) in a project (e.g. to build a plant). The expected value of this project follows a multiplicative binomial process: in each period, the project value either increases by an up factor $u = 1.8$ or decreases by a down factor $d = 0.6$. That is, the expected value will be \$180 million if the market moves up ($V^{+} = 180$) or \$60 million if the market moves down ($V^{-} = 60$). There is an equal probability ($q = 0.5$) that the project will move up or down in any year. The discount rate is $k = 20\%$ and the risk-free interest rate is $r = 8\%$. Figure 4-1 illustrates the binomial lattice of the cash flow. The objective is to determine the net present value of the project. In addition, when flexibility is present, the value of flexibility needs to be assessed.

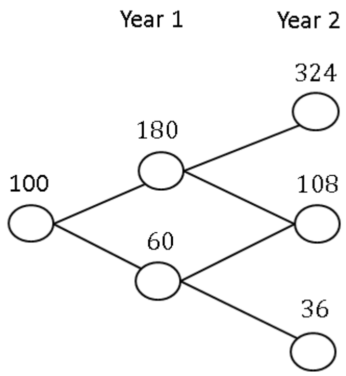


Figure 4-1: The binomial lattice of the cash flow

4.2.1 Flexibility to defer investment

Suppose the firm has the exclusive right to defer undertaking the project in a given year. What is the value of the investment opportunity provided by the flexibility to defer investment? It is evident that the flexibility to defer undertaking the project has a positive value as it maintains the opportunity to benefit from favorable future scenarios and provides the right to avoid loss in unfavorable market circumstances. To evaluate the value of the flexibility to defer, a simple stochastic program is built following the generic model described in Chapter 3.

Because the flexibility to defer the project grants DMs the right, but not the obligation, to invest in a given year, they will wait and construct the plant only if the project value in the next year turns out to be favorable. Therefore, the decision rule to capture the decision making can be expressed as: wait until Year 1, and invest in the project if the gross project value in year one V_1 exceeds a critical value V^*; otherwise, do not invest. A binary variable e is used to capture the decision of exercising the flexibility to invest in Year 1: $e = 1$ when $V_1 \geq V^*$; otherwise $e = 0$. The problem can be formulated as:

$$\max_{V^*} E\left(\frac{e(V_1 - I_1)}{1 + r}\right) \tag{4.1}$$

$$s.t.\ e = 1(V_1 > V^*) \tag{4.2}$$

where $E(\cdot)$ denotes the expectation and $1(\cdot)$ the indicator function. The constraint (4.2) can be formulated using the big M method:

$$V_1 - V^* > M(e - 1) \tag{4.3}$$

$$V_1 - V^* \leq Me \tag{4.4}$$

where M is a sufficiently large constant.

By subscribing the expectation function and big M representation, Problem (4.1) and (4.2) can be expanded as:

$$\max_{V^*} \frac{pe^+(V_1^+ - I_1) + (1-p)e^-(V_1^- - I_1)}{1 + r} \tag{4.5}$$

$$s.t.\ e^+ = 1(V_1^+ > V^*) \tag{4.6}$$

$$e^- = 1(V_1^- > V^*) \tag{4.7}$$

where p is the risk-neutral probability,

$$p = \frac{(1+r)-d}{u-d} \tag{4.8}$$

Upon solving this simple optimization problem, the net present value (NPV) of the project is \$25.07 million. The project per se has a negative NPV of \$4 million if taken immediately. Therefore, the value of the flexibility to defer investment is \$29.07 million. These results are the same as the results obtained using the CCA by Trigeorgis (1996).

Besides the results regarding the valuation of the flexibility to defer, the results also reveal guidelines for the DMs to make a decision in Year 1. According to the results, the threshold to determine whether to invest the plant in Year 1 is $V^* = 60$. This translates into a decision that the DMs should invest in the project only when the gross value of the project in year one is larger than 60: when the market moves up ($V_1^+ = 180$), the DMs should invest; when the market moves down, DMs should not invest. This decision rule is in line with the decisions generated from the CCA by Trigeorgis (1996).

4.2.2 Flexibility to expand

Once the project is implemented, the DMs may have the flexibility to change it in different ways at different time periods throughout its lifespan. The flexibility to expand enables the DMs to expand the project by making additional investment if the market turns out better than originally expected. In this example, suppose that the DMs have the option to make an additional investment of \$80 million one year after the project is undertaken. This follow-on expansion would double the scale of the project. With this expansion in Year 1, the DMs can decide either to operate the plant on the original scale of production or on twice that original scale to receive double the project value with additional cost. This problem can be modeled as:

$$\max_{V^*} E\left(\frac{e(2V_1 - I_1') + (1-e)V_1}{1+r} - I_0\right) \quad (4.9)$$

$$s.t.\ e = 1(V_1 > V^*) \quad (4.10)$$

Upon solving this optimization problem, the total value of the investment opportunity is \$33.04 million. The value of the flexibility to expand is therefore equal to $33.04 - (-4)$ = \$37.04 million. The threshold to exercise the flexibility to expand is $V^* = 60$. In the upside scenario, $V_1^+ = 180 > 60$, therefore $e = 1$, the plant is expanded to receive twice the project value. In the downside scenario, $V_1^- = 60$, $e = 0$, the project remains the same. A comparison shows that the results are again the same as the solutions by Trigeorgis (1996).

4.2.3 Flexibility to contract

The flexibility to contract is akin to the flexibility to expand. It enables the system to reduce the operation scale of a project if the market turns out worse than originally expected. The flexibility to contract can be seen as a put option that reduces the project's exposure to risk.

In this example, assume that the investment cost of the project is to be spent over two years. Specifically, an initial investment of \$50 million ($I_0 = 50$) is required to initiate the project and a follow-up cost of \$58.32 (the future value of \$54 million) ($I_1 = 54$) is to be spent to maintain the scale of operation in year one. In one year, DMs will have the option to reduce to half of the scale of the project by spending less, $I_1'' = \$25$ million. In this way, the management may find it valuable to exercise this option if the market does not accept the product as well as expected. The formulation of the problem is:

$$\max_{V^*} E\left(\frac{(1-e)(V_1 - I_1) + e(0.5V_1 - I_1'')}{1+r} - I_0\right) \tag{4.11}$$

$$s.t.\ e = 1(V_1 \leq V^*) \tag{4.12}$$

Upon solving this optimization problem, the total value of the project with flexibility to contract is $\$-2.16$ million. The value of the flexibility to contract is therefore equal to $-2.16-(-4)$ $= \$1.84$ million. The threshold to exercise the flexibility to contract is $V^* = 60$. In the upside scenario, $V_1^+ = 180 > 60$, therefore $e = 0$, the project remains the same. In the downside scenario, $V_1^- = 60$, $e = 1$, the scale of the project is halved to save expenses. The results are the same as those reported in Trigeorgis (1996).

4.2.4 Flexibility to temporarily shut down

If the revenue of a project in a given year is lower than its operating cost, the flexibility to temporarily shut down production may significantly reduce its potential loss. In this example, suppose that the cost in year one can be divided into fixed cost, $FC = \$18.32$, and variable cost, $VC = \$40$ and that the cash revenue of the project in a given year equals to 30% of the project value, i.e. $C = 0.3V$. The fixed cost is to be paid yearly after the project has been launched whereas the variable cost is necessary to be spent in order to acquire the cash revenue. However, if the market turns out unfavorable and the cash revenue in the next year is less than the variable cost, the DMs may choose to exercise the flexibility to temporarily shut down the production to save variable cost and relinquish the cash revenue. In other words, the flexibility enables the DMs either to operate the plant in a given year and receive the value of project minus the variable costs, or to temporarily shut down production and receive the value of project minus the cash revenue. The formulation of the problem is:

$$\max_{V^*} E\left(\frac{(1-e)(V_1 - VC) + e(V_1 - 0.3V_1) - FC}{1+r} - I_0\right) \qquad (4.13)$$

$$s.t.\ e = 1(V_1 \leq V^*) \qquad (4.14)$$

The results show that the value of the project with flexibility to temporarily shut down is \$8.22 million. The value of flexibility is $8.22 - (-4)$ = \$12.22 million. This result is the same as that in Trigeorgis (1996). The threshold to temporarily shut down production is $V^* = 60$. In the upside scenario, $V_1^+ = 180 > 60$, $0.3V_1^+ = 54 > 40$, therefore $e = 0$, the project remains the same. In the downside scenario, $V_1^- = 60$, $0.3V_1^- = 18 < 40$, thus $e = 1$, the plant will be temporarily shut down.

4.2.5 Flexibility to abandon

Besides the flexibility to temporarily shut down production of the project, the DMs may enjoy the flexibility to abandon the project to receive the salvage value if the market condition is exceedingly unfavorable. In this example, assume that the project can be abandoned in exchange for its salvage value, A, which fluctuates over time as follows:

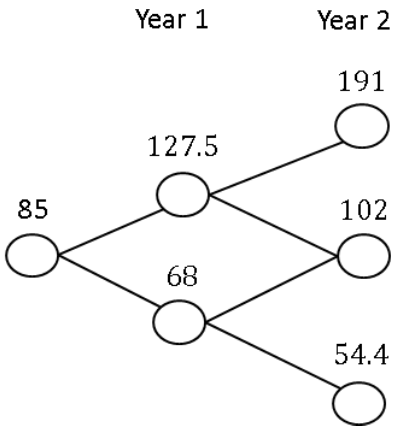


Figure 4-2: The binomial lattice of the salvage value

Assume that DMs would abandon the project early if the difference between the value of the project and its salvage value is lower than a threshold V^*. The problem can be formulated as:

$$\max_{V^*} E\left(\frac{eV_1 + (1-e)A_1}{1+r} - I_0\right) \tag{4.15}$$

$$s.t.\ e = 1(V_1 - A_1 \leq V^*) \tag{4.16}$$

Upon solving this optimization problem, results show that the value of the project with flexibility to abandon is \$0.44 million. The value of flexibility is $0.44 - (-4) = \$4.44$ million. Again, this result is the same as that in Trigeorgis (1996). The threshold to abandon the project is $V^* = 0$, implying that the project should be abandoned when the project value is lower than its salvage value. In the upside scenario, $V_1^+ - A_1 = 72.5 > 0$, therefore $e = 0$, the project goes on nonetheless. In the downside scenario, $V_1^- - A_1 = -8$, thus $e = 1$, the project will be abandoned to receive the salvage value.

4.2.6 Flexibility to switch

The abandonment can be viewed as a switching option in which abandoning the project is viewed as a second operating mode of the project. In addition to abandoning the project, a project may have multiple operating modes so that the DMs have the flexibility to switch to different modes as uncertainty reveals. To model this type of flexibility, formulations similar to the structure of Problem (4.15) and (4.16) can be used.

4.3 Case study I: Capacity expansion of a WTE system using AD technology

The preceding section demonstrates formulations of different types of flexibilities using generic examples. These examples are uncomplicated given that the main purpose is to demonstrate the ease with which different types of flexibility can be modeled using the proposed decision rule approach. In this section, the approach is applied to a real-world system: the design of an upcoming AD plant that treats food waste in Singapore. The goals of this case study are twofold. Firstly, it demonstrates how the proposed approach can be utilized to design and manage flexibility in engineering systems in practice. Secondly, it enables a comparison between the proposed decision rule approach and standard ROA, and evaluates thoroughly their similarities and differences.

4.3.1 Problem analysis

The study builds upon and extends the work by Hu and Cardin (2015), who considered embedding flexibility into the system design as a mechanism to deal pro-actively with uncertainty of the amount of food waste collected. After analyzing the uncertainty and interdependency of the system elements in an AD plant, two system elements related to capacity are identified as valuable opportunities to embed flexibility (i.e. tipping floor and major tankage). Using these design enablers, it is assumed that the AD plant is designed with the ability to expand capacity in a flexible manner, as needed. More specifically, one assumes that the AD plant is modularly designed, which means it can expand the capacity by units of modules. Abandonment is not considered in this paper, i.e., the capacity is increasing monotonically. The goal of DMs is to select the appropriate capacity expansion strategy to maximize the expected total profit, i.e., ENPV, in a lifespan of T years.

It is assumed that the centralized AD plant is to be built in Tuas, using trucks to collect food waste from households and food courts around the city. Let ξ_t denote the amount of food waste collected in year t. The food waste is turned into biogas, compost and residue after a series of processes in the plant. The biogas is further used to generate electricity, the compost can be sold for agriculture, while the residue and any unprocessed feedstock have to be sent to landfill for disposal by paying disposal fee. The revenue of the AD plant mainly comes from three sources: the sale of electricity to the grid, the sale of compost, and the tipping fee collected from the household and food courts. The cost of the AD plant consists of installation cost, maintenance cost, land rental cost, labor cost, transportation cost, as well as disposal cost. The profit function r_t of the AD plant in period $t \geq 1$ can be expressed as:

$$r_t = R_t - C_t - P_t \tag{4.17}$$

where R_t is the revenue function, C_t is the cost function, and P_t is the penalty function due to the capacity shortage. They are defined as below:

$$R_t = (z_1 + z_2)p(\xi_t - f_t) + z_3\xi_t \tag{4.18}$$

$$\begin{aligned} C_t = z_4\xi_t + z_5(x_t - x_{t-1}) + (z_6 + z_8 + z_9)x_t \\ + z_{10}(1 - p + p\tau)(\xi_t - f_t) + z_7(x_M - x_t) \end{aligned} \tag{4.19}$$

$$P_t = z_{10}f_t \tag{4.20}$$

where x_M is the designed maximum capacity, $f_t = \max(0, x_t - \xi_t)$ represents the capacity shortage, p is the purity ratio of the food waste, τ is the residue rate, z_1 is the net unit revenue from electricity generation, z_2 is the unit revenue from compost sale, z_3 is the unit revenue from tipping fee, z_4 is unit transportation cost, z_5 is unit capacity installation cost, z_6 is unit land rental fee, z_7 is unit reserved land fee, z_8 is unit labor cost, z_9 is unit maintenance cost, and z_{10} is unit disposal cost.

The AD plant is modularly designed: the capacity can be expanded in units of modules, each module with a unit capacity o_u tons per day. Abandonment is not considered, i.e., the capacity is increasing monotonically. The total expected profit, i.e., ENPV, of the AD plant is considered in a lifespan of T years.

The main source of uncertainty is the amount of food waste collected. Historical data in the past 10 years show that the amount of food waste collected in Singapore has a deterministic growth rate, but the amount variation in each period is random. Based on this observation, it is suitable to model the fluctuating waste amount using geometric Brownian motion (GBM):

$$d\xi_t = \mu\xi_t dt + \sigma\xi_t dz_t \tag{4.21}$$

where variable μ is the annual growth rate of the food waste amount, σ is the volatility of the food waste amount, and dz_t is the basic Wiener process giving a random shock to μ. The first term at the right hand side models the deterministic trend, and the second term models the uncertainty shock occurring at each period. With these two parts, the GBM formulation captures the stochastic properties of the waste generation process.

4.3.2 Binomial lattice analysis

In order to apply ROA over a discrete time horizon, the model of the uncertainty can be simplified using the binomial lattice approach proposed by Cox et al. (1979). Assuming food waste amount can move up at rate u with probability q, or down at rate d with probability $1 - q$, such that $d = 1/u$, the rate and probability of movement are given as:

$$u = e^{\sigma\sqrt{\Delta t}} \tag{4.22}$$

$$q = \frac{1}{2} + \frac{1}{2}\left(\frac{\mu}{\sigma}\right)\sqrt{\Delta t} \tag{4.23}$$

where Δt is the length of each time interval.

In each period t, the DM must choose an option of capacity x_t from a set of feasible options X_t to maximize the total expected profit, given that the capacity selected in the preceding time is x_{t-1}, and the realization of the food waste amount is ξ_t. The value R of the total profit at time t and state (x_{t-1}, ξ_t) is defined with the following recursive equation:

$$R_t(x_{t-1}, \xi_t) = \max_{x_t} \left[r_t(x_{t-1}, x_t, \xi_t) + \frac{1}{(1+\pi)} \sum_{j=1}^{n} p_j R_{t+1}\left(x_t, \xi_{t+1,j}\right) \right], 0 < \mathrm{t} < \mathrm{T} \tag{4.24}$$

where $r_t(x_{t-1}, x_t, \xi_t)$ is the profit in time period t, x_t is the capacity chosen in time t, $R_t(x_{t-1}, \xi_t)$ is the total expected profit from time t to the last time period, x_{t-1} is the capacity applied in time $t-1$, n is the number of jumps from each node (in the binomial lattice, $\mathrm{n} = 2$), π is the discount rate, $\xi_{t+1,j}$ is the food waste amount in node order j of the following n nodes at time interval $t+1$, and p_j is the according probability of the state.

To solve the dynamic programming problem, it starts from the last period and go back one time period at each iteration. The expected total profit in the last time period can be calculated by:

$$R_T(x_{T-1}, \xi_T) = \max_{x_T} r_T(x_{T-1}, x_T, \xi_T) \tag{4.25}$$

When the first node is reached, the optimal solution is obtained. The solution of the binomial lattice model consists of two parts: the first part is the maximum of the total expected profit of the program R_1; the second part is the optimal decision for the first period x_1. The results will be compared to the results of the proposed approach in the Section 4.3.4.

4.3.3 Multistage stochastic programming with conditional-go decision rules

To apply the proposed stochastic programming model with decision rules, a set of conditional-go decision rules is considered. The type of decision rule can be expressed as: *at the end of time period* $t-1$, *if the observed amount of waste collected in the last year is more than a certain level (i.e.* $(x_{t-1} - \alpha_t)o_u$) , *then expand the capacity by* $\beta_t o_u$. Here, x_t is an integer representing the number of modules installed at time t; α_t is a parameter in unit of number of modules representing the severity level of the capacity shortage at time t, a higher (lower) α_t means the DM is more (less) keen to expand capacity to prevent capacity shortage; and β_t represents the scale of each expansion at time t (i.e. the number of modules deployed). To fit to the framework in Section 3.2, Constraint (3.4) about the decision rule can be represented by

$$\xi_{t-1}^k - (x_{t-1}^k - \alpha_t^k)o_u \geq M(e_t^k - 1), \quad t = 2 \ldots T, \forall\, k \tag{4.26}$$

$$\xi_{t-1}^k - (x_{t-1}^k - \alpha_t^k)o_u \leq M e_t^k, \quad t = 2 \ldots T, \forall\, k \tag{4.27}$$

$$h_t^k \leq \beta_t^k o_u, \quad t = 2 \ldots T, \forall\, k \tag{4.28}$$

$$h_t^k \geq \left(e_t^k - 1\right)M + \beta_t^k o_u, \qquad t = 2 \ldots T, \forall\, k \tag{4.29}$$

$$h_t^k \leq e_t^k M, \qquad t = 2 \ldots T, \forall\, k \tag{4.30}$$

where M is a large enough number (as a rule of thumb, the value for M should be at least 100 times larger than the largest value of any variable in the problem), α_t^k and β_t^k are the replications of the corresponding decision rule variables in scenario k, e_t^k is a binary variable indicating whether to expand in year t in scenario k, and h_t^k is the amount of capacity to be added. When the waste amount in year $t-1$ reaches a certain threshold, i.e. $\left(x_{t-1}^k - \alpha_t^k\right)o_u$, (4.26) and (4.27) will force $e_t^k = 1$, which means the flexibility of expanding capacity should be exercised in year t. Meanwhile, (4.28), (4.29), and (4.30) will force h_t^k to be equal to $\beta_t^k o_u$, the amount of capacity to be added. Conversely, when the waste amount in the previous year is less than the threshold, e_t^k will be equal to 0 and the amount of capacity to be added in year t, i.e. h_t^k, will be 0.

Constraint (3.2) defines the set of available options in each time, and can be represented by:

$$x_t^k o_u = x_{t-1}^k o_u + h_t^k,\ t = 2 \dots T, \forall\, k \quad (4.31)$$

$$x_t^k \le x_M^k, \quad \forall t, k \quad (4.32)$$

$$x_1^k = \varepsilon^k, \quad \forall k \quad (4.33)$$

$$o_u x_t^k + f_t^k \ge \xi_t^k,\ \ t = 1,2, \dots, T, \forall k \quad (4.34)$$

where ε^k is the number of modules installed in the first year in scenario k, x_M^k is the maximum number of modules allowed to be expanded in scenario k. Constraint (4.31) defines the incremental of the capacity, constraint (4.32) requires the capacity to be no larger than the maximum capacity designed, constraint (4.33) defines the initial capacity, and constraint (4.34) defines the capacity shortage f_t^k.

The decision variables parameterizing the decision making process are the decision rule variables α_t, β_t, and the initial design variables ε, x_M. Let $\theta = (\alpha_2 \dots \alpha_T, \beta_2 \dots \beta_T, \varepsilon, x_M)$ denote the set of decision variables and provide a complete solution to design and manage the flexible system. In the above constraints, a replication of these decision variable, θ^k, is made for each scenario, so as to make it convenient to decompose the problem later. In order to satisfy the requirement of nonanticipativity, the equality of replications must be forced, i.e.

$$\boldsymbol{\theta}^1 = \cdots = \boldsymbol{\theta}^K = \boldsymbol{\theta} \tag{4.35}$$

The stochastic programming problem with decision rules can be formulated as:

$$\max_{\boldsymbol{\theta}} \sum_{k=1}^{K} p^k \sum_{t=1}^{T} \left(\frac{1}{1+\pi}\right)^t r_t^k\left(x_t^k, \xi_t^k\right), \quad s.t.\ (4.26)-(4.35) \tag{4.36}$$

where p^k is the weight associated with scenarios k. To make a fair comparison with standard ROA, the scenarios of uncertainty of the food waste amount are generated from the binomial lattice. A lattice of T time periods contains 2^T scenarios.

The above formulation enables different expansion judgment criteria and different levels of expansion at each stage by allowing different values of α_t and β_t. This is consistent with standard ROA. However, for simplicity and demonstration purposes, α_t and β_t are assumed to be respectively equal at each stage in the computational experiments, i.e. $\alpha_2 = \cdots = \alpha_T, \beta_2 = \cdots = \beta_T$. In this way, the decision rule becomes even simpler and practical to use, because the expansion judgment criteria and expansion level are the same at each stage and throughout the project lifetime. The stochastic program enables finding the optimal value of each such parameter across a given range of scenario samples.

Problem (4.36) is a MILP. The number of constraints and decision variables increase exponentially as the number of scenarios considered increases. To solve it efficiently, Lagrangian decomposition is used by dualizing the coupling constraint (4.35) with a set of Lagrange multipliers, and then decomposing the problem into K scenario subproblems. The algorithm described in Section 3.4 is applied and implemented in C++ by calling CPLEX. The details of the solution are presented in the following section.

4.3.4 Computational experiments

Numerical Results

This section presents the numerical results of the standard ROA and proposed decision rule approaches. The main assumptions of the AD plant used in the numerical study are listed in Table 4-1. Based on historical data of the food waste amount in Singapore, parameters of the uncertainty can be inferred in Table 4-2. Then the binomial lattice is generated, as shown in Figure 4-3.

Table 4-1: List of assumptions for the model

Parameters	Value	Definition	Comments and sources
T	9	Time span of the system considered	
p	70%	Purity ratio of the food waste feedstock	In Singapore, the food wastes from industrial and commercial areas have about 30%-40% impurities (Evangelisti, Lettieri, Borello, & Clift, 2014).
τ	10%	Residue ratio of the AD process	The residues rate for incineration technology is 10% in Singapore (Bai & Sutanto, 2002).
z_1	S$22,469/tpd*	Revenue from electricity generation per tpd food waste processed	It is assumed that the electricity generation rate is 228 kWh/t (IUT Global, 2006). Singapore electricity tariff is S$0.27/kWh based in 2013 (Singapore Power, 2013).
z_2	S$1,336/tpd	Revenue from compost per tpd waste processed	Compost generation rate is 18% (IUT Global, 2006). Selling price of compost is assumed to be S$20/t.
z_3	S$28,105/tpd	Revenue from tipping fee per tpd waste collected	Average tipping fee paid by food courts to dispose of residue is S$77/t.
z_4	S$700/tpd	Transportation cost per tpd food waste collected	It is assumed that the capacity of each truck is 25 tonnes, the average distance per collection trip is 114 km, petrol consumption cost is S$ 0.4/km, and vehicle daily cost is $90.
z_5	S$75,000/tpd	Capacity installation cost per unit capacity	IUT Global (2006)
z_6	S$816/tpd	Land rental cost per unit capacity installed	Utilized land rental fee is S$20,000/month/hectare.
z_7	S$204/tpd	Land rental cost per unit capacity reserved	Reserved land rental fee is S$5,000/month/hectare.
z_8	S$675/tpd	Labor cost per unit capacity	IUT Global (2006)
z_9	S$225/tpd	Maintenance cost per unit capacity	IUT Global (2006)
z_{10}	S$28,105/tpd	Disposal cost per tpd food waste disposed in landfill	Fee paid by AD plants to dispose of residues in incineration plants is S$77/t (NEA, 2013).
π	8%	Discount rate	A general discounted rate
o_u	30 tpd	Capacity of an unit module	

*tons per day (tpd) is used to as the unit of waste amount and the capacity of the AD plant.

Table 4-2: Parameters of uncertainty

Parameters	Value	Definition
μ	14.1%	Annual growth rate
σ	16.4%	Volatility
u	1.18	Upside factor
d	0.85	Downside factor
q	93%	Probability of moving up

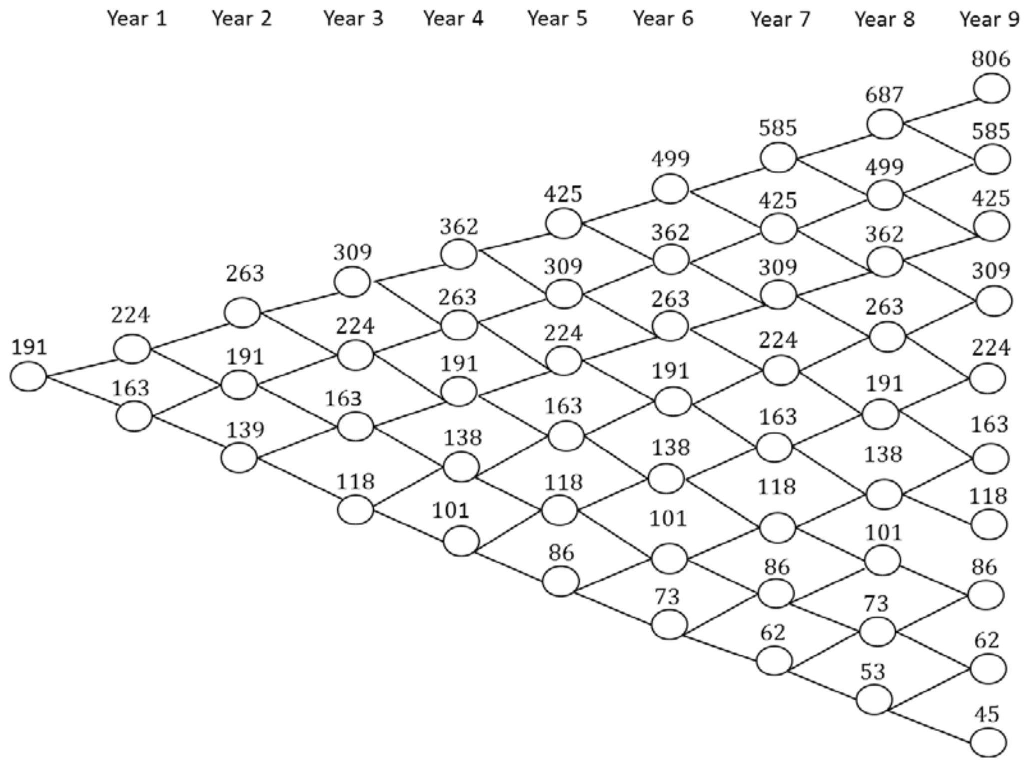


Figure 4-3: Binomial lattice of the waste amount

To make a fair comparison, two configurations of experiments are emphasized. Firstly, the uncertainty data used in the stochastic program (4.36) are generated from the same paths in the binomial lattice shown in Figure 4-3. Secondly, the action space in the ROA is set to be consistent with the decision rule approach: it is assumed that the AD plant can be installed with the same capacity range as the result of the decision rule approach, i.e., in each time t, the DM can choose a capacity from $X = \{\varepsilon o_u, (\varepsilon + 1)o_u, (\varepsilon + 2)o_u, \dots, x_M o_u\}$, where ε and x_M are the values of the corresponding decision variables in the decision rule approach.

The multistage stochastic program (4.36) is solved using the Lagrangian decomposition algorithm described in Section 3.4. The algorithm is terminated when the gap between the upper and lower bound is smaller than 5% or after 100 iterations. The program is run on a PC with Intel Core i5-2500 @ 3.30GHz quad core processor and 8GB memory. After solving the problem with a size of 512 scenarios (all paths from the binomial lattice) and 9 year periods, it shows that the algorithm is able to get feasible solutions with low duality gap very fast. Table 4-3 shows the progression of bounds in the proposed Lagrangian decomposition algorithm. It shows that the best ENPV of $38.7 million is obtained within 100 iterations, and the final gap between the upper and lower bounds is 2.3%. To show the efficiency of the algorithm, the program runs under different number of scenarios (which are generated based on Formula (4.21) using the Monte Carlo approach). As can be seen in Table 5-4, the solution time of the original model using CPLEX MIP solver increases exponentially as the size of the problem increases. It becomes not solvable when the number of scenarios is as large as 500. However, the solution time of the Lagrangian algorithm increases linearly as the size of the problem increases. This shows that the proposed algorithm is capable of efficiently solving the problems of large size. In addition, based on the observations of the available results, the difference between the ENPV obtained by using the proposed algorithm and by using CPLEX MIP solver, which is the real optimal solution, is less than 1%.

Table 4-3: Bounds from the Lagrangian decomposition algorithm

Iterations	Lagrangian solution (upper bound) ($, million)	Postulated lower bound ($, million)	Gap between lower and upper bounds
2	98.7	31.4	214.3%
10	56.2	36.8	52.8%
20	41.2	38.7	6.6%
50	40.2	38.7	4.0%
100	39.6	38.7	2.3%

Table 4-4: Comparison of the results for 9 years

No. of scenarios	CPLEX		Proposed algorithm		Difference of ENPV
	ENPV ($, million)	Solution time (s)	ENPV ($, million)	Solution time (s)	
10	35.2	2	34.9	8	0.9%
50	34.9	37	34.7	42	0.6%
100	33.8	157	33.6	74	0.6%
200	34.3	25,632	34.0	157	0.9%
500	N/A*	N/A	33.8	401	N/A

*N/A means the problem is not solvable as the PC runs out of memory.

The value of flexibility, which means the ENPV of the flexible design compared to the inflexible design, is measured to compare the performance of the models. The expected value of flexibility is defined as:

$$\text{Expected value of flexibility} = \text{ENPV}_{\text{flexible}} - \text{ENPV}_{\text{inflexible}} \tag{4.35}$$

To calculate the value of flexibility, a baseline inflexible design is formulated as:

$$\max_{x_f} \sum_{k=1}^{K} p^k \sum_{t=1}^{T} \left(\frac{1}{1+\pi}\right)^t r_t^k(x_f, \xi_t^k) \tag{4.36}$$

where x_f is the capacity of the AD plant throughout the lifespan. One should note that building a large rigid system can benefit from economies of scale, i.e., the average unit capacity installation cost is lower. In this study, unit capacity installation cost of the inflexible design is assumed to be 90% of that of the flexible designs.

Table 4-5 shows the solutions for the three optimization models. The ENPV of the inflexible design is \$36.9 million. The ENPV using standard ROA is \$40.8 million. Thus \$3.9 million of additional value can be achieved compared to the inflexible design. As for the decision rule model, the ENPV can be as high as \$38.7 million, with expected value of flexibility of \$1.8 million.

Table 4-5: Solutions for optimization models

Models	Solutions	ENPV (\$ million)	Value of flexibility (\$ million)	Computation time (s)
Inflexible design	$x_f = 14$	36.9	-	0.146
ROA	$x_1 = 8$	40.8	3.9	0.015
Decision rule approach	$\varepsilon = 9$, $x_M = 23$, $\alpha = 1, \beta = 2$	38.7	1.8	73

The valuation results are of similar order of magnitude, and show that standard ROA can gain the highest ENPV. This is not surprising, since the backward induction process finds the best capacity deployment path through the lattice at each stage. This contrasts with the decision rule approach based on a heuristics, which by design deploys the same capacity in each expansion phase to ease the management process. A key observation here is that both approaches recognize a similar amount of value from flexibility using a similar capacity expansion strategy. Also, the performance improvement is non-negligible as compared to the inflexible system, which is in line with the results obtained in the literature.

One may conclude from the results in Table 4-5 that by enabling flexibility in the WTE system, the ENPV improves significantly. However, this is based on the assumption that the unit cost of capacity installation for the inflexible design is 90% of that of the flexible designs due to economies of scale, and the fact that a flexible design may require additional upfront costs. Intuitively as the economies of scale factor decreases (i.e. economies of scale becomes stronger), the value of flexibility should decrease, because there is more economic incentive to build large. To see how valuable the flexibility is compared to the economies of scale in this system, a sensitivity analysis is conducted by varying the factor of economies of scale from 50% to 100%. Results in Table 4-6 show as expected that the value of flexibility decreases as economies of scale become stronger (i.e. lower economies of scale factor). The value of flexibility is offset by economies of scale when the factor is as low as 50% (note: industry standard is typically no lower than 60%).

Table 4-6: Sensitivity analysis on the factor of economies of scale

Factor of economies of scale	100%	90%	80%	70%	60%	50%
ENPV of inflexible design ($ million)	36.4	36.9	37.3	37.8	38.2	38.7
Value of flexibility ($ million)	2.43	1.8	1.4	0.9	0.5	0

Using the Solution

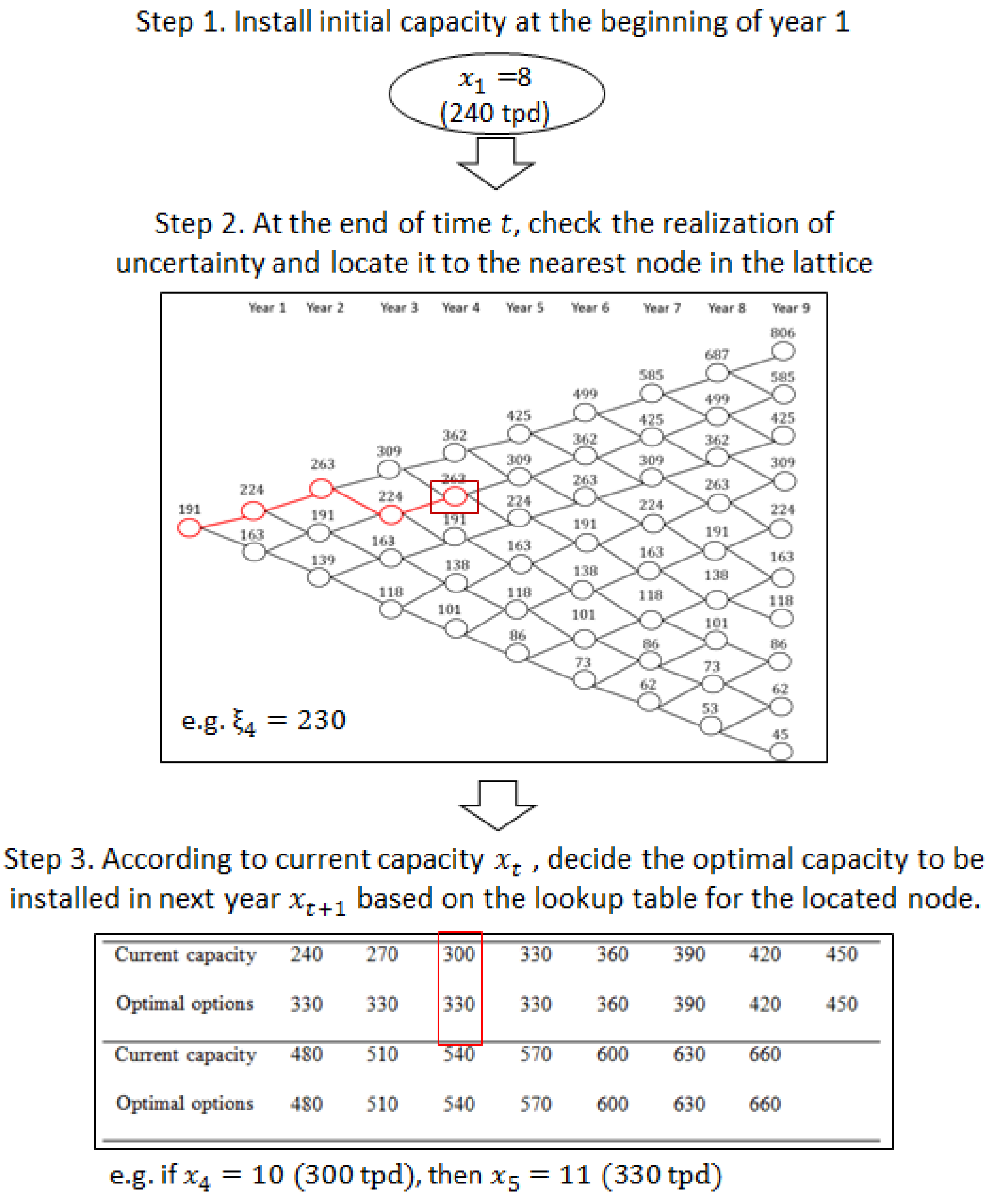
This section describes the forms of the solutions under each approach, and how to use them to exercise the flexibilities in operations. For the inflexible design, decision making is simple: build a system with capacity of 14 modules (14 modules × 30 tpd/module = 420 tpd) in the first period, and do not make any change in the future.

The solutions of the standard ROA require conducting a backward induction process at each node, which can be stored in a lookup table showing the optimal capacity for the next year based on the current state. For instance, Table 4-7 shows the lookup table of the possible choices for node $n_{4,2}$ (defines the kth node in period t in the lattice as $n_{t,k}$). Such table must be created each time a decision must be made because it depends on the capacity installed in the possible previous states. At the beginning of each time period, the DM must determine the current position (i.e. node, characterizing the stage/state) in the binomial lattice and the path followed up to that node, and then identify the optimal decision based on the position.

Table 4-7: Lookup table for node $n_{4,2}$ in the lattice

Current capacity	240	270	300	330	360	390	420	450
Optimal options	330	330	330	330	360	390	420	450
Current capacity	480	510	540	570	600	630	660	
Optimal options	480	510	540	570	600	630	660	

One practical disadvantage of using the lookup tables to make decisions, however, is that it does not provide clear guidance when the realization of uncertainty falls outside the values of the lookup nodes in the lattice. One way to approximate the problem is to locate the realization of uncertainty to the nearest corresponding node in the lattice. Figure 4-4 illustrates the decision making procedure. For instance, if the realized waste amount in year 4 is 230 tpd and the waste amount in year 3 has been allocated to the node $n_{3,2}$, then the waste amount in year 4 will be allocated to the node $n_{4,2}$ (with value of 263) as it is closer than node $n_{4,3}$ (with value of 191). Based on Table 5-7, if current installed capacity is 300 tpd, expansion to 330 tons per day should be done. If current capacity is 360 tpd, no flexibility should be exercised, and capacity should remain at 360 tpd. There is no unique optimal decision on each node because current capacity varies depending on the path of the uncertainty realization up to that point. Therefore, the DM has to keep checking the path of the uncertainty realization recursively and refer to the lookup table produced for each node. The correctness of the decision depends on the ability to locate the correct position in the binomial lattice, and apply the recursive process correctly. Of course, the best way to use the standard ROA is to conduct the backward induction process in each year based on realized uncertainty information to find the optimal decisions. This, however, increases computational effort.



Current capacity	240	270	300	330	360	390	420	450
Optimal options	330	330	330	330	360	390	420	450
Current capacity	480	510	540	570	600	630	660	
Optimal options	480	510	540	570	600	630	660	

Figure 4-4: Illustration of decision making procedure following results of standard ROA

Under the decision rule approach, the system should be designed with initial capacity of $\varepsilon = 9$ modules (270 tpd) in the first year, and extra land should be reserved to facilitate maximum capacity of $x_M = 23$ modules (690 tpd) in the future (land should also be reserved under standard ROA). Every year, the DM should expand the capacity by $\beta = 2$ modules (60 tpd) once the amount of waste collected in the previous year is higher than the value of the current capacity minus the equivalent of $\alpha = 1$ module of capacity (i.e. $(x_{t-1} - 1) * 30$ tpd). For example, if installed capacity is 300 tpd and waste generated in the previous year reached 270 tpd or more, expansion to 360 tpd should occur. One observation is that that the decision making process under the decision rule approach is quite readily applicable as compared to standard ROA, and does not rely on backward induction.

Out-of-Sample Studies

To validate and compare the performance of the three decision making approaches numerically, an out-of-sample study is conducted. Three simulation models are built to capture the decision making processes described in the previous sub-section. A number of 10,000 sample scenarios are generated based on formula (4.21) by the Monte Carlo approach, using the inferred parameters in Table 4-2. It is assumed that each scenario has the same weight, i.e. $p^k = \frac{1}{10000}, \forall k$.

The results of the out-of-sample test are summarized in Table 4-8. The performance under the decision rule approach is again of the same order of magnitude as under standard ROA, only 1.4% less on average. This difference stems again from the same capacity being deployed in each expansion phase under the decision rule approach. Both approaches rank order the design alternatives in a consistent manner (i.e. flexible solution is better than the inflexible solution). Table 4-8 shows that the computation time of the decision rule approach is also similar to that for standard ROA (0.02s). As expected, the ENPV of each approach is lower than the optimal objective value obtained in the optimization models. This is because the optimization model finds a solution that fits better the sample scenarios from the binomial lattice, while both solutions must perform under unseen scenarios in the out-of-sample studies.

Table 4-8: Results of out of sample simulation (10,000 scenarios)

Models	ENPV ($ million)	Value of flexibility ($ million)	Computation time (s)
Inflexible design	32.3	-	0.16
ROA	34.8	2.5	0.02
Decision rule approach	34.3	2.0	0.02

4.3.5 Discussions

Influence of uncertainty

The preceding analysis shows that the performance under the decision rule approach is of the same order of magnitude as that under standard ROA in terms of the ENPV, only 1.4% less on average. This difference is attributed to the abilities of different capacity expansion strategies to handle the uncertainty in the waste amount. To elucidate how the uncertainty affects this difference, sensitivity analysis was conducted by varying the volatility of the waste amount from 14.2% to 24.6%. The ENPVs of the two approaches in out-of-sample test are shown in Figure 4-5. As can be seen, the ENPVs decrease as the volatility increases. In particular, the difference between the ENPV of standard ROA and that of the decision rule approach becomes slightly larger as the volatility increases. This means that the increase of uncertainty in the food waste amount weakens the ability of the decision rule approach to obtain a high ENPV to a greater extent than it affects that of the ROA approach. The reason for this is that the decision rule approach deploys the same capacity in each expansion phase to ease the management process. When the volatility becomes higher, the change of the waste amount becomes more uncertain. In some scenarios, the increment of waste amount may be so high that an overall-best amount of capacity expansion is difficult to satisfy the requirement. Due to the flaw of average, the opportunity lost in these extreme scenarios may not be compensated by cost savings occurring in downside scenarios. In contrast, the standard ROA approach enables more flexibility in the expansion amount in each stage. Therefore, the difference of performance of these two approaches increases as the volatility increases. It is anticipated that when more flexible decision rules are utilized, this gap will be smaller. A more flexible decision rule, however, will diminish its ease of use in management practice. There is a trade-off between the high performance and the ease of use in selection of decision rules.

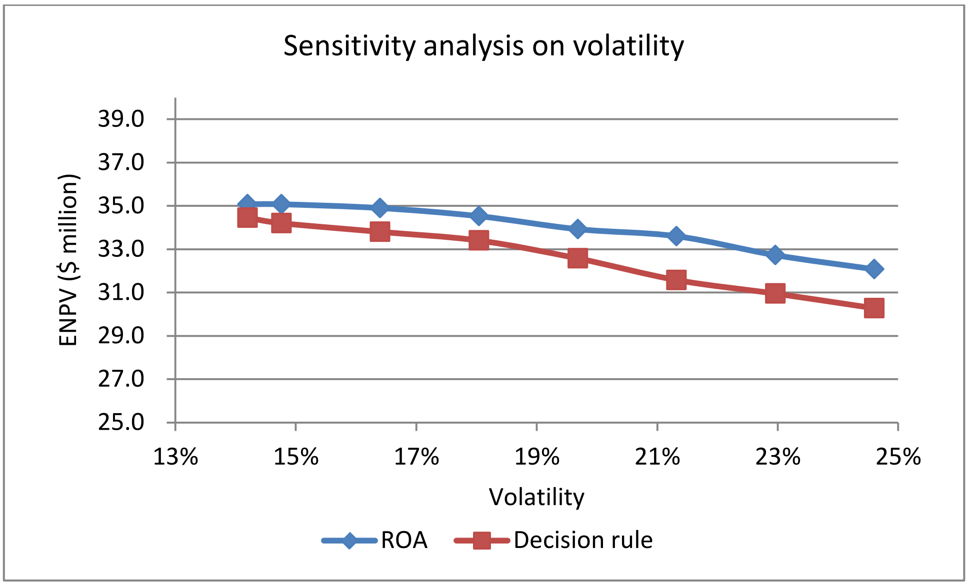


Figure 4-5: Sensitivity analysis on volatility

Cost of having simple decision rules

From a more general perspective, the solutions of standard ROA can be also considered a type of decision rule as represented by dynamic programs or lookup tables (as approximation of dynamic programs solutions). Though this decision rule provides higher ENPVs, it is less intuitive for the DMs in practice. In contrast, the conditional-go decision rule provides intuitive and readily usable guidelines to DMs for exercising the flexibility in operations, but its performance is compromised in terms of the ENPV. It is evident that there is a trade-off between the ease of use and the performance in the selection of the decision rules. To observe this trade-off, another type of decision rules – the constant decision rule – is applied to solve the same problem. The performance of these three decision rules are then compared and discussed.

As introduced in Section 3.3.2, a constant decision rule determines the capacity to be deployed in each time period, regardless of the realization of uncertainty in practice. The output of the stochastic programming model is a set of decision variables indicating the capacity to deploy in each time period. The scale of this model is much smaller than the model for the conditional-go decision rule as it does not require binary variables to represent the capacity expansion processes and can therefore be solved directly using the CPLEX MIP solver. The optimization model is solved under the same uncertainty scenarios used in Section 4.3.4. A simulation model is built to conduct an out-of-sample test using the capacity deployment strategy obtained from the optimization model. The result is listed in Figure 4-6 alongside the results of the other two strategies.

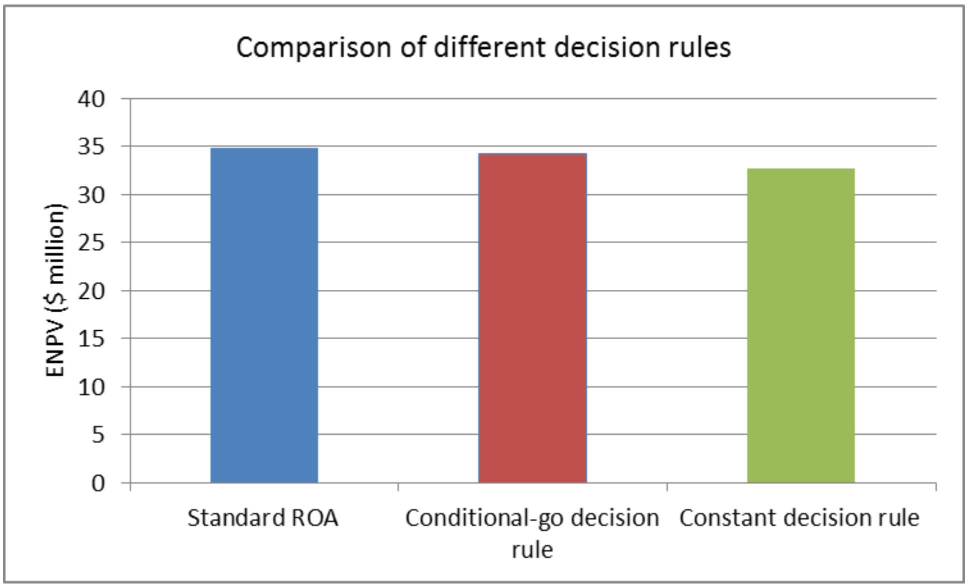


Figure 4-6: Comparison of performances of different decision rules

The performance comparison between the three different types of decision rule approaches reveals that the highest ENPV in out-of-sample simulation is obtained via standard ROA, followed by the conditional-go decision rule (intermediate), and lastly the constant decision rule (lowest). The ranking of ENPVs mirrors the ranking of their ease of use in reverse order. The rule associated with the greatest ease for the DMs to follow is the constant decision rule (by dint of its fixed capacity deployment), followed by the conditional-go decision rule (intermediate), and lastly the standard ROA (most difficult as it requires solving backward reduction). This observation leads to a conclusion that the ease of use of a decision rule comes with a cost in its performance: the greater ease of use of a decision rule relates to greater compromise in its performance.

4.4 Summary

This chapter illustrates how the generic model proposed in Chapter 3 can be applied to analyze flexibilities in engineering systems. Firstly, simple projects are used as examples to demonstrate the formulations of different types of flexibilities with comparison to the work by Trigeorgis (1996). The results show that the proposed approach is easily applicable to analyze different types of flexibility. Then, a case study on a WTE system is used to demonstrate the application of the approach in real-world systems. In the case study, the results show that the decision rule approach not only recognizes a similar amount of value stemming from flexibility compared with standard ROA in terms of the ENPV in the out-of-sample test, but also requires similar computational time. It also rank orders the design alternatives in a similar fashion as standard ROA (i.e. showing that the flexible design is expected to perform better over time than an inflexible solution). The form of the solution is reasonably intuitive to be used by the DMs in operations.

Chapter 5 – Modeling Compound Flexibilities and Multiple Uncertainty Sources

5.1 Introduction

Chapter 4 demonstrates the analysis of six simple flexibilities using the proposed decision rule approach through some simple examples and a case study on an AD plant for which the standard ROA is likewise readily applicable. In practice, however, it is very common to see combinations of these flexibilities in complex systems. One challenge of using standard ROA to analyze these complex systems is that the calculation effort increases dramatically when the complexity of the problem increases as more uncertainty drivers and decision variables are considered. In contrast, as mentioned in Section 3.2, the proposed decision rules approach lends itself naturally to the analysis of more complex systems. In this chapter, a more complex engineering system – a hybrid WTE system – with multiple flexibilities and uncertainty sources is analyzed to exhibit important advantages of the proposed approach.

5.2 Case study II: Hybrid WTE system with AD and gasifier technology

In this section, a hybrid WTE system with AD and gasifier is considered. In such a system, two uncertainty sources and two flexibility strategies are considered simultaneously. This section shows that the proposed approach lends itself naturally to the analysis of more complex systems with multiple uncertainty sources and flexibility strategies.

5.2.1 Problem analysis

In the hybrid WTE system, there are two types of technologies to treat organic waste: AD and gasification. Both technologies are able to generate gas from organic waste, and then generate electricity from the gas using a gas engine. In particular, the AD unit is better at treating high moisture organic waste, such as food waste, while the gasifier is better at treating low moisture organic waste such as paper, wood and horticultural waste. Therefore, organic waste is divided into two categories: food waste and other organic waste (i.e. paper, wood and horticultural waste). In this hybrid system, all food waste is treated by AD, and other organic waste is mainly treated by the gasifier. If the capacity of the gasifier is not high enough to handle all other organic waste, the untreated feedstock will be transferred to the AD.

The AD unit is assumed to be similar to the AD plant studied in case study I, i.e., it is modularly designed. However, unlike the AD unit, the capacity of the gasifier unit, y_t, is a continuous decision variable - it can be changed continuously. Denote ξ_t as the amount of food waste as before and introduce η_t as the total amount of other organic waste in year t. Historical data in the past 10 years show that the amount of food waste and other organic waste collected has a deterministic positive growth rate, but the amount of variation in each period is random. Based on this observation, it is suitable to model the fluctuating waste amount using standard GBM.

The profit function r_t of the hybrid WTE system in year t is defined as:

$$r_t = T_t + R_{A_t} + R_{G_t} - C_{A_t} - C_{G_t} - P_t \tag{5.1}$$

where T_t is the tipping fee, R_{A_t} and R_{G_t} are the revenue generated by the AD and gasifier respectively, C_{A_t} and C_{G_t} are the cost of AD and gasifier respectively, P_t is the penalty function incurred by capacity shortage in AD. By reusing the notations for AD in Section 4.3, the definitions of the functions are as below:

$$T_t = z_3(\xi_t + \eta_t) \tag{5.2}$$

$$R_{A_t} = (z_1 + z_2)(p(\xi_t - f_t) + p'f'_t) \tag{5.3}$$

$$\begin{aligned} C_{A_t} = z_4\xi_t + z_5(x_t - x_{t-1}) + (z_6 + z_8 + z_9)x_t \\ + z_{10}\tau(p(\xi_t - f_t) + p'f'_t) \\ + z_{10}(1 - p)(\xi_t - f_t) + z_7(x_M - x_t) \end{aligned} \tag{5.4}$$

$$R_{G_t} = z_{11}p'(\eta_t - f'_t) \tag{5.5}$$

$$\begin{aligned} C_{G_t} = z_4\eta_t + z_{15}(y_t - y_{t-1}) + (z_6 + z_{12} + z_{13})y_t + z_{10}\tau' p'(\eta_t \\ - f'_t) + z_{10}(1 - p')\eta_t + z_7(y_M - y_t) \end{aligned} \tag{5.6}$$

$$P_t = z_{10}f_t \tag{5.7}$$

where p' is the purity ratio of other organic waste, f'_t is the capacity shortage for the gasifier, y_M is the maximum capacity reserved for the gasifier, z_{11} is the revenue from electricity sale of per ton per day waste treated in the gasifier, z_{12} is the total of labor, admin, maintenance cost per ton per day waste treated in the gasifier, z_{13} is the cost of refuse derived fuel process per ton per day waste treated in the gasifier, z_{15} is the capital cost of per ton per day capacity of the gasifier, τ' is the residue ratio of the gasifier.

5.2.2 Multinomial lattice analysis

Based on the binomial lattice approach by Cox et al. (1979), Kamrad and Ritchken (1991) developed a multinomial lattice procedure to value options with multiple sources of uncertainty. The main challenge of lattice based methods, however, is that the computational effort increases dramatically when the dimension of the state variables increase, which makes them difficult to apply when there are more than two state variables.

Figure 5-1 shows a lattice for two sources of uncertainty. There are five possible movements emerging from each node, each with a probability of occurrence (Kamrad & Ritchken, 1991). As there is no recombination in the multinomial lattice, the number of nodes in period T is 5^T. When $T = 9$ is considered, the lattice becomes extremely large – the number of nodes in the last period is nearly 2 million. This exponential increase causes the first curse of dimensionality for the multinomial lattice method.

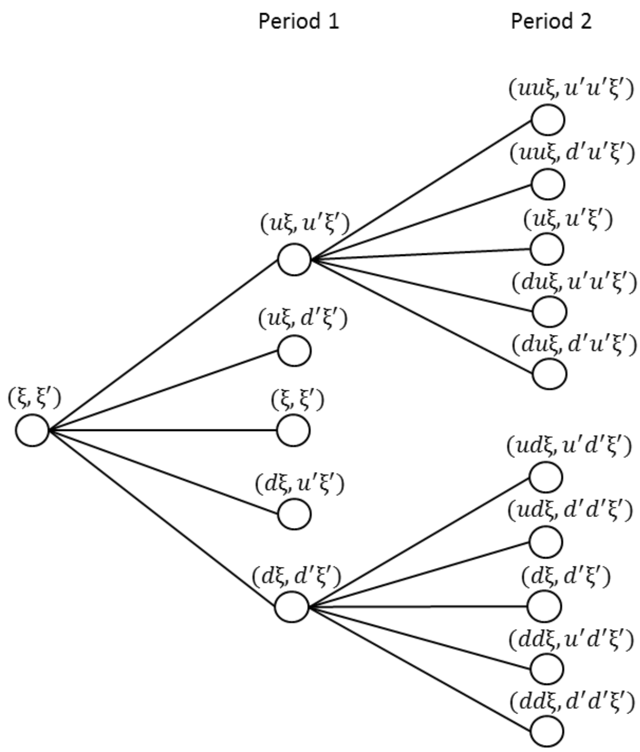


Figure 5-1: A multinomial lattice

Similar to the binomial lattice approach, the multinomial lattice is solved using a backward induction process. At the end of each period t, DMs must decide on capacities of next period x_{t+1} and y_{t+1} that will maximize the total expected profit based on the current state of the system, x_t and y_t, and information on uncertainty realization, ξ_t and η_t. The recursive reward function is:

$$R_t(x_t, y_t, \xi_t, \eta_t) = \max_{x_{t+1}, y_{t+1}} \left[r_t(x_t, y_t, \xi_t, \eta_t) + \frac{1}{(1+\pi)} \sum_{j=1}^{n} p_j R_{t+1}\big(x_{t+1}, y_{t+1}, \xi_{t+1,j}, \eta_{t+1,j}\big) \right], 0 < t < T \tag{5.8}$$

Since variable y_t is continuous, it needs to be discretized to simplify the calculation of the dynamic program. A simple method is to discretize it to an integer variable, i.e. $Y_t = \{\varepsilon', \varepsilon' + 1 \ldots y_M\}$. Therefore, the number of possible decision choices in period t is $|X_t| * |Y_t|$. It can be seen that the number of decisions choices increases exponentially as the dimension of the decision variables increases. The multidimensionality of the decision variables is the second curse of dimensionality for this multinomial lattice method.

Due to the curses of dimensionality, the multinomial lattice method becomes impractical for complex problems. In particular, calculations using standard backward dynamic programming show that it is unable to solve the hybrid WTE problem with two dimensions of uncertainty sources and two flexibility strategies.

To get some results of the multinomial lattice model, an approximated dynamic programming (ADP) approach is used to solve the problem. ADP is a modeling and algorithmic framework for solving stochastic optimization problems with multidimensional random variables and multidimensional decision variables. To apply ADP, the multinomial lattice model should be reformulated from the perspective of dynamic programming. Define state variable $S_t = (x_t, y_t, \xi_t, \eta_t)$. The total expected profit starting from period t until the last period can be represented using the equation bellow:

$$R_t(S_{t-1}) = \max_{x_t, y_t} \left\{ \sum_{j=1}^{n} p_j \left(r_t(S_{t-1}, S_{t,j}) + \frac{1}{1+\pi} R_{t+1}(S_{t,j}) \right) \right\}, 0 < t < T \quad (5.9)$$

where $n = 5$ for a multinomial lattice of two sources of uncertainty, p_j represents the probability of each emerging path from a node, $S_{t,j}$ represents the state corresponding to the emerged path j.

The key idea of ADP is to use a value function to approximate the $R_{t+1}(\cdot)$ in equation (5.9). Using an approximation to the value function, the decision making process can be simulated forward in time by generating samples of uncertainty paths. Then the approximation can be iteratively updated using regression methods based on observations in the simulation. Linear functions are widely used in the literature as they are easy to implement, and powerful to approximate complex value functions. In this paper, $R_{t+1}(\cdot)$ is approximated using a weighted linear combination of a set of basis functions $\phi_{t+1}(\cdot)$, associated with weights $\boldsymbol{\rho}_{t+1}$, i.e. $R_{t+1}(\cdot) = {\boldsymbol{\rho}_{t+1}}^T \boldsymbol{\phi}_{t+1}(\cdot)$. Figure 5-2 describes the least square policy iteration algorithm used to solve the hybrid WTE system problem.

Step 0. Initialization.

Step 0a. Fix the basis function $\phi_t(S)$:

$$R_t(S_{t-1}) = \boldsymbol{\rho}_t{}^T \boldsymbol{\phi}_t(S_{t-1}) = \sum_{f \in \mathcal{F}} \rho_{t,f} \phi_{t,f}(S_{t-1})$$

Step 0b. Initialize $\rho_{t,f}^0$ for all t.

Step 1. Do for $h = 1,2,\ldots,H$:

Step 2. Do for $i = 1,2,\ldots,I$:

Step 3. Choose a sample path $(\boldsymbol{\xi}^{h,i}, \boldsymbol{\eta}^{h,i})$.

Step 4. Do for $t = 1,\ldots,T$:

Step 4a. Compute

$$(x_t^{h,i}, y_t^{h,i}) = \arg\max_{x_t,y_t} \left(\sum_{j=1}^n p_j \left[r_t(S_{t-1}^{h,i}, S_{t,j}^{h,i}) + \frac{1}{(1+\pi)} \boldsymbol{\rho}_{t+1}^{h-1\,T} \boldsymbol{\phi}_{t+1}(S_{t,j}^{h,i}) \right] \right)$$

Step 4b. Update the states

$$S_t^{h,i} = (x_t^{h,i}, y_t^{h,i}, \xi_t^{h,i}, \eta_t^{h,i})$$

Step 5. Initialize $\hat{R}_{T+1}^{h,i} = 0$

Step 6. Do for $t = T, T-1, \ldots, 1$:

$$\hat{R}_t^{h,i} = r_t(S_{t-1}^{h,i}, S_t^{h,i}) + \frac{1}{(1+\pi)} \hat{R}_{t+1}^{h,i}$$

Step 7. Produce $\widehat{\boldsymbol{\rho}}^h$ using least square linear regression

$$\widehat{\boldsymbol{\rho}}_t^h = \left[\left(\boldsymbol{\phi}_t^{h,i}\right)^T \boldsymbol{\phi}_t^{h,i} \right]^{-1} \left(\boldsymbol{\phi}_t^{h,i}\right)^T \hat{R}_t^{h,i}$$

Step 8. Update ρ_t^h

$$\boldsymbol{\rho}_t^h = (1-\alpha_{h-1}) \boldsymbol{\rho}_t^{h-1} + \alpha_{h-1} \widehat{\boldsymbol{\rho}}_t^h, where\ \alpha_h \in (0,1)$$

Step 9. Return the regression coefficients $\boldsymbol{\rho}_t^H$ for all t = 1, …, T.

Figure 5-2: Least square policy iteration algorithm (pseudo-code)

5.2.3 Multistage stochastic programming with decision rules

To apply the decision rule approach to analyze the hybrid WTE system, two types of decision rules are used. As the AD unit has basically the same characteristics of the system in Section 4.3, the same conditional-go decision rule is used to model this component. Thus, all of the constraints of Problem (4.36) can be reused in the new problem, except for constraint (4.34) that is revised as:

$$o_u x_t^k + f_t^k \geq \xi_t^k + p'\tau'(\eta_t^k - f'^k_t) + f'^k_t, \quad t = 1,2,\ldots,T, \forall k \tag{5.10}$$

The revised constraint takes the untreated feedstock of the gasifier as the feedstock of AD. As the capacity of the gasifier can be adjusted to any real number, a **linear decision rule** is applied to determine the capacity based on the information over the past few years. Linear decision rules are a class of decision rules that are linearly dependent on the observed uncertainty data. In this demonstration, the form of linear decision rule that determines the capacity of the gasifier is a linear function of the waste amount over the past three consecutive years.

The constraints regarding the gasifier are as below:

$$y_t^k = \gamma_{1t}^k \eta_{t-1}^k + \gamma_{2t}^k \eta_{t-2}^k + \gamma_{3t}^k \eta_{t-3}^k, \quad t = 4 \ldots T, \forall k \tag{5.11}$$

$$y_1^k = y_2^k = y_3^k = \varepsilon'^k, \quad \forall k \tag{5.12}$$

$$y_t^k \leq y_M{}^k, \quad \forall k \tag{5.13}$$

$$y_t^k + f'^k_t \geq \eta_t^k, \quad \forall k \tag{5.14}$$

Constraint (5.11) defines the linear relationship of the capacity of the gasifier with the uncertainty realizations in the past three years, where $\gamma_{1t}^k, \gamma_{2t}^k, \gamma_{3t}^k$ are the coefficients of the linear function to be optimized. ε'^k is the capacity of the gasifier in the first three years, $y_M{}^k$ is the maximum capacity of the gasifier needed to be reserved. Now the set of decision rule variables $\boldsymbol{\theta}$ becomes

$$\boldsymbol{\theta} = (\alpha_2 \ldots \alpha_T, \beta_2 \ldots \beta_T, \varepsilon, x_M, \gamma_{14} \ldots \gamma_{1T}, \gamma_{24} . . \gamma_{2T}, \gamma_{34} \ldots \gamma_{3T}, \varepsilon', y_M)$$

In order to satisfy the nonanticipativity requirement, all the decision variables should be equal over all scenarios, i.e.$\boldsymbol{\theta^1} = \cdots = \boldsymbol{\theta^K}$. Similar to Section 4.3, for simplicity and demonstration purposes, $\alpha_t, \beta_t, \gamma_{1_t}, \gamma_{2_t}$ and γ_{3_t} are assumed to be respectively equal at each time period. Thus this form of the decision rule is constant throughout the lifetime, which is readily usable for the DMs to apply in operations. Therefore,

$$\alpha_2^1 = \alpha_t^k, \beta_2^1 = \beta_t^k, \qquad \forall t, k \tag{5.15}$$

$$\gamma_{1}{}_4^1 = \gamma_{1}{}_t^k, \gamma_{2}{}_4^1 = \gamma_{2}{}_t^k, \gamma_{3}{}_4^1 = \gamma_{3}{}_t^k, \qquad t = 4, \dots, T, \forall k \tag{5.16}$$

The stochastic programming problem with decision rules for the hybrid WTE system is formulated as:

$$\begin{aligned} &\max_{\theta} \sum_{k=1}^{K} p^k \sum_{t=1}^{T} \left(\frac{1}{1+\pi}\right)^t r_t^k\left(x_t^k, y_t^k, \xi_t^k\right), \\ &s.t.\ (4.26) - (4.33), (5.10) - (5.16) \end{aligned} \tag{5.17}$$

Problem (5.17) is also an MILP. It can be solved using the same algorithm as described in Section 3.4.

5.2.4 Computational results

According to the technical parameters from existing WTE technologies (Klein, 2002), the main assumptions for the gasifier model are listed in Table 5-1. The parameters for the uncertainty driver can be inferred based on historical data of organic waste generated in Singapore, as shown in Table 5-2.

Table 5-1: List of assumptions for the gasifier unit

Parameters	Value	Definition
p'	70%	Purity ratio of the other organic waste feedstock
τ'	20%	Residue ratio of the gasifier
z_{11}	S$62,678/tpd	Revenue from electricity generation per tpd waste processed in the gasifier
z_{12}	S$5,840/tpd	Total of labor, admin, maintenance cost per tpd waste treated in the gasifier
z_{13}	S$2,920/tpd	Cost of the RDF process per tpd of waste treated in the gasifier
z_{15}	S$96,970/tpd	Capital cost of per tpd capacity of the gasifier

Table 5-2: Parameters of uncertainty drivers

Parameters	Definition	Food waste	Other organic waste
μ	Annual growth rate	14.1%	6.0%
σ	Volatility	16.4%	4.1%
$\xi_0/\ \eta_0$	Waste amount in year 0	191 tpd	2,823 tpd

The least square policy iteration algorithm described in Figure 5-2 is programmed using C++. The number of sample paths generated in each iteration is $I = 40$. The results converge well after $H = 1000$ iterations. As it uses a linear function of the state variables to approximate the value functions $R_t(\cdot)$, the results are the exact forms of $R_t(\cdot)$ at each time period. The value of $R_1(\cdot)$ corresponds to the ENPV of the system, as shown in Table 11. Based on the forms of $R_t(\cdot)$, decisions on the respective capacities for AD and gasifier can be made by solving the optimization problem at each time period t:

$$(x_t, y_t) = \arg\max_{x_t, y_t} \left(\sum_{j=1}^{n} p_j \left[r_t(S_{t-1}, x_t, y_t) + \frac{1}{(1+\pi)} \boldsymbol{\rho}_{t+1}^{h-1^T} \boldsymbol{\phi}_{t+1}(S_t) \right] \right) \tag{5.18}$$

Problem (5.17) is solved under 512 scenarios of uncertainty generated based on Equation (4.21) via the Monte Carlo approach. Table 5-3 shows the solutions for the three models. For the inflexible design, ENPV = $751.1 million. For standard ROA using multinomial lattice and ADP, ENPV = $765.2 million. As for the decision rule model, ENPV = $765.1 million. As can be seen, the decision rule approach recognizes performance for the flexible system similar to standard ROA using multinomial lattice and ADP – only a 0.01% difference. Both the decision rule and ROA/ADP approaches recognize additional value from flexibility in approximately the same amount, as compared to the inflexible system (i.e. benchmark expected value of flexibility is $765.2 million – $751.1 million = $14.1 million, and about $14.0 million under the decision rule approach). Both approaches can solve more complex problems with multiple uncertainty sources and multiple flexibility strategies. Computation is much faster for the decision rule approach (333 seconds), however, as opposed to standard ROA (4254 seconds).

Table 5-3: Results of the hybrid WTE system

	Solutions		ENPV ($ million)	Computation time (s)
	AD	Gasifier		
Inflexible design	$x_f = 570$	$y_f = 3668$	751.1	0.2
ROA based on ADP	Values of $\boldsymbol{\rho}_t$ to approximate $R_t(\cdot)$ by $R_t(\cdot) = \rho_{t0} + \rho_{t1}x_{t-1} + \rho_{t2}\xi_{t-1} + \rho_{t3}y_{t-1} + \rho_{t4}\eta_{t-1}$		765.2	4254
Decision rule approach	$\varepsilon = 11$, $x_M = 1470$, $\alpha = 2, \beta = 3$	$\varepsilon' = 3219$, $y_M = 6382$ $\gamma_1 = 0.47, \gamma_2 = 0.28, \gamma_3 = 0.35$	765.1	333

Using the Solution

This section describes the forms of the solutions under each approach, and how to use them to exercise the flexibilities in operations. The comparison aims to support the view that the solution from the decision rule approach is more intuitive to use in operations than from standard ROA.

In the standard ROA using multinomial lattice and ADP, a linear function of the state variables is used to approximate the value functions $R_t(\cdot)$, and the results are the exact forms of $R_t(\cdot)$ at each time period. Based on the forms of $R_t(\cdot)$, decisions on the respective capacities for AD and gasifier can be made by solving the optimization problem at each time period t:

$$(x_t, y_t) = \arg\max_{x_t, y_t} \left(\sum_{j=1}^{n} p_j \left[r_t(S_{t-1}, x_t, y_t) + \frac{1}{(1+\pi)} \boldsymbol{\rho}_{t+1}^{h-1^T} \boldsymbol{\phi}_{t+1}(S_t) \right] \right) \tag{5.19}$$

subject to capacity currently installed x_{t-1} and y_{t-1}, and uncertainty realization for variables ξ_{t-1} and η_{t-1}.

Under the decision rule approach, the AD should be designed with initial capacity of $\varepsilon = 11$ modules (330 tpd) and extra land should be reserved to facilitate maximum capacity of $\mathrm{x}_M = 1470$ tpd in the future. The gasifier should be designed with initial capacity of $\varepsilon' = 3219$ tpd with maximum capacity of $y_M = 6382$ tpd. At the end of every year $t-1$ $(t \geq 2)$, the DM should decide on the capacity of the AD unit for year t based on the amount of food waste collected in year $t-1$: if it is higher than the value of the current capacity minus $\alpha = 2$ modules of capacity ($i.e.$ $x_{t-1} - 2*30\ \ tpd$), then the capacity should be expanded by $\beta = 3$ modules ($i.e.$ 90 tpd). At the same time, the DM should adjust the capacity of the gasifier starting from year 4: set the capacity of the gasifier as described by the linear function of the amount of other organic waste over the last three consecutive years, i.e., $y_t = 0.47\eta_{t-1} + 0.28\eta_{t-2} + 0.35\eta_{t-3}$.

One may notice that the decision rule approach provides readily applicable guidance on the decision making process in operations in each time period. The capacity to deploy for both plants can be determined straightforwardly by following the decision rules, subject to realizations of the two uncertainty drivers. In contrast, the form of the solution under ADP requires solving the optimization program in (5.19) at each time period to determine the capacity for both plants. This is typical of the form of solutions obtained from multinomial and ADP approaches. It is obvious that this form of solutions is more challenging to use for DMs as compared to the proposed decision rule approach.

5.3 Summary

In this chapter, the proposed decision rule approach is applied to solve a more complex flexible hybrid WTE system design problem. The analysis demonstrates that the decision rule approach can be augmented in a straightforward manner to analyze more complex systems when multiple uncertainty sources and flexibility strategies are considered simultaneously. Computational results show that it not only is readily applicable to solve such problem but also provides intuitive guidance to DMs in operations. Conversely, standard ROA based on multinomial lattice and ADP proves more challenging due to the curse of dimensionality. It leads nonetheless to similar ENPV performance results as the decision rule approach, but requires more computational time to find a solution, and additional optimization to determine the physical capacity of the system in each time period. Both approaches recognize value improvements stemming from flexibility, as compared with an inflexible benchmark design.

Chapter 6 – A Framework for Analyzing Flexibilities Using Decision Rules

6.1 Introduction

In the preceding chapters, the decision rule approach has been introduced and its capability of analyzing various flexibilities in engineering systems has been demonstrated, especially in complex systems. With the basics of the decision rule approach outlined, this chapter is now concerned with its application in design practice. Specifically, a six-step framework is proposed to guide designers to apply the approach throughout the design process. The framework addresses the idea of design for operation by focusing on generating decision rules throughout the design phase. With this framework, designers can start with a baseline design and generate a valuable flexible design that is practical to operate by exploiting the concept of decision rules.

6.2 A framework for analyzing and managing flexibility in engineering design using decision rules

Table 6-1 summarizes the six-step design framework. It illustrates the procedure that designers must undertake when designing engineering systems by exploiting the concept of decision rules. The details of each step are introduced as follows.

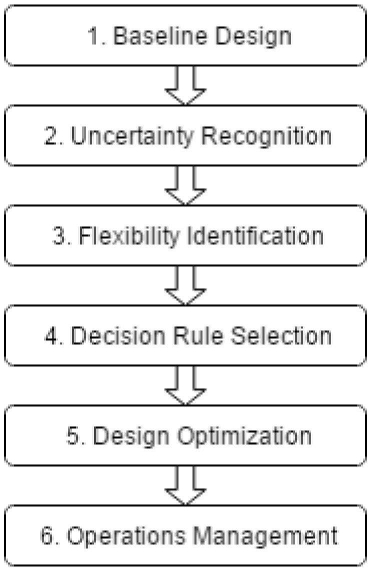


Figure 6-1: Framework for analyzing and managing flexibility in engineering design using decision rules

6.2.1 Step 1: Baseline design

Design for flexibility must use an existing design concept as a starting point. Traditional design practices usually intend to optimize designs based on the forecasting of main uncertainty factors like future markets, customer demands and requirements, etc. The outcome of these approaches is often a rigid design with fixed design variables and parameters that it is unable to adapt to uncertain future. However, one should believe that by explicitly considering uncertainty and flexibility in the design, the lifecycle performance of the system can be improved. Here, this design configuration is referred to as the baseline design concept, in the sense that they serve as points of comparison to the flexible design concepts generated by following this framework.

Step 1 helps designers build their knowledge of the system. The design architecture must be able to be expanded to consider uncertainty and flexibility in subsequent phases. According to the taxonomy by Cardin (2014), a baseline design can be created using approaches such as the systemic approach (Pahl & Beitz, 2013), axiomatic design (Suh, 2001), concurrent design (Roos, Womack, & Jones, 1990), Concept-Knowledge theory (Hatchuel & Weil, 2009), function-based failure analysis (Kurtoglu, Tumer, & Jensen, 2010), and architecture generation using Bayesian network (Moullec et al., 2013).

6.2.2 Step 2: Uncertainty recognition

Engineering systems inevitably face numerous uncertainty sources during their long lifespans. The lifecycle performance of engineering systems is affected by uncertainty in different ways. While uncertainty may bring opportunities for better performance when its realization is more favorable than expected, it may also undermine the performance when conditions are unfavorable.

In Step 2, designers identify and model main uncertainty sources affecting lifecycle performance which are then modelled as stochastic processes. When knowledge is available about the underlying phenomena, probability and possibility theories are useful to determine the stochastic process. When information is not readily available, designers may rely on methods like experts survey, the Dempster-Shafer method (Dempster, 1967; Shafer, 1976) or scenario planning (Helmer, 1967) etc. When historical data is available, the information of the stochastic process can be inferred using statistical techniques. With the information of the stochastic process, a number of scenarios of realizations of uncertainty can be generated using Monte Carlo simulation. These scenarios serve as the input for the optimization model in Step 5.

It is noteworthy that when the system faces multiple uncertainty drivers, each uncertainty driver is respectively modelled using a stochastic process. In this case, a scenario consists of realizations of all uncertainty sources.

6.2.3 Step 3: Flexibility identification

In this step, designers generate flexible design concepts to handle uncertainty identified in Step 2. A flexible design concept consists of two parts: a flexible strategy and flexibility enablers. The flexible strategy describes how the system adapts itself in the face of changing conditions. The flexibility enablers are essential elements to be embedded in the system to render possible the exercise of flexible strategy. The procedure in this step can be classified into two categories: strategy generation and enabler identification.

Generation of flexibility strategy

Several types of flexibility strategies can be considered in engineering system design (Trigeorgis, 1996).

1) Deferral of investment. The option to defer gives DMs the right, but not the obligation, to defer a project for a period of time. When future market or technology is highly uncertain, it is prudent to wait until more information of uncertainty unfolds before investing in a system.

2) Capacity adjustment (expansion and contraction). Once a system is implemented, the DMs may have the flexibility to change it in different ways at different time periods throughout its lifespan. When the realization of market is optimistic, the option to expand its capacity enables the system to

capture more revenue. When the realization of market is not as good as expected, the option to contract its capacity enables the system to reduce the exposure to loss.

3) Abandonment of projects. If one has the right, but not the obligation, to terminate a project to receive salvage value, it is called the flexibility to abandon a project. Abandonment options are important for some projects to prevent further loss, such as exploration and development of natural resources.

4) Temporarily shutting down. If the revenue of a system is lower than its operating cost, the option to temporarily shut down may significantly reduce potential loss. This type of flexibility is common in the mining industry.

5) Switching options. A system may have several operating modes. The option to switch enables the system flexibility to operate in different modes at different times so as to obtain the highest lifecycle performance.

6) Combinations of above.

The forms of these strategies vary depending on the system of interest. Creativity is needed for designers to instantiate in the system of interest. Several techniques are available to aid in the recognition of valuable flexibility strategies for the system at hand. Mikaelian, Nightingale, Rhodes, and Hastings (2011) introduced an integrated real-options framework to support strategy generation by characterizing a real option as a mechanism and type. Flexibility types are mapped to different mechanism patterns upon recognition of main uncertainty sources. Cardin et al. (2013) suggested that a prompting mechanism and explicit training can help in flexibility strategy generation.

This technique includes a short lecture and a structured prompting mechanism to help designers understand more about the influence of uncertainty and lead them to generate flexibility concepts.

Identification of flexibility enablers

After flexibility strategies are generated, the designers need to identify valuable opportunities (i.e. enablers) to embed flexibility in the system. The following techniques in the literature can be used to support flexibility enabler identification.

Industry Guidelines. Principles in industry guidelines can be used to enable flexibility in engineering systems design, e.g. ideality, simplicity, modularity, embedding safeguards, parts reduction, spatial principle, interface decoupling, adjustability, etc. (Fricke & Schulz, 2005; Gil, 2007; Keese, Seepersad, & Wood, 2009; Qureshi et al., 2006; Rajan, Van Wie, Campbell, Wood, & Otto, 2005).

Design Structure Matrix (DSM). Many DSM-based procedures have been developed to identify valuable opportunities to embed flexibility in engineering systems. Giffin et al. (2009) applied change propagation analysis in the design of a complex sensor system. Hu and Cardin (2015) proposed a DSM-based method by integrating the Bayesian network to model change propagation in the flexibility identification process. The DSM method is further extended to sensitivity DSM (Kalligeros, 2006), engineering system matrix (Bartolomei, Hastings, de Neufville, & Rhodes, 2012), logical multiple domain matrix (Mikaelian, Rhodes, Nightingale, & Hastings, 2012), etc.

Screening Model. The screening model is a simplified, conceptual, low-fidelity model to screen for the most important variables and interesting flexibility of the system. For example, in the design of hydroelectric dams case by Tao Wang (2005), a non-linear programming model that optimizes the system (assuming a deterministic state) is used to represent the system and to screen for the promising candidates designs. De Weck, Neufville, and Chaize (2004) used a similar approach to identify valuable candidate design variables for flexibility in the design of a satellite system.

6.2.4 Step 4: Decision rule selection

In this step, appropriate decision rules are recommended to analyze and manage flexible designs generated in Step 3. A table is used as a guideline on the types of decision rules that should be considered for the different types of flexibility strategies.

Types of decision rules

Three generic types of decision rules that can be applied readily to the management of flexibility in engineering systems are briefly discussed below. The formulations of these decision rules have been introduced in Section 3.3. Decision rules specific to a given system may be generated using systematic concept generation, and typically rely on the designer's creativity and expertise with the system. Many decision rules exist and can be explored, depending on the system of interest, uncertainty drivers, and system mission or purpose.

Conditional-go decision rule

With conditional-go decision rules, the decision at each time stage is based on an estimate of future conditions and past information. The rule is usually expressed as “*if the uncertainty realizations in the past satisfy a certain set of criteria, then exercise the flexibility; otherwise maintain the status quo*.” There are various ways to formulate the conditional-go decision rules; binary variables are usually introduced to facilitate this.

Linear decision rule

Linear decision rules are a class of decision rules that are linearly dependent on the observed uncertainty data. The decisions to be made can be expressed as linear combinations of the observed realization of uncertainty. This type of decision rule has been widely used to approximate hard optimization problems under uncertainty.

Constant decision rule

If the decision to be made in each time period is independent of the observations of the uncertainty data up to that time period, then the decision rule belongs to a class called constant decision rules. This is a special case of a multistage problem: the problem of determining a decision rule function degenerates to one determining a single sequence of decisions to be made at each stage. The shortcoming of this class of decision rules is that it does not follow a fully rational process because it forces the DMs to make decisions for all time stages before realizing any of the uncertainties. In some cases, however, it can provide an insurance policy against the worst possible outcomes.

Choice of decision rules

Based on the assumption of rational decision making for different flexibility strategies and the qualitative properties of the decision rule types, a guideline on the types of decision rule to consider when analyzing a certain type of flexibility strategy is summarized in Table 6-1. Note that the guidelines below are not exhaustive, and may be altered in the future. They are useful to provide guidance, and may not be the only guidelines available to analysts.

Table 6-1: Choice of decision rules for each type of flexibility

	Constant decision rules	Linear decision rules	Conditional-go decision rules
Deferral options	√		√
Capacity adjustment	√	√	√
Abandonment options	√		√
Temporarily shutting down	√		√
Switching options	√		√
Combination of flexibilities	√	√	√

As can be seen, both constant decision rules and conditional-go decision rules are applicable to every type of flexibility strategy. As constant decision rules are unable to adapt decisions to the realizations of uncertainty, they do not make full use of flexibility. They are therefore recommendable only when the volatility of uncertainty source is low or to provide an insurance policy against the worst possible outcomes. Conditional-go decision rules are another type of decision rules that can be applied to every type of flexibility strategy. This is because the “if-then” statement emulates a system operator’s decision-making process and simplifies it greatly. In most circumstances, conditional-go decision rules are useful in the management of flexibility in practice.

Linear decision rules are applicable for only the strategy of capacity adjustment when the capacity can be adjusted continuously. This is because the linear combination of uncertainty realizations is usually a real number. When the capacity of a system can be adjusted continuously, linear decision rules provide a good approximation of optimal decisions.

As can be seen in Table 6-1, several decision rules are available for analysis of every type of flexibility strategy. The choice of the type of decision rules to apply should be made based on the characteristics of the system of interest. For example, all the three types of decision rules are available for the strategy of capacity adjustment. If a system is modularly designed (i.e. its capacity belongs to a set of discrete numbers), then conditional-go decision rules can be used whereas linear decision rules are not applicable. In another case where the capacity of a system can be adjusted continuously, then linear decision rules are more suitable than conditional-go decision rules as they are more computationally efficient. In any circumstance, constant decision rules can be used, but it usually cannot recognize as much value of flexibility as other types of decision rules. If it is not evident that which type of decision rules suits the system better, one may conduct analysis using every type of decision rule available and then choose the best one based on comparison of their performances.

6.2.5 Step 5: Design optimization

In this step, the decision rules and design variables need to be optimized to obtain the best performance of the flexible system in operations. Several techniques may be used to optimize the design, such as the stochastic programming proposed in Chapter 3 and simulation-based optimization. Simulation-based optimization is a powerful method to generate approximate solutions for complex problems in which the objectives and constraints may be non-linear, non-convex or non-smooth. However, weaknesses of simulation-based optimization are that the optimization process can run for a long time and there is no guarantee on result accuracy (Vazan & Tanuska, 2012). Applications of simulation-based optimization in flexibility analysis can be found in Deng (2015). For convex problems with linear constraints and objective functions, stochastic programming is effective to find optimal solutions in some sense. Therefore, it is usually recommendable to apply stochastic programming approach if the problem can be formulated under the stochastic programming framework. In this thesis, the focus is on the stochastic programming approach.

By instantiating the generic stochastic programming model introduced in Chapter 3 with the characteristics of the system studies, a typical solution of the model will consist of two parts. One part contains the physical system design variables describing the initial physical state of the system; the other part contains the optimal value of parameters characterizing the decision rules selected in Step 4. The details of the model have been introduced in Chapter 3.

6.2.6 Step 6: Operations management

Steps 1-5 focus on the design of flexible systems. Through these steps, valuable flexibility is embedded in the system. In operations, however, the value of flexibility may be lost if the system operators are unware of when and how to exercise it. This step addresses the issue of managing the exercise of flexibility in the implementation phase of the system design.

The outcome of the optimization problem in Step 5 consists of two parts. The first part is physical design variables, which specify the design of the system in the initial stage. The other part is the decision rule, which provides straightforward guidance on when and how to exercise flexibility in subsequent time periods. Therefore, upon the launch of the system, the DMs should keep observing the realizations of uncertainty and make decisions on the exercise of flexibility following the decision rule. Take the WTE system in Case Study I in Section 4.3 as an example: the design optimization results tell the designer to install a capacity of nine modules in the first year. In the following years, the DM should expand the capacity by two modules (60 tpd) once the amount of waste collected in the previous year is higher than the value of the current capacity minus the equivalent of one module of capacity. As can be seen, an advantage is that this approach renders decision-making process simple and straightforward.

6.3 Case study III: Design of a multi-storey recycling facility

In this section, a case study on an MSRF is conducted to demonstrate the application of the proposed framework. The MSRF is a first-of-its-kind facility planned by Singapore as a solution to reduce land-take while creating more space for essential activities undertaken by the waste management industry. An MSRF facility is envisaged to be a multi-story, multi-tenanted pilot facility processing different waste streams that could share common facilities and services such as weighbridges and a vehicle-parking depot. It achieves land-saving by hosting recycling activities for different types of wastes on different stories.

6.3.1 Baseline design

A fixed MSRF designed under deterministic conditions is considered to be a baseline design. The fixed design consists of five stories of which the ground level is for unloading waste feedstocks and parking whereas the first to fourth floors are used for recycling metal, paper, plastics, and organic waste, respectively. The waste feedstock is fed into the system on the ground floor, and then transferred up to upper floors by conveyors. On each floor, there are machines to select specific waste. After selection and further processing, the recyclables (plastics, paper and metal) are packed and sold as raw materials to the corresponding factories whereas the organic waste is treated using gasifiers to generate electricity.

The location of this pilot MSRF is planned to be at the existing Sarimbun Recycling Park (NEA, 2014b). It is expected to process the four types of waste generated in one of Singapore's six public waste collection sectors – Jurong. Let it be supposed that the lifespan of the MSRF is 20 years. Based on historical data of population statistics (Brinkhoff, 2015) and waste generation (NEA, 2014a) in past ten years, it is forecasted that the total amount of the four types of waste generated in Jurong will reach about 8,000 tons per day (tpd). Therefore, the capacity of the baseline MSRF design is set as 8,000 tpd, i.e. 2,000 tpd on each floor.

A discounted cash flow model is built to calculate the NPV of the MSRF design.

$$NPV = \sum_{t=1}^{T} \frac{TR_t - TC_t}{(1+r)^t} \tag{6.1}$$

where TR_t denotes the total revenue in year t and TC_t represents the total cost in year t. The cost data of such a facility is inferred based on the work by Dubanowitz (2000) whereas the economic data of waste recycling is obtained from the report by the Asian Development Bank (2013). Results of the calculation show that NPV of the baseline MSRF design is $1.96 billion.

6.3.2 Uncertainty recognition

The main uncertainty sources are the amount of each type of waste generated in the future. An examination of the historical data for the past ten years reveals that the amount each type of waste has a deterministic growth rate, but the amount variation in each period is random. Based on this observation, it is suitable to model the fluctuating waste amount using the GBM:

$$d\xi_t = \mu\xi_t dt + \sigma\xi_t dz_t \tag{6.2}$$

where ξ_t is the waste amount in year t, μ is the annual growth rate of the waste amount, σ is the volatility of the waste amount, and dz_t is the basic Wiener process giving a random shock to μ.

Monte Carlo simulation is used to generate samples to evaluate the ENPV of the design under uncertainty. Results show that the ENPV of the baseline MSRF design under uncertainty is $1.94 billion, which is lower than the NPV under deterministic conditions. This difference of performance shows that the uncertainty affects the system's performance – the value of the project is overestimated by ignoring the uncertainty. This is attributed to the flaw of average: in the upside scenarios where the waste amount is higher than the capacity, the facility is unable to capture the opportunity for more profit due to the limitation of the capacity; thus the low revenue in downside scenarios where the waste amount is very low cannot be compensated by higher revenue in upside scenarios. Hence, uncertainty modeling provides a more accurate view of the true performance of the system.

6.3.3 Flexibility identification

The uncertainty in the waste amount affects the performance of the system. When the realization of the waste amount increases more quickly than expected, the fixed design is unable to capture the opportunity of generating more revenue by processing more feedstock. Conversely, if the realization of the waste amount does not increase as much as expected, the fixed design ends up with wasting investment of excess capacity. In addition, as the amounts of the four types of waste are independent of each other, some of them may increase more quickly than others. Accordingly, it is evident that equally allocating capacity to each type of waste is not the most efficient way to utilize the capacity. Therefore, the flexibility strategy of capacity expansion is considered to improve the MSRF design. To embed this strategy, a two-phase design is considered. The MSRF starts with a small plant with only half the capacity of the baseline design (five stories, the capacity of each storey is 1,000 tpd), but with the potential to expand a similar Phase 2 plant in future. This flexibility can be realized by building large conveyors, etc. Furthermore, each floor of the Phase 2 plant can be configured to handle any type of waste as needed. This flexibility would enable the system to adapt to the change in the composition of waste feedstock. Once the Phase 2 plant is built, the DMs can allocate recycling technologies on each floor eventually as needed. For the flexible MSRF design, designers need to decide when to expand Phase 2 and how to allocate the recycling technologies to the Phase 2 plant. Figure 6-2 illustrates the comparison between the baseline design and the flexible design concepts.

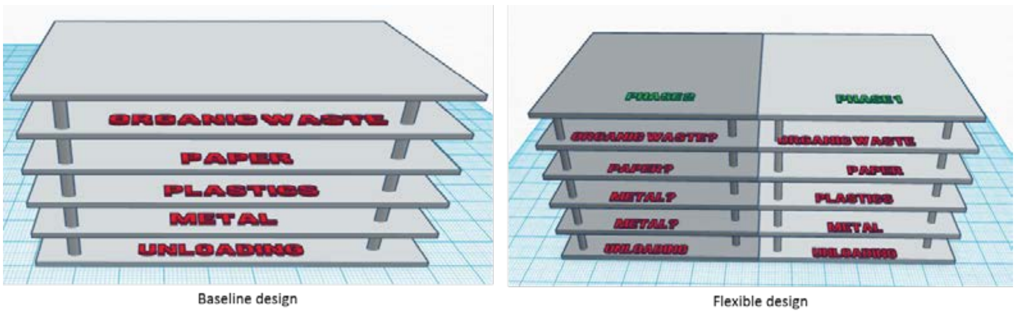


Figure 6-2: Illustration of the flexible design and the baseline design

6.3.4 Decision rules selection

According to Table 6-1, all the three types of decision rules are applicable for capacity expansion. As the capacity of the MSRF is measured by the number of stories deployed, it is a discrete number, for which the linear decision rule is not directly suitable. The conditional-go rule is sufficiently flexible to emulate the decision on the expansion of Phase 2 and allocation of technology on each floor. Therefore, the conditional-go decision rule is used in the design and management of the flexible MSRF system.

Two decisions are to be made throughout the lifespan of the flexible MSRF system: the first one is when to deploy Phase 2 whereas the other is how to allocate technologies on each floor of Phase 2. Thresholds are defined as decision variables to facilitate the decision-making. Two decision rules regarding these two decisions are as below.

Decision rule 1: When the amount of a certain type of waste is more than a threshold more than the capacity installed, then deploy one more floor of facility for this type of waste.

Decision rule 2: When any type of waste facility is triggered to expand, construct Phase 2.

6.3.5 Design optimization

The general stochastic programming model described in Section 3.2 is instantiated with the feature of the MSRF system. The objective function is to maximize the ENPV. Denote $\xi_{i,t}$ as the amount of the i^{th} type of waste generated in year t, where $i = 1,2,3,4$ represents metal, paper, plastics, and organic waste respectively. Let α_i denote the threshold to expand facility for the i^{th} type of waste. Then the stochastic programming model becomes:

$$\max \sum_{k=1}^{K} p^k \sum_{t=1}^{T} \frac{TR_t^k - TC_t^k}{(1+r)^t} \qquad (6.3)$$

$$n_{i,1}^k = 1, \qquad \forall k, i \qquad (6.4)$$

$$Me_{i,t}^{k} \geq \xi_{i,t-1}^{k} - \left(un_{i,t-1}^{k} + \alpha_{i}^{k}\right), \qquad t > 1, \forall k, i \tag{6.5}$$

$$M\left(e_{i,t}^{k} - 1\right) \leq \xi_{i,t-1}^{k} - \left(un_{i,t-1}^{k} + \alpha_{i}^{k}\right), \quad t > 1, \forall k, i \tag{6.6}$$

$$n_{i,t}^{k} = n_{i,t-1}^{k} + e_{i,t}^{k}, \qquad t > 1, \forall k, i \tag{6.7}$$

$$\sum_{i=1}^{4} n_{i,t}^{k} \leq 4N_{t}^{k}, \qquad \forall t, k \tag{6.8}$$

$$Me'^{k}_{t} \geq \sum_{j=1}^{t} \sum_{i=1}^{4} e_{i,t}^{k}, \qquad t > 1, \forall k \tag{6.9}$$

$$M\left(e'^{k}_{t} - 1\right) \leq \sum_{j=1}^{t} \sum_{i=1}^{4} e_{i,t}^{k} - 1, \qquad t > 1, \forall k \tag{6.10}$$

$$N_{t}^{k} = 1 + e'^{k}_{t}, \qquad t > 1, \forall k \tag{6.11}$$

$$\alpha_{i}^{1} = \alpha_{i}^{k}, \qquad t > 1, \forall k, i \tag{6.12}$$

$$f_{i,t}^{k} + un_{i,t}^{k} \geq \xi_{i,t}^{k}, \qquad \forall t, k, i \tag{6.13}$$

where $n_{i,t}^{k}$ is the number of floors of the facility for waste i in year t in scenario k, $e_{i,t}^{k}$ is a binary decision variable indicating whether to expand one floor of facility for waste i in year t in scenario k, M is a sufficiently large number (typically 100 times larger than the value of any variable in the program), u is the capacity of each floor (1,000 tpd), N_{t}^{k} is the number of buildings installed in year t in scenario k, e'^{k}_{t} is a binary decision variable indicating whether Phase 2 is built, and $f_{i,t}^{k}$ is the amount of waste i that is untreated because of lack of capacity.

Decision rule 1 is realized by constraints (6.5) to (6.7). If the amount of waste i reaches a certain threshold, i.e. $un_{i,t-1}^{k} + \alpha_{i}^{k}$, then constraints (6.5) and (6.6) will force $e_{i,t}^{k} = 1$, which means that one more floor of facility for waste i

should be installed. Decision rule 2 is realized by constraints (6.9) to (6.11). If the expansion of capacity for any waste has been triggered, i.e. $\sum_{j=1}^{t}\sum_{i=1}^{4} e_{i,t}^{k} > 0$, then constraints (6.9) and (6.10) will force ${e'}_{t}^{k} = 1$, which means that Phase 2 is deployed. Constraint (6.12) is the coupling constraint that forces the decision-rule variables to be the same in different scenarios.

Problem (6.3) - (6.13) is solved using the algorithm described in Section 3.4. Table 6-2 lists the optimal value of the thresholds α_i for each type of waste. The ENPV of the flexible MSRF design is $2.00 billion. As can be seen, by embedding flexibility in the system, the flexible design achieves a significant improvement of $60 million in terms of ENPV comparing to the inflexible design. This is because the flexibility enables the system to capture revenues by expanding capacity in scenarios when the waste amount increases rapidly and to avoid excess investment in scenarios when the waste amount increases slowly. The next section will describe how this is achieved by managing the flexibility following the decision rules.

Table 6-2: Optimal value of thresholds for each type of waste

Waste type	Metal	Plastic	Paper	Organic
α_i	336	114	190	1,217

6.3.6 Operations management

Upon solving the optimization problem, optimal decision rules are determined to guide decision-making in the operations of the MSRF system. The imperative actions needed to be done by the DMs after the system starts is to keep observing the realization of waste amounts and to accordingly decide whether to build Phase 2 and how to allocate the facility by following the rules as below:

Rule 1: If the amount of metal (plastic/paper/organic) waste in the previous year exceeds the current capacity for treating metal (plastic/paper/organic) by 336 tpd (114/190/1217 tpd), then one more floor of facility should be added to treat metal (plastic/paper/organic).

Rule 2: If any type of waste treatment facility is triggered to expand capacity, Phase 2 should be built. The floors of Phase 2 are gradually deployed with required facility as needed.

These rules are simple and straightforward for the DMs to follow. With these rules, the DMs are able to adapt their decisions to exercise the flexibility according to the realization of uncertainty. Figure 6-3 depicts the deployment of waste facilities by following the decision rules in five different scenarios. As can be seen, the capacity deployed for each type of waste varies in different scenarios. By following the decision rule, it adapts to the realization of uncertainty. In scenarios where the amount of waste increases quickly, more floors of capacity are installed (e.g. scenarios 3-5). Conversely, in scenarios where the amount of waste does not increase so much, less capacity is deployed (e.g. scenarios 1 and 2). Furthermore, the space of the MSRF is allocated dynamically according to the realization of amount of each type of waste. When the amount of a certain type of waste increases more significantly than others, more floors in Phase 2 will be allocated to process that type of waste. For example, the capacity for metal is the highest among all the five scenarios; this is because the amount of metal waste is the highest. In particular, the number of floors for treating metal is as high as five floors in scenario 3, which means the whole Phase 2 is deployed for metal waste because the amount of metal increases to so significant an extent.

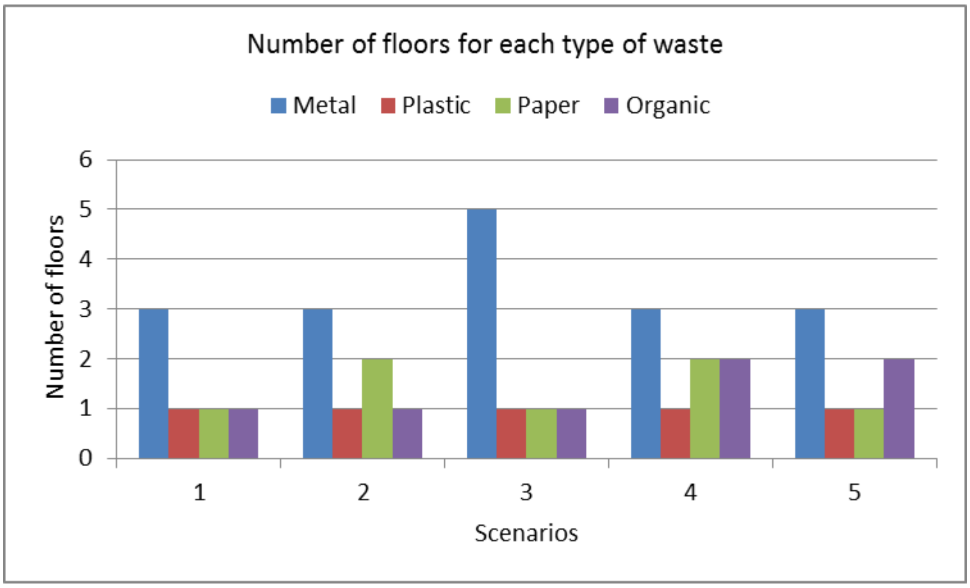


Figure 6-3: Capacity deployment in five scenarios

6.4 Comparison with existing ROA approaches

This section presents a detailed comparison between the proposed framework and a standard ROA approach. In particular, the binomial lattice approach is used as the baseline for comparison as it is the most commonly used tool in real options analysis. The procedures of the binomial lattice approach are summarized and compared to the proposed decision rule framework in Figure 6-4.

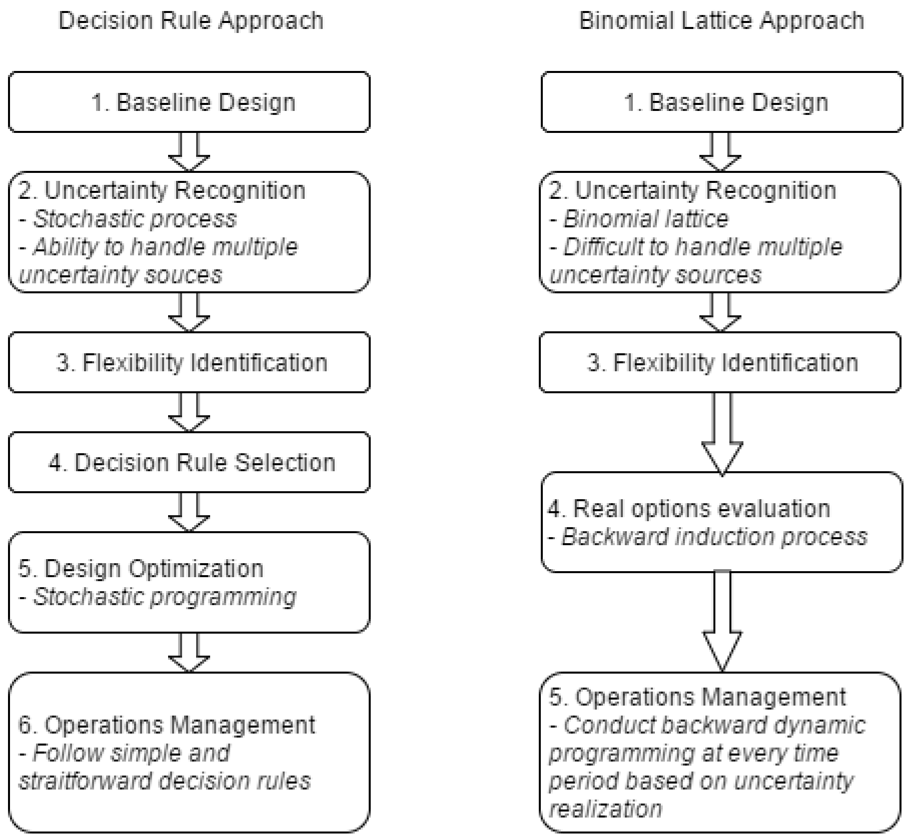


Figure 6-4: Comparison of decision rule approach with the binomial lattice approach

The first and third steps of both approaches are similar, both of which requiring a baseline as a starting point and applying similar methods to generate flexibility concepts. The difference, however, surfaces in the uncertainty recognition step. As for the decision rule approach, a distinct advantage can be seen in its modeling multiple uncertainty sources as it can use a vector to represent the uncertainty sources and model them as stochastic processes. As for the binomial lattice approach, it is a challenging task to model multiple uncertainty sources. Even though the lattice can be extended to a multinomial lattice to model multiple uncertainty sources, the computational effort increases dramatically as the dimensions of the uncertainty and state variables increase. Due to the curse of dimensionality, the lattice method becomes impractical for complex problems.

Upon identification of flexibility strategies, the binomial lattice approach applies a backward induction process based on dynamic programming to quantify the value of flexibility. In contrast, the decision rule approach first selects a form of decision rule, whereupon a multistage stochastic programming model is built to evaluate the value of flexibility and generate the best decision rules. As may be observed, both methods rely on advanced mathematical techniques (i.e. dynamic programming for the binomial lattice approach, stochastic programming for the proposed approach); this may pose challenges to wider applicability in practice. However, with regards to the operations management, practitioners may find the decision rule approach more intuitive, since the decision rules generated can emulate the decision-making process in a firm or organization and do not require application of a dynamic programming-based backward induction process or to determine the state of the system in the lattice to choose the optimal expansion policy. The decision-making criteria do not change over time since stochastically optimal parameters for the decision rules are found. The deployment path will adjust dynamically as uncertainty unfolds, but the rules governing the strategy will not.

6.5 Summary

This chapter introduces a framework for the design and management of flexibility in engineering systems focusing on the perspective of practicability in the implementation phase. By incorporating decision rules in the design process, this framework not only generates optimal system designs, but also provides intuitive guidance for the DMs to implement the system in practice.

The case study demonstrates how the framework can be used to guide the design of flexibility in an MSRF system. A qualitative comparison of the framework with the procedures relying on a binomial lattice approach was then performed, whence two main advantages of the proposed framework emerge. One is that the decision rule approach provides straightforward decision rules and simplifies decision-making in operations. The other advantage is that the decision rule approach is superior to the lattice approach in that it is able to handle multiple uncertainty sources.

Chapter 7 – Conclusions

7.1 Summary

This thesis has proposed a new approach to analyze flexibility in engineering systems design based on multistage stochastic programming and decision rules. The work of this thesis can be summarized by answering the five research questions in Section 2.5.

1. How to provide intuitive guidance for DMs to operate the systems in practice, besides assessing the value of flexibility in engineering systems?

This thesis focuses on introducing decision rules in the flexible design of engineering systems. Decision rules provide practical guidance on when it is appropriate to and how to exercise the flexibility. They are intuitive for DMs to follow in operations because they enable emulating directly the decision making process in reality. Analysis in Chapter 4-6 have shown that by providing intuitive guidance using decision rules, DMs are more likely to achieve the value of flexibility in operations.

2. *How to analyze flexibility exploiting the idea of decision rules?*

A generic multistage stochastic programming model has been developed to illustrate the approach in Section 3.2. One key feature of this model is that its solutions not only enable assessing the value of flexibility and suggesting values for the physical system design variables, but also providing decision rules for guiding decision-making dynamically based on available information as uncertainty unfolds. Furthermore, the formulation of the model indicates that the approach can deal with complex problems with multiple uncertainty drivers and multiple flexibility strategies, while also leading to similar valuation outcomes as standard ROA techniques.

3. How to solve the stochastic programming model with decision rules?

For simplicity, the model proposed in Section 3.2 is converted to a deterministic structure by assuming the finiteness of uncertainty scenarios. A Lagrangian decomposition approach is used as a solution algorithm to solve the large stochastic programming model. Numerical experiments in Section 4.3 have shown that this algorithm is capable of efficiently solving the problems of large size.

4. How to guide designers to apply the decision rule approach during the design process?

A framework has been developed for applying the proposed decision rule approach in design practice. The framework consists of six steps, it provides step-by-step guidance on how to design and manage a flexible system embedding the decision rule concept. The framework differs from existing design procedures by focusing on the perspective of practicability in implementation phase throughout the design process. A case study on a MSRF system demonstrates how the framework can be used to guide design of flexibility in engineering systems.

5. How to validate the efficiency and effectiveness of the proposed approach?

Numerical studies have been used to demonstrate the efficiency and effectiveness of the proposed approach. First, case examples from Trigeorgis

(1996) have been used to demonstrate the ability of the proposed approach to model different types of flexibility. Besides, this, two WTE systems have been studied to demonstrate the performance of the proposed approach.

In the first case study on the AD plant in Section 4.3, the results show that the decision rule approach recognizes a similar amount of value stemming from flexibility as standard ROA in terms of ENPV in the out-of-sample test, and also requires similar computational time. It also rank orders the design alternatives in a similar way as standard ROA (i.e. showing that the flexible design is expected to perform better over time than an inflexible solution). The form of the solution is reasonably intuitive to be used by the DMs in operations.

The second case study on a hybrid WTE system in Section 5.2 demonstrates that the decision rule approach can be augmented in a straightforward manner to analyze more complex systems when multiple uncertainty sources and flexibility strategies are considered simultaneously. Computational results show that it is readily applicable to solve such problems and provide intuitive guidance to the DMs in operations. Standard ROA based on multinomial lattice and ADP proves more challenging due to the curse of dimensionality. It leads nonetheless to similar ENPV performance results as the decision rule approach, but requires both more computational time to find a solution and additional optimization to determine the physical capacity of the system in each time period. Both approaches recognize value improvements stemming from flexibility, as compared with an inflexible benchmark design.

To summarize, there are three contributions in this thesis. The main contribution is to propose a new decision rule-based approach for analyzing and managing flexibility in engineering systems design. This approach not only recognizes the inherent value stemming from flexibility, it also provides solutions with intuitive guidance on how to manage the flexibility in operations. The second contribution is a framework for applying the proposed approach in design practice. With this framework, designers can start with a baseline design and generate a valuable flexible design that is practical to implement in operations by exploiting the concept of decision rules. The third contribution of this study is the three case studies on WTE systems. Managerial insights are provided to improve the design and management of these systems.

7.2 Limitations and future work

There are important limitations to consider in this thesis. First of all, there are limitations in the decision rule methodology. Firstly, the freedom of enabling the analysis of a wide array of decision rules warrants the need for more systematic approaches for identifying relevant decision rules in complex engineering systems. Questions that require further exploration – which ones to focus on, how to enable them in the system design, and how to best manage in operations – abound, as outlined by Cardin (2014). Secondly, the proposed decision rule approach also relies on an advanced mathematical technique (i.e. stochastic programming) to identify feasible solutions. Because of such complexity, it is possible that DMs will not trust the solution and therefore not use it in operations. This is, however, a shortcoming shared by standard ROA as well. Thirdly, the value of flexibility depends heavily on the quality of the decision rule. Good decision rules may generate more value whereas bad ones may undermine it. Therefore, designers and planners must investigate carefully the space of possible decision rules and rely on their expertise with the system to make good choices. Creativity is needed on the one hand, and quantitative evaluation is needed on the other hand to determine whether a possible flexibility strategy indeed creates value, as suggested by Cardin, et al. (2013). Fourthly, the proposed decision rule approach is of course limited by computational power. More complex decision rules coupled with multiple uncertainty drivers may be difficult to analyze under the proposed framework at some stage, if too many are considered – also an issue for standard ROA. Finally, the value of flexibility may be limited by the constraint that forces the decision rule parameters to be the same in each time period. If such parameters could be adjusted depending on the scenario (e.g. capacity added), more value could ostensibly be extracted. However, it would be difficult for the DMs to determine the best value for such parameters in each time period, and would require determining their position on the evolution path of the uncertainty (similar to standard ROA). Therefore, the proposed approach trades off some value-enhancement potential in the flexibility valuation process for enabling decision-making that is more readily applicable by practitioners.

Furthermore, there are limitations in the framework. Firstly, the framework assumes that probability distribution information of uncertainty sources throughout the system life span is known. This is a limitation due to the very nature of the stochastic programming approach employed. In practice, however, the environment in which an engineering system operates in can change over time. In another case, the distribution of uncertainty may be simply unavailable. Secondly, not every complex system can be analyzed by following the decision rule framework. As the framework uses stochastic programming to model and solve the problem, some systems maybe too complex that they cannot be described as MILPs. In this case, simulation based optimization can be used to find the optimal design and decision rules. For example, Deng (2015) developed a simulation optimization approach to analyze the planning of mobility on demand system.

Finally, there are some limitations in the case studies. Firstly, the case studies presented in this study are studied only from a lifecycle economic perspective. As WTE systems are closely related to urban sustainable development, future work may extend the models to multi-objective performance attributes to evaluate WTE systems from social, environmental as well as economical perspectives. Secondly, the case studies rely on many assumptions on cost parameters. As the WTE systems studied are pioneer research projects, many parameters are not available. Therefore, the cost parameters are collected from successful applications of similar technologies in Europe, United States, and Singapore. It represents the best available data since only one AD plant has been built in Singapore, no gasifier or MSRF has been built in Singapore, and limited information about the Singapore market is publicly available. Thirdly, the discount rate is assumed to be constant throughout the life span. In reality, however, the discount rate may change over time. Fourthly, the case studies use ENPV as objective function. This assumes that the decision maker is risk neutral which may not be true in practice. To improve this, future work may extend the model to use mean variance objective function to consider both the return and risk of the systems.

More opportunities exist for future work, as motivated from the limitations described above. Firstly, it is possible to investigate other formulations for the decision rules (e.g. enforcing a number of consecutive years of increase or decrease before making a decision). While small percentage differences exist between the performance of the flexible systems as recognized under standard ROA and the decision rule approach, it is possible that decision rules formulated differently could generate better value and performance. Secondly, in the framework, the selection of types of decision rules is mainly based on the type of flexibility studied. The characteristics of the uncertainty drivers, however, should also impact the choice of the best form of decision rules. Future research opportunities exist in matching the forms of decision rules to the types of stochastic processes.

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