A Screening Model to Explore Planning Decisions in Automotive Manufacturing Systems under Demand Uncertainty

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Abstract

Large-scale, complex engineering systems, as for automotive manufacturing, often require significant capital investment and resources for systems configuration. Furthermore, these systems operate in environments that are constantly changing due to shifts in macroeconomic, market demand and regulations, which can significantly influence systems' performance. It is often very difficult or prohibitively expensive to change these engineering systems once they are in place. Thus, a critical question is how to design engineering systems so they can perform well under uncertainty. Conventional engineering practice often focuses on the expected value of future uncertainties, thus leaving the value of flexible designs unexplored.

This research develops a new framework to design and plan large-scale and complex manufacturing systems for uncertainty. It couples a screening model to identify promising candidate solutions with an evaluation model to more extensively quantify the performance of identified solutions. The screening model adaptively explores a large decision space that is otherwise computationally intractable for conventional optimization approach. It integrates strategic and operational flexibility in a system to allow systematic consideration of multiple sources of flexibility with uncertainty. It provides a means to search the space for system's improvement by integrating the adaptive one-factor-at-a-time (OFAT) method with a Response Surface method and simulation-based linear optimization. The identified solution is then examined with Value at Risk and Gain chart and a statistics table.

Two cases are studied in this thesis. The first case is a simple hypothetical case with two products and two plants. It considers product to plant allocation, plant capacity, and overtime operation decisions that affect manufacturing flexibility. It demonstrates the value of considering demand uncertainty and overtime operational flexibility in making manufacturing planning decisions and the interactions between multiple sources of flexibility. The second case explores these manufacturing planning decisions for Body-In-White assembly systems in the automotive industry by applying the developed screening model. It shows that the screening model leads to system design with about 40% improvement in expected net present value, reduced downside risks and increased upside gains as compared to a traditional optimization approach.

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Nomenclatures

Acronyms

BIW	Body in White
CCD	Central Composite Design
DA	Decision Approach
DOE	Design of Experiments
ENPV	Expected Net Present Value
EOS	Economies of Scale
INV	Investment
NPV	Net Present Value
OFAT	Adaptive one-factor-at-a-time
PV	Present Value
RSM	Response Surface Methodology
SLP	Simulation-based Linear Programming
VaRG	Value at Risk and Gain

Symbols

CAP_j	Maximum capacity for a plant
d	Market demand for a product
DM	Design matrix for the designed experiments in the RSM model
F_b	Investment cost for building
F_e	Investment cost for equipment
F_t	Investment cost for tooling
H	A number used in optimization problems as the Big M technique
i	Subscript index of products
j	Subscript index of plants
k	Subscript index for allocation plans explored in the screening model
LBC_j	Lower bound for capacity of plant j
m	Total number of plants considered in a problem
MIN	the minimal NPV for a strategic decision under simulated demands
MAX	the maximal NPV for a strategic decision under simulated demands
n	Total number of products considered in a problem
$N_{allocation}$	Number of allocation alternatives for a problem
N_{cap}	Number of capacity decision alternatives by the exhaustive search method for a problem
p_i	Price for product i
q	Subscript index of experiments in the RSM model
r	Discount rate

R^2	R square to measure the goodness of fit
s	Subscript index of demand scenarios
SD	Standard deviation of NPVs for a strategic decision under simulated demands
t	Subscript index of time periods
T_e	Computational time estimated for the exhaustive search method
T_p	Computational time estimated for the screening model
T_{so}	Computational time estimated for stochastic optimization
UBC_j	Upper bound for capacity of plant j in the gridded exhaustive search method
VCn_i	Variable cost during normal production time for product i
VCo_i	Variable cost during overtime production time for product i
w_{ijt}	Normal time production of product i at plant j during period t
x_{ij}	Allocation decision variable for product i in plant j
y_j	Capacity decision variable for plant j
z_{ijt}	Overtime time production of product i at plant j during period t
α	Economy of scale
β_j	Tool flexibility upcharge for a plant j
β_0	Base tool flexibility upcharge for a flexible assembly process
β_1	Additional tool upcharge for having a different platform to the upcharge of an additional style.
β_2	Additional tool upcharge for difference between platforms.
δ_j	Interval examined in the exhaustive search method for plant j
η_{it}	Ratio of standard deviation to expected value of demand at time t for product i
θ	Maximal ratio of overtime capacity to total normal time capacity
$\rho_{i,j}$	Demand correlation between two products i and j
σ_{it}	Standard deviation of demand for product i at time t
λ	Regression coefficients in the regression model in the RSM model
μ_{it}	Expected value of demand for product i at time period t
v_i	Demand decreasing rate each year for product i

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1 Introduction

1.1 Motivation

Scale and complexity are inescapable characteristics of many modern engineering systems. Automotive manufacturing systems provide a notable example of a system for which scale and complexity amplify the challenges associated with system design and management. In response to market dynamics, these characteristics are expected to intensify. In 1955, six models accounted for 80% of all cars sold in the US. Since the 1970s, the automotive market has become highly competitive and, as a result, there is much more product variety now than in the past. In the United States and Europe, the industry is rapidly approaching 400 models, up from fewer than 300 in the mid-1990s — a 25% increase in ten years (Taub et al. 2007). Thus, each company has to offer more product types to the market in order to compete effectively, which requires more manufacturing facilities. One major automaker, General Motors, now has more than 20 plants in North America alone and offers approximately 60 product variants for the North American market each year (GM 2009), not to mention other markets.

Another dramatic change during the last few decades in automotive manufacturing systems (as well as other manufacturing systems) is that they have become much more capital intensive due to the wide application of computer integrated equipment. Since robots were introduced into automotive plants in the 1970s, they have replaced a significant number of manual assembly workers to achieve the high volumes requested by markets. As a result, today's manufacturing system is highly capital intensive. A typical assembly plant consists of about 700 robots, mainly used for joining, but also for moving materials into place (Taub et al. 2007). Along with robotic equipment, there are tools used to hold the parts in position that require about the same level of investment as equipment. The capital expenditure for building one new assembly plant can easily reach a billion dollars.

Furthermore, once the automotive manufacturing system is built, it is very difficult to make changes without incurring significant expense, both in terms of resources and time. As an example, the vehicle assembly process (the case focus of this thesis) is highly customized to specific product designs and to a given production capacity. Thus, increasing its net output (even for the product it was designed for) may require redesign and reconfiguration of the whole line. This cannot be done within a short period of time, i.e. in days or weeks. By extension, models that were not designed for a specific assembly process cannot be produced on that process without significant change to one or the other. Although the application of computer integrated machines allows robots to be used for different models with only a redesign of the software, a large number of tests and pilot runs is still required to make sure the lines are running correctly. Also hardware changes are inevitable since tools would have to be replaced or added. Thus, an addition of any new product to a line causes the whole production line to be stopped or significantly slowed down. The resulting loss of production volume for the existing models running on the process leads to large economic losses.

The combination of capital intensiveness and difficulty of change make the planning and designing of automotive manufacturing systems critical. Their scale and scope make this planning challenging. In this context, planning decisions are further confounded by the presence of variation, and the uncertainty it engenders. On one hand, because it takes a long time to construct the system, i.e. 2-4 years, manufacturing planning and design decisions have to be made several years before production when market demand is unknown. On the other hand, market uncertainty continues to evolve even after the system is built. As is well known, demand variation and uncertainty can have a major impact on the performance of manufacturing systems. Thus, uncertainty must become a central consideration in planning and designing of manufacturing systems.

The research presented in this thesis is an effort to address the challenges of planning and designing for uncertainty for large-scale and complex manufacturing systems. The central question that is studied in this research is how to plan and design manufacturing systems so that they can perform well under demand uncertainty.

1.2 Demand uncertainty

Demand uncertainty is one of the uncertainties to which manufacturing systems are often exposed. It can be due to many reasons. Financial crisis, economic downturn and fuel price changes are typical examples of sources of market uncertainties. Since the onset in 2007 of the current financial crisis, the Dow Jones Index has plunged from more than 14,000 points to between 7000-8000 points today with extreme volatility in the short term, as shown in Figure 1. Such changes have a great impact on market demands for many products, including automobiles. As indicated by Figure 2, sales for both cars and light trucks in the US market have significantly decreased from 2007 to 2009.

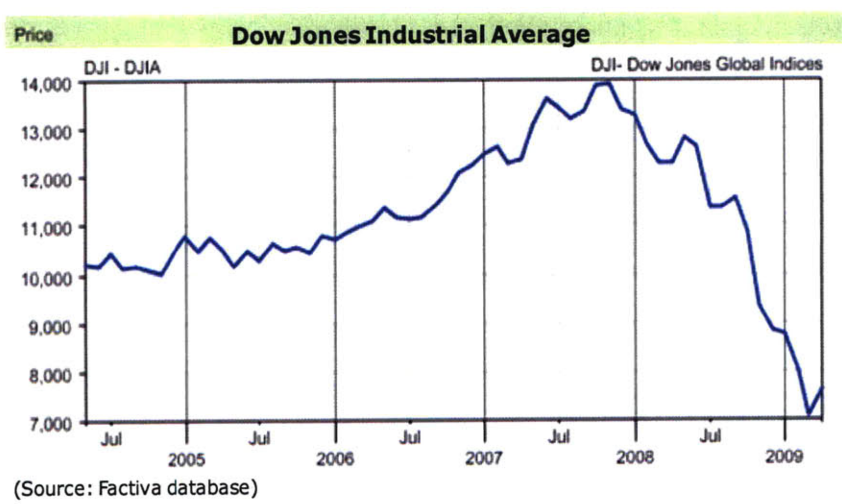

Figure 1 Graph of the DJIA from May 2004 to May 2009. Source: Factiva database

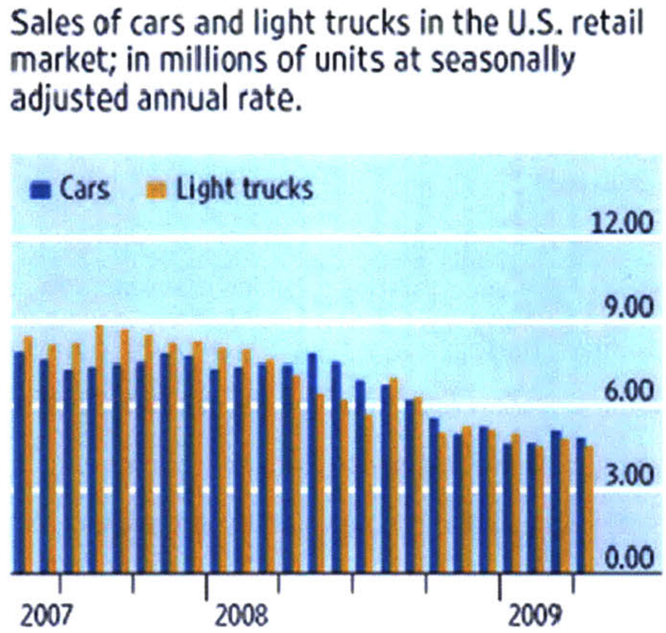

Figure 2 Cars and light trucks sales in the U.S. retail market from 2007 to 2009 in millions of units at seasonally adjusted annual rate. Source: Wall Street Journal online market data center [1]

Figure 3 shows the volatility of the U.S. regular gasoline price from 1970's to 2009, which is another factor that can affect demand uncertainty. As a recent example, the price has fallen back to around $1.5 per gallon in early 2009 after soaring towards $4 per gallon in 2007, representing 166% change within two years. The change in gasoline prices clearly has impact on consumer preferences on automobiles. Comparing Figure 3 and Figure 4, one can see that the declining period of gasoline price decline corresponds to the steady increase period of market share for SUV around 1980-2000, which comes with the decline of market share for cars. Since then, price of gasoline has been increasing rapidly while the increase of market share for SUV has lost its momentum and started to show some decrease around 2007.

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[1] (http://online.wsj.com/mdc/public/page/2_3022-autosales.html#autosalesB), Accessed on May 21,2009

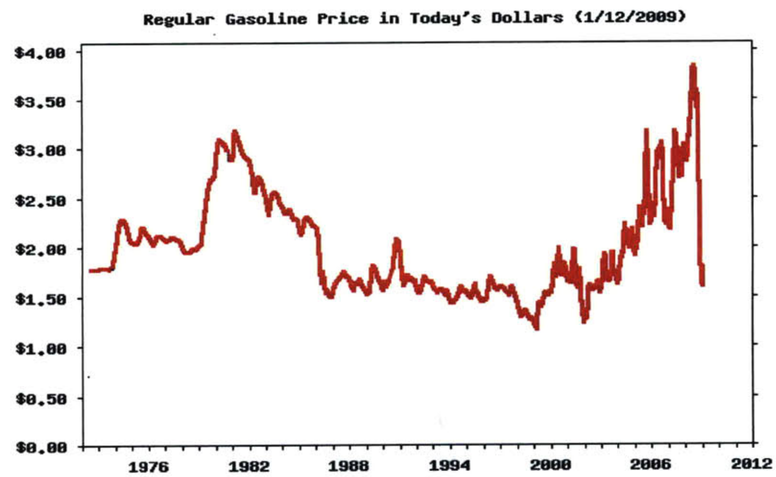

Figure 3 Regular gasoline price volatility from 1970 to 2009. Price is F.O.B cost for imports in nominal dollars. Source: EIA history

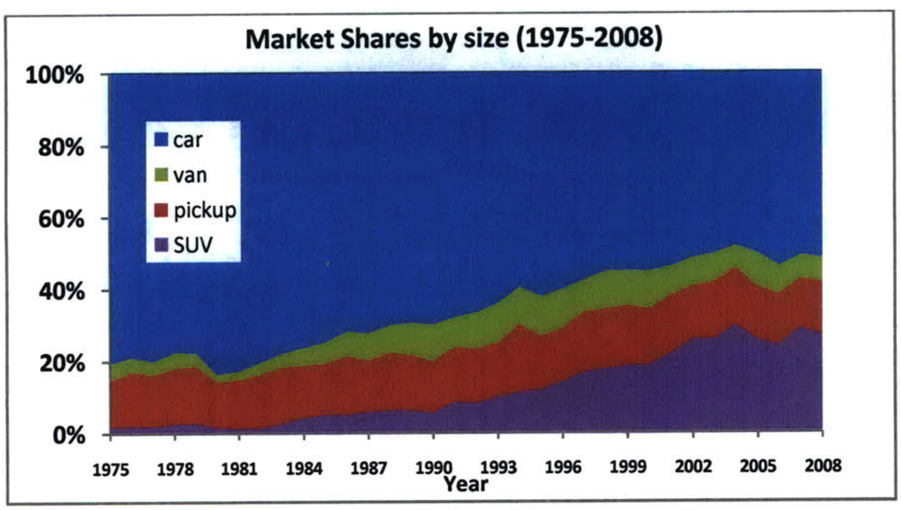

Figure 4 Market shares by size for the US market. Source: Transportation energy data book[2] and WARD's Yearbook

Even without uncertainties in the economy or fuel prices, predicting future demand for products is not easy since it is hard to tell how consumers will react to new products. For

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[2] (http://cta.ornl.gov/data/tedb27/Spreadsheets/Table4_09.xls)

example, the Pontiac Solstice, as shown in Figure 5, is a small sports car that GM introduced to the US market in mid 2005. The forecasted sales were 20,000 a year with the first year production capacity at 7,000. However, there were 7,000 orders during the first 10 days and another 6,000 before the end of the first year.

Figure 5 Picture of the Pontiac Solstice, a small sports car that General Motors launched in 2005

Figure 6 shows a study of the degree of volatility in market demand in the automotive industry (Jordan 1989). The horizontal axis is the time in quarters before start of production. The vertical axis is the percent of difference between the actual production volume and the planned volume. The analysis here is done at nameplate carline level. It shows that the multi-year forecasts (2+ years) of sales for individual vehicles typically have large forecast errors with standard deviations of 40% and these errors can get significantly larger for niche vehicles and for forecast horizons approaching five years (Jordan and Graves 1995).

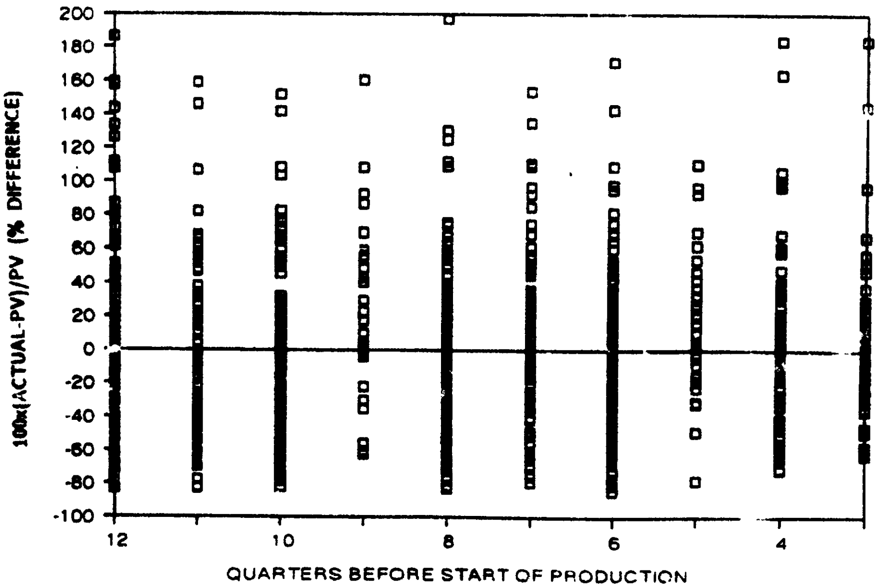

Figure 6 Demand forecast variation during the manufacturing planning stage, adopted from (Jordan 1989).

Market demand uncertainty can have a significant impact on the economic performance of manufacturing systems. On one hand, market uncertainty creates the risk of economic loss for manufacturing systems. Manufacturing systems require large capital expenditures for construction and operations. This includes costs such as equipment, real estate, purchase of raw materials, human resources hiring, etc. Some costs are incurred before any revenue from sales is generated. If sales revenue is insufficient to recoup those costs, those expenditures will lead to net economic losses. However, on the other hand, it is also possible for market uncertainty to create opportunities to increase economic value beyond expectations if the market turns out to be better than expected and companies have the resources (and have configured their operations) to take advantage of favorable circumstances.

Given the impact of market uncertainty on manufacturing systems, it is very important to build a flexible manufacturing system so that it can achieve better performance under uncertainty.

The next section discusses flexibility in a manufacturing system and sources of flexibility that may be used to respond to uncertainties.

1.3 Multiple sources of flexibility in manufacturing systems

The definition of manufacturing flexibility will be discussed in detail in Section 2.1. Here in this research, similar to definitions in the literature, manufacturing flexibility is defined as "the ability of a manufacturing system to change or respond to customer demand with reduced penalty in time, cost, effort and performance". Manufacturing flexibility has emerged as a competitive advantage for some manufacturing companies. "Manufacturing managers in a broad array of industries agree that achieving lower cost and higher quality is no longer enough to guarantee success. In the face of fierce, low cost competition, and an army of high-quality suppliers, companies are increasingly concentrating on flexibility as a way to achieve new forms of competitive advantage. "(Upton 1995)

Manufacturing flexibility can emerge from many aspects of the systems. Figure 7 provides examples of such aspects that can affect manufacturing flexibility in assembly systems. These examples are divided into three categories: system architecture, technology, and operations. The following sections provide a detailed discussion to explain each of these and how they affect manufacturing flexibility in assembly systems. Note that they are by no means exhaustive, but just some examples commonly seen in manufacturing systems; there are many more means that flexibility can be enabled or impacted in practice.

- System architecture
  - Product to plant allocation (Process flexibility)
  - Capacity
- Technology
  - Tooling Technology
  - Equipment automation

Strategic Planning Decisions

(Strategic Flexibility)

- Operation
  - Shifts selection
  - Overtime operation
  - Inventory

Operational Decisions

(Operational Flexibility)

Figure 7 Multiple sources of manufacturing flexibility

1.3.1 Flexibility from system architecture

Examples of decisions pertaining to system architecture in assembly systems that affect manufacturing flexibility include product to plant allocation decisions and capacity decisions.

Products to plant allocation decisions address which products should be produced at which plants. Product to plant allocation decisions determine process flexibility in the sense that a manufacturing plant and process that can produce multiple products provides more flexibility than a system that can only produce one product. Process flexibility has been studied extensively in the literature and deemed a very important strategy for manufacturing flexibility in practice for companies that offer multiple products to different markets. Many automotive companies have invested heavily in transforming plants to be flexible. For example, the Chrysler Group has invested in the Sterling Heights Assembly Plant to make them capable of producing multiple products. In 2004, Nissan's Canton facility was able to produce a sedan (Altima), a minivan (Quest), a full-size pickup (Titan), and two full-size SUVs (Pathfinder Armada & QX56).

GM's Lansing Grand River assembly plant is capable of producing five different products on a single line. A Ford Motor Co. plant in Oakville, Ontario, makes three different vehicles, and many plants can produce slightly different styles based on one car or truck design. Honda has gained a reputation for "being the most flexible" by having the capability to produce very different vehicles on the same assembly line. Its plant in East Liberty in Ohio is able to produce 120 Civic compacts and CR-V crossover with just five minutes to switch the line between vehicles. This enables it to match consumer demand faster than its rivals (Linebaugh 2008).

Automakers' transforming to flexible plants helps to mitigate the impact of market segmentation on their profitability. More product varieties and decreased volume per product on average have put downward pressure on automaker profit margins that have already been squeezed by fierce competition. If automakers build dedicated plants for each product, the lower production volumes do not allow them to enjoy economies of scale typically associated with higher capacity production. However, flexible plants allow the automakers to operate large plants producing multiple vehicles to capture the benefits of economies of scale while also providing them with a means to better manage demand uncertainty. Furthermore, in an environment where profit margins are thin, having flexible plants can be a decisive capability for competing in the automotive market. For example, skyrocketing fuel prices have softened demand for Sport Utility Vehicles, leading to a shift to small cars with higher fuel efficiency. Under this situation, a company with a flexible manufacturing system that is able to quickly switch the production capacity from SUVs to small cars will not only reduce losses from the declining market for SUVs, but will also capture more profits from the increasing market for smaller cars. In contrast, a firm with an inflexible manufacturing system will have to leave the capacity for SUVs idle and will require additional investment to increase capacity for small cars in order to respond to the changing market demand, leading to high investment costs and low overall capacity utilization.

Another important decision that affects the manufacturing flexibility of a system concerns the capacity of the plant. Capacity decisions at the manufacturing planning stage determine the configuration of the manufacturing process, which then determine purchasing or retrofitting requirements for equipment, tools and buildings. Because these resources require a long time to be built and delivered, (i.e., making tools takes between one and two years, typically), capacity decisions have to be made during the early planning stage. Once the capacity decision is made and executed, it can be costly to change during operation of the manufacturing process. Planning in slack capacity is often used as a way to respond to future demand uncertainty in cases where demand is higher than forecast. In this way, capacity decisions not only provide a critical boundary for the systems' capability to meet market demand, but also affect systems' flexibility to respond to uncertainty.

1.3.2 Flexibility from technologies

Flexibility can also be affected by technologies selected for the manufacturing processes. For example, in order for assembly workers or robots to weld or join parts, tools are often needed to hold parts in position. Traditional tooling technology is dedicated to only one part with a specific geometry and as such cannot be broadly applied to other vehicles. Over years, some flexible tooling technologies have been developed to extend the tooling capability to be able to handle parts with different geometries. One approach has been the use of indexing or sliders in tools so that they can be manipulated with holders that move into place when the particular style arrives at the station. In cases where the tools cannot be manipulated to handle multiple styles because the variations between parts is too large, multiple single style tools are placed on a single "carrier." Carriers may be turntables that spin to put the correct fixture in place, or shuttles that slide the fixtures back and forth, depending on which style is next to arriving at the station. More recent years, GM has developed a flexible tooling technology called C-FLEX, as shown in Figure 8. It is "a servo-driven, programmable tooling system that can adjust to the contours and size of various automotive models and body components moving down a production line" (Iversen 2004). This flexible tooling technology further reduces the need to have model specific tooling for automotive manufacturing. This technology improves GM's ability to build different vehicles on the same assembly line and thus save both money and manufacturing floor space. According to (Iversen 2004), "along with other manufacturing improvements, this technology will reduce GM's cost of introducing new products into a body shop by about $100 million, while saving up to 150,000 square feet in body shop floor space. "Another advantage of this new tooling technology over older technologies is that it has a greater flexibility in changeover of products. When new products are to be produced on an assembly line, older technologies require rebuilding of tools customized to new product while C-FLEX only needs to be reprogrammed, and thus saves a lot of times, cost and efforts.

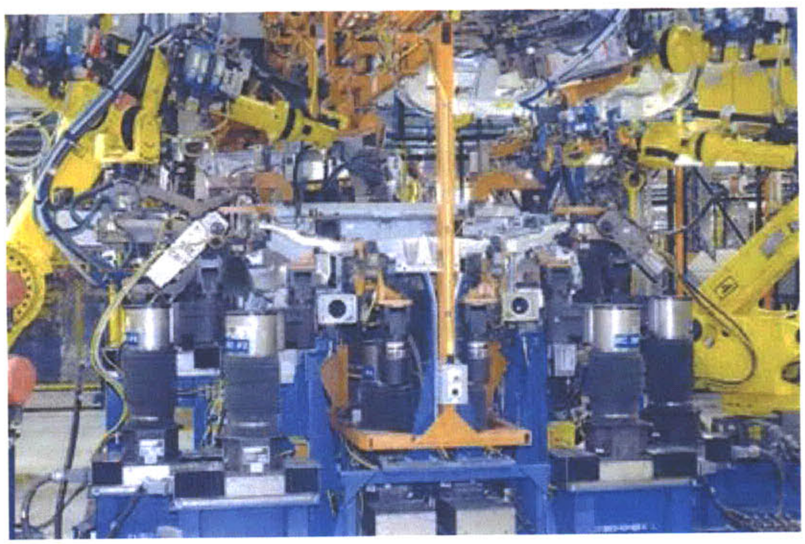

Figure 8 Station comprised of several C-FLEX units surrounded by robots, adopted from (Povelaites 2005)

Other than tooling technology, equipment technology can also affect flexibility of an assembly system. An assembly line composed of highly automated equipment can be less flexible than a manual line since changes may require reorganization, or at a minimum reprogramming, of the line, while workers can more easily be issued a new set of instructions.

1.3.3 Flexibility from operations

Although the examples above indicate different means of enabling manufacturing flexibility, they have one common characteristic that all of these require implementation prior to the beginning of actual production. Thus, these are referred to as strategic planning decisions and the flexibility of the system that emerges from these decisions is defined as strategic flexibility. However, even when there is no flexibility offered by these or other decisions made during the planning stage, there can still be flexibility during the operation of the manufacturing systems. Inventory, overtime and shift schedules are common examples of ways in which firms can react to changes in demand.

Shifts selection refers to the operational option that a manager of a manufacturing system has to select the number of shifts during production. Normally companies can run one, two or three shifts depending on the capacity of the manufacturing process and market demand. Operations can be scheduled for one shift, typically 8 hours of production during daytime, two shifts, typically using two sets of workers for 8 hours each for a total of 16 hours of production, or even three shifts, which typically runs a bit less than 8 hours per shift to allow some time for machine maintenance. Decisions about the number of shifts are usually made months in advance in order to coordinate hiring practices. If more short term flexibility is needed, overtime operations can be used to meet upward swings in market demand. Inventory can act as a buffer between a manufacturing system and the market to maintain an inventory of products that are not needed immediately after being produced in case demand is higher than expected in the future.

Decisions about the use of flexibility enablers are complex given the inherent trade-off between the costs of these flexibility enablers and the potential advantages they provide. Moreover, because some of these decisions must be made during the early planning stages, and set the boundaries for the system's future capability to respond to uncertainty, while others are available at the time of production, do these issues need to be considered together in a systematic way, or is it sufficient to treat strategic decisions without consideration of operational opportunities? This thesis will explore the interactions among these decisions, first, to determine the benefits of considering operational opportunities when making strategic manufacturing planning decisions, and second to address how to systematically consider all of the issues together, if these benefits are substantial. Before exploring this question, let us first look at the manufacturing planning process in practice to see how these decisions are currently considered.

1.4 Manufacturing planning process in practice

Figure 9 provides a schematic view of the manufacturing planning process in the automotive industry. In this figure, circles refer to responsibilities handled within particular departments while squares refer to information flows between departments as suggested by directional arrows.

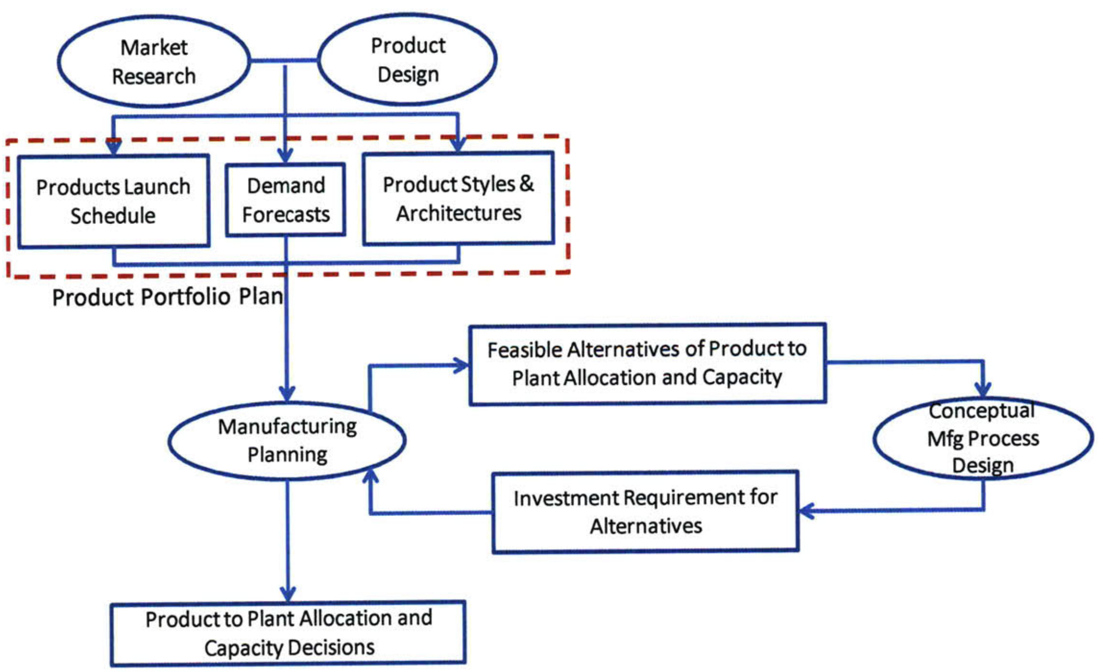

Figure 9 Schematic view of the automotive manufacturing planning process.

The product development cycle starts with the interaction between market product research and product design. Market research investigates consumer needs and market trends so that the company can develop concepts for future products. The interaction between market research and product design produces a product portfolio plan. In addition to product characteristics such as product style and architecture, the product portfolio plan also includes information about the time to launch production and projected market demand each year.

The product portfolio plan is given to the manufacturing planning department, which evaluates the financial feasibility of the manufacturing plan based on information about production resources. Two important decisions are considered during the evaluation. (1) To which plants should these products be allocated? This is associated with process flexibility of plants, e.g., how many different products can be built on a single assembly process. (2) What is the capacity for each plant? These are determined by the amount and type of equipment and tools required for the process, which determines investment, and by personnel operation plans such as shift structure and overtime.

The manufacturing planning department generates feasible plans for product to plant allocation and capacities of plants based on a large number of factors, including product life cycle demand, launch time, plants' capacity availability, labor union contracts, and tax policies, just to name a few. The capacities for plants are decided based on the forecasted demand. If a manager believes that demand for the products allocated to that plant is likely to exceed the forecast, a safety stock capacity is included.

These decisions, including process flexibility and capacity, are written into a manufacturing requirement document that is given to engineers. The engineers then will conceive possible design alternatives for the manufacturing process of each plant that meets the production requirements. The process design with the lowest investment requirement will be selected. This lowest investment, combined with other financial estimations such as material purchasing costs, future revenue and engineering development costs, among others, is used to evaluate the financial viability of producing products in the portfolio plan.

1.5 Research question in manufacturing planning decision making

While the manufacturing planning process described above may appear to be simple, issues such as the high degree of product complexity, the large number of possible approaches to manufacturing, and the large number of decision makers in the organization result in a highly complex, iterative process. Further complicating the process are the need to simultaneously consider multiple products, the uncertain demand environment along with the corresponding desire for flexibility and the multiple approaches to manufacturing flexibility. Several of these issues are discussed in more detail below.

(1) Consideration of demand uncertainty

In the current manufacturing planning process, all decisions are made based on deterministic forecasts of demand. The implicit assumption is that the company is able to produce a realistic demand forecast. Under this assumption, choosing a plan that incurs minimal investment seems to be a reasonable strategy for maximal profitability given that revenues from all investment plans are identical, calculated by multiplying the unit price and the quantity sold, the forecasted demand. However, in reality, demand is uncertain and unpredictable (see discussion in Section 1.2). Thus, the revenue from different investment plans can indeed be different. Some plans requiring more investment may be more flexible, and as such can capture upside swings in demand resulting in higher revenues. Thus, decisions made looking only at required investment levels assuming deterministic market demand may underestimate the value of some alternatives resulting in sub-optimal choices.

(2) Consideration of operational flexibility

There are many manufacturing approaches that provide firms with a degree of flexibility in response to demand uncertainty. Some are determined at the strategic planning stage while others are determined during operational stage after the system is configured. While it may be natural to consider the strategic approaches at strategic planning stage, it is not clear whether the operational approaches should be considered at the strategic planning stage and what is the impact of considering them at strategic planning stage on strategic decisions and performance of the system under uncertainty. Furthermore, is there any interaction between operational approaches and strategic approaches in responding to demand uncertainty?

(3) Evaluation of the value of flexibility during strategic manufacturing planning stage

There are many manufacturing approaches that provide automakers with a degree of flexibility in response to demand uncertainty. Some are determined at strategic planning stage while others are determined during operational stage. However, by assuming deterministic market demand forecast, the current approach to evaluate strategic decision alternatives is not able to appreciate the value of flexibility that some decision alternative may provide, nor can it comprehend the interactions among multiple sources of flexibility in the system, which may provide a great value for the system by reducing risks and allowing the firm to take advantage of opportunities that arise from market uncertainty. More sophisticated approaches which can address issues related to market uncertainty are needed.

(4) Effective exploration of the decision space during the planning stage

As engineering systems grow in scale and complexity, more and more components are incorporated into the system, and their interactions become more complex. As a result, the decision space for planning and designing the systems grows increasingly large, and it is very difficult to identify good decision candidates. This becomes even more challenging when uncertainty is incorporated into the decision making process. In short order, possible future scenarios make the decision space scale exponentially so that it becomes computationally intractable. Therefore, how to effectively explore a decision space that is computationally intractable is a very important issue to be addressed for large-scale and complex engineering systems.

This research is an attempt to address these issues. It develops a systematic approach that considers multiple sources of flexibility and explicitly incorporates market uncertainty. This approach is composed of an integrated screening model that uses methods in Design of Experiments, including Adaptive one-factor-at-a-time (OFAT) and Response Surface Methodology (RSM), and Simulated-based Linear Programming (SLP), to adaptively search in the strategic planning decision space to identify good decision candidates and an evaluation model. The approach is based on simulation and a Value at Risk and Gain chart that examine identified decision candidates and provide a comprehensive means to evaluate the value of flexibility in decision candidates under market uncertainty. Instead of trying to take all decisions that may affect flexibility of manufacturing systems, this research develops the approach based on three decisions as shown in Figure 10: the product to plant allocation decisions, the plant capacity decisions and the overtime operation decisions. The reasons for choosing these three decisions are:

(1) Attempting to incorporate all possible manufacturing decisions that might impact firms' performance in response to demand uncertainty is not only unrealistic, but also can be distracting in finding answers to the questions of the interest.

(2) These three decisions are selected because they are among the most common issues faced by manufacturing firms. Most companies that have multiple products and multiple plants must make both product to plant allocation and capacity decisions, and these decisions must be made during planning stages. Furthermore, these decisions need to be made every time new products are launched into the market. By contrast, while the

selection of specific tooling technologies or different levels of equipment automation levels can affect manufacturing flexibility, they may not have to be decided for every project. At the operational level, although there are many ways to respond to demand uncertainty, overtime operation is a very common approach, one that requires very little lead time or additional planning and thus is represents decisions can that be made as demand develops. Other operational approaches to flexibility, such as switching to a different shift pattern, may require more planning and higher lead times to due constraints in hiring and training the additional workers required. As such, the use of overtime operations provides an excellent contrast with the strategic levels decisions which must be made very early in the manufacturing planning process.

(3) These three decisions are also frequently studied in the literature and thus provide an excellent basis for understanding the different approaches to these decisions. Chapter 2 will discuss in details the literature that has studied these decisions.

- System architecture
  - ***Product to plant allocation***
  - ***Capacity***
- Technology
  - Tooling Technology
  - Equipment automation

Strategic Planning Decisions

(Strategic Flexibility)

- Operation
  - Shifts selection
  - ***Overtime operation***
  - Inventory

Operational Decisions

(Operational Flexibility)

Figure 10 Decisions studied in this thesis

1.6 Thesis outline

This thesis is organized as follows. Chapter 2 provides a review of relevant literature concerning manufacturing planning decision making. It emphasizes how manufacturing flexibility and uncertainty are considered. Based on the reviewed literature, research opportunities are identified. Chapter 3 reviews and discusses methodologies for decision making under uncertainties and evaluation of flexibility. Different methods are introduced and their advantages and disadvantages are compared. Challenges and limitations of methods when applied to uncertainty and flexibility related problems in complex engineering systems are discussed. In Chapter 4, a simple case study is presented to demonstrate the value of a systematic approach during planning stages and to explore the interactions among decisions at different stages and their effect on systems flexibility. Chapter 5 proposes a framework for exploring large decision space for large-scale and complex engineering systems. It includes an integrated screening model for exploring manufacturing planning decision making that considers multiple sources of flexibility in manufacturing systems under uncertainty, and an evaluation method to allow decision makers to evaluate decision alternatives more extensively. Chapter 6 applies the screening model in the context of the automotive industry to study manufacturing planning decisions under demand uncertainty. In Chapter 7, the screening model is evaluated in terms of its computational effectiveness and efficiency. Finally, Chapter 8 summarizes the conclusion and contributions of this work and limitations that future work should address.

2 Literature review

This chapter reviews the literature that is relevant to decisions makings in manufacturing systems, based on which research opportunities are identified. Because manufacturing flexibility is a key concept in this research, this chapter starts with a brief review of the literature on the definition and classification of manufacturing flexibility; then it focuses on the quantitative modeling work that concerns the decisions that are of the interest to this research as discussed above, including capacity decision and product to plant allocation decision at strategic level and decisions at operational level. In the discussion of these researches, special attention is given to whether market demand uncertainty is considered and how manufacturing flexibility is considered. Then a gap analysis is conducted to identify research opportunities and indicate the potential contribution of the research presented here.

2.1 Definition and classification of manufacturing flexibility

A review of manufacturing flexibility has been extensively conducted in the literature, including the work by Sethi and Sethi (1990), Gerwin (1993), Toni and Tonchia (1998), Koste and Malhotra (1999), and De Toni and Tonchia (2005). While many have examined the definition of manufacturing flexibility, there is no uniformly accepted definition. However, most of these definitions of manufacturing flexibility are very similar. In general, manufacturing flexibility is referred to as the ability of a manufacturing system to respond to changes in the environment with little penalty in time, effort, cost and quality (Upton 1994).

Classification of manufacturing flexibility is another area that has been widely explored by many researchers, including Falkner (1986), Sethi and Sethi (1990) and Gerwin (1993). This is an important area because it is difficult to address the flexibility issue if one does not know what type of flexibility is required. However, the numerous classification of manufacturing flexibility found in the literature appears to confirm that "flexibility is a complex, multi-dimensional and hard-to-capture concept"(Sethi and Sethi 1990).

A flexibility classification often cited in the literature is that by Browne et al. (1984), who considers eight different types or dimensions of manufacturing flexibility: machine flexibility, product flexibility, process flexibility, operation flexibility, routing flexibility, volume flexibility, expansion flexibility, production flexibility. Based on this work, Sethi and Sethi (1990) distinguish eleven types of flexibility, adding material handling flexibility (after machine flexibility), program flexibility (after expansion flexibility) and market flexibility (after production flexibility). As shown in Figure 11, this classification is based on a vertical logic from basic component flexibility to system flexibility and aggregate flexibility.

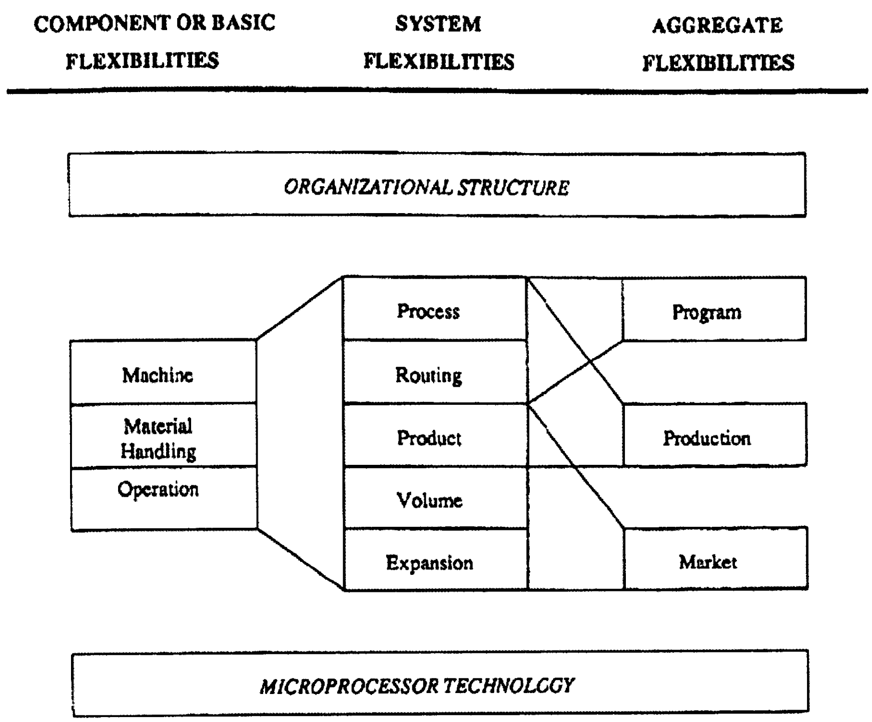

Figure 11 Classification of manufacturing flexibility by Sethi and Sethi (1990)

Gerwin (1993) classifies manufacturing flexibility according to seven types of uncertainty: mix flexibility, changeover flexibility, modification flexibility, volume flexibility, rerouting flexibility, material flexibility, flexibility responsiveness as shown in Figure 12.

Table 2 Dimensions of Flexibility

Type of Uncertainty	Strategic Objective	Flexibility Dimension
Market acceptance of kinds of products	Diverse product line	Mix
Length of product life cycles	Product innovation	Changeover
Specific product characteristics	Responsiveness to customers' specs	Modification
Aggregate product demand	Market share	Volume
Machine downtime	Customers' due dates	Rerouting
Characteristics of materials	Product quality	Material
Changes in the above uncertainties	Strategic adaptability	Flexibility responsiveness

Figure 12 Classification of manufacturing flexibility by Gerwin (1993)

The definitions of all types of manufacturing flexibility discussed in the literature are not repeated here given that it is not the intention of this research. However, the definitions for volume flexibility and process flexibility are discussed here because of their relevance to this research:

Volume flexibility According to Sethi and Sethi (1990), volume flexibility of a manufacturing system is defined as "its ability to be operated profitably at different overall output levels". The purpose of volume flexibility is to address the uncertainty in the level of demand. As shown in Figure 11, it is defined as a system level of flexibility. Similarly, Gerwin (1993) defines it as a flexibility required by the uncertainty in the amount of customer demand. Volume flexibility permits increases or decreases in the aggregate production level in response to changes in demand levels.

Process flexibility Browne et al. (1984) and Sethi and Sethi (1990) define process flexibility as a capability relating to the set of part types that the system can produce without major setups. This type of flexibility is also referred to as "mix flexibility" in the literature. It "satisfies the strategic needs of simultaneously be able to offer to customers a range of product lines"(Sethi and Sethi 1990). This definition is applicable for various types of manufacturing systems, such as part fabrication processes and assembly processes. For example, Hauser and de Weck (2007) studied six different part fabrication processes ranging from punching to laser cutting and evaluated the flexibility of these processes under market uncertainty. Some of these processes, such as traditional metal stamping require customized, part specific tools, while others, such as laser cutting, can be used to manufacture different parts without making any physical change of equipment. For assembly processes, a flexible system is one which can be used to assemble different groups, where the difference can be the number of parts in the group, the geometry of those parts or of the entire group, and the types of joining methods used or the number of operations required. For example, Povelaites (2005) studied automotive assembly lines with different tooling technologies where tools are used to hold parts in position for robots or assembly workers to make joints. While traditional dedicated tooling systems cannot accommodate different part geometries, flexible tooling technologies, such as those with adjustable pins or reprogrammable robots, such as C-FLEX, can be used to hold parts with different shapes, thus enabling an assembly line with process flexibility. The degree to which these systems can handle variation in part geometry varies further defining the flexibility enabled by each.

The definitions of these two types of flexibility are applicable in this research. However, one thing needs to be noted: Although both process flexibility and volume flexibility are the system level of flexibility that addresses different type of demand uncertainty, they are not exclusive to each other. In particular, although process flexibility is directly related to the uncertainty regarding different product varieties, it can also be used to respond to demand uncertainty with volume variations. In this regard, process flexibility in this research is more referred to as one enabler for volume flexibility. Together with other enablers, such as overtime operational flexibility, it contributes to the ability of the firm to react to demand uncertainty in volume variations.

2.2 Review of manufacturing systems decision making literature

As the focus of this research is concerned with the impact of considering demand uncertainty and operational flexibility on strategic planning decision making, in particular, capacity decision and product to plant allocation decision, this section will review literature addressing quantitative modeling work in the areas of (1) capacity decision making (2) product to plant allocation decision making, (3) operational decisions making and (4) strategic decision making with consideration of operational decisions.

2.2.1 Research studying capacity decisions under demand uncertainty

For a company that needs to produce multiple products, one question that often needs to be answered at strategic planning decision stage concerns the capacity of the manufacturing facility considering the demand uncertainty. Furthermore, when manufacturing resources differ in terms of their flexibility to produce different products, this question then becomes how much of this capacity should be flexible and therefore able to produce multiple products and how much can remain dedicated to a single product. However, there is a trade-off since flexible manufacturing systems typically require higher levels of investment than their dedicated counterparts. In studying this question, Fine and Freund (1990) develop a single-period, two-stage stochastic program to determine in a firm's capacity levels of multiple dedicated resources and one flexible resource that is capable of producing all products. At the first stage, the company chooses the capacity levels of multiple dedicated resources and one flexible resource such that all products can be produced considering uncertain demand. At the second stage, the firm determines production quantities after demand realization. Their work characterizes the sufficient and necessary conditions for a firm to invest in a flexible resource in order to protect efficiently against uncertainty in demand. They also explored the sensitivity of the optimal capacity decisions to the difference in investment required by the flexible and dedicated systems, as well as sensitivity to demand correlation and variability. Van Mieghem (1998) also studied the optimal investment for flexible manufacturing capacity as a function of product prices (margins), investment costs and multivariate demand uncertainty. This work considers a firm that produces two products and can invest in dedicated and/or flexible capacity. The analysis shows how cost differential, price differential and correlation of demand affects optimal investment decisions for flexible capacity and finds that flexible capacity may even be beneficial under perfectly positively correlated demand if one product is more profitable than the other. In similar work done by Netessine et al. (2002), impacts of demand correlation on flexibility investment are also analyzed, and show that for the case of two products, increasing correlation causes a shift from flexible to dedicated resources in the investment decision. For the case of three or more products, the changes in the investment decision follow an alternating pattern. Bish and Wang (2004) studied the optimal resource investment decision faced by a two-product, price-setting firm that has the option to invest in dedicated resources and/or a more expensive, flexible resource that can satisfy both products. The study shows the conditions under which investment in flexible resources can be optimal, depending on the profitability of the two products and demand correlation.

In summary, the literature discussed above provides great analytical insights on the trade-off between costs and benefits of flexible resources and how the optimal capacity is sensitive to demand uncertainty. However, as Jordan and Graves (1995) pointed out, their application is limited by one common assumption, which is that they all assume the flexible resource is completely flexible, meaning that it can produce any kind of product. Why this assumption limits the usefulness of the work discussed above is further discussed in the next section.

2.2.2 Research studying allocation decisions under demand uncertainty

By assuming the flexible resource is completely flexible, meaning that it can produce any kind of product, the work discussed in the preceding section focuses on the question as to whether and how much to invest in dedicated capacity versus the completely flexible capacity. As such, product to plant allocation decision is bound together with the capacity investment decision. Once the capacity of the flexible resource is determined, it implies that all products can be produced using this resource to the limit of its capacity. This may be appropriate in some industries or for limited product varieties, but is not realistic in some industries. For example, an automotive company may have many products and many plants. It is neither technically feasible nor economically viable to build a plant that can produce all of their products. Under this situation, the product to plant allocation and capacity investment decision has to be addressed separately. Jordan and his collaborators have pioneered the research on partial flexibility under demand volume uncertainty. Jordan and Gonsalvez (1990) developed a model called CAPPLAN, which evaluates the flexibility of a given product to plant allocation and capacity decision. They found that a high percentage of the benefits of total flexibility can be achieved by a small amount of flexibility. Based on this work, Jordan and Graves (1995) provided the well-known chaining theory as principles for allocating products to plants. They define a chain as "... a group of products and plants which are all connected, directly or indirectly, by product assignment decisions". They emphasize the fact that chaining configuration provides virtually the same benefits as a fully flexible configuration and demonstrate that the benefits decrease as the number of chains increase. This idea is illustrated in Figure 13:

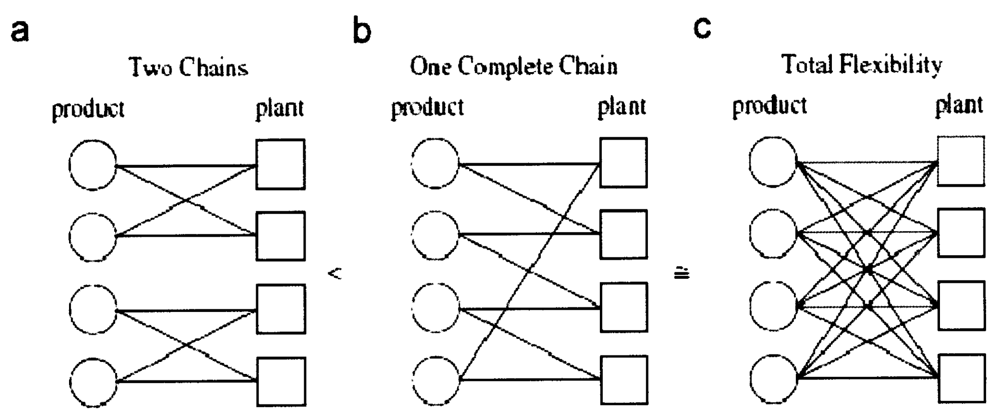

Figure 13 Illustration of chaining theory in Jordan and Graves (1995), adopted from (Francas et al. 2007)

This very insightful principle has been applied and verified by many other researches. Based on the chaining theory, Inman and Gonsalvez (2001) developed a model for allocating products to plants by minimizing the lost sales, balancing the utilization of capacities among plants, and maximizing the number of plants chained together. However, in this model, product demand is assumed to be deterministic. Francas et al. (2007) developed a mixed integer stochastic programming model that is able to determine the optimal flexibility configuration facing uncertain and dynamic demand along the product lifecycles. Through a case study in the context of the automotive industry, this paper shows that consideration of product lifecycles has a big impact on evaluation of strategic process flexibility.

However, all models described above concern only product to plant allocation decisions and take the capacity investment decision as a given. Furthermore, operational flexibility is not considered in these models.

2.2.3 Research studying operational decisions under demand uncertainty

Operational decisions concern the operation of manufacturing systems which are configured based on capital investment decisions made during strategic planning stage. Research addressing the use of operational decisions to cope with demand uncertainty resides in the literature of production planning or aggregate planning. This is effectively a problem concerning the "acquisition and allocation of limited resources to production activities so as to satisfy customer demand over a specified time horizon"(Graves 2002). Note that "production planning" or "aggregate planning" here, in spite of also containing planning activities, is an activity that happens after the strategic planning stage. Strategic planning decisions typically address capital resource acquisition while "production planning" or "aggregate planning" decisions are more concerned with resources such as workforce size, inventory planning, subcontracting and overtime scheduling. For example, the model presented by Wild and Schneeweiss (1993) is used for planning the regular workforce and the use of flexible labor instruments such as temporary workers, overtime, and cross trained workers when demand is uncertain. It demonstrates the importance of the interplay between long-term capacity decisions and the availability of flexible labor instruments (i.e. temporary workers) for short term decisions. Similarly, Askar and Zimmermann (2006) present a model that considers multiple flexibility instruments that allow for adjusting production levels in automotive plants, including changing the cycle time, number of shifts, and operation time per shift (overtime), among others. However, these models do not consider capacity investment or product to plant allocation decisions. The reason, as pointed out by Van Miehem (2003), is that "while nothing precludes the inclusion of capital equipment adjustments in aggregate planning models, the planning horizon typically is short-to-medium, i.e. days, weeks or months, such that capital equipment is fixed but its utilization and allocations to products over time is variable".

2.2.4 Research studying strategic decisions and operational decisions

There are models that include both strategic decisions and operational decisions in manufacturing systems. Fleischmann et al. (2006) developed a strategic planning model to optimize BMW's global product to plant allocation and capacity expansion over multiple periods by minimizing the sum of the supply chain cost, the investment and the production cost. The supply chain cost includes the cost of acquiring materials as well as distribution of finished cars to global markets. Investment pertains to three production departments, body assembly, paint shop and final assembly. The production cost consists of costs during both normal production time and during overtime. It is a very inclusive model in incorporating various costs associated with an allocation plan; however, it is a deterministic model in that the model assumes that "the revenue is fixed" (Fleischmann et al. 2006). Consequently, minimizing investment and costs will be sufficient to evaluate allocation plans. Bradley and Arntzen (1999) present a mixed-integer program to maximize returns on assets and then apply it to two firms to illustrate the capacity-inventory tradeoff. Rajagopalan and Swaminathan (2001) explore the interaction between production planning and capacity acquisition decisions in environments with demand growth. However, in these models, the demand is assumed to be known and therefore, the analysis is based on a deterministic approach. Thus, the effects of uncertainty on optimal capacity plan cannot be appreciated in these models.

The model developed by Chandra et al. (2005) evaluates enterprise-level of benefits of manufacturing flexibility, which are characterized by the expected net present value under uncertainty. Flexibility enablers considered include flexible assembly plants capacity, part commonality, and supply base flexibility as well as overtime flexibility. Demand uncertainty is explicitly incorporated in the model. Costs for setting up plant capacity, supply base capacity, part production, and overtime are included. Revenue is a function of uncertain demand and the capacity decisions. The model can be used to determine the optimal capacities of plants for a given allocation decision. However, it does not incorporate the cost of the allocation decision (Chandra et al. 2005) and thus is insufficient to select the optimal product to plant allocation.

2.3 Research Gap Analysis

A key question for any research project is what gap in knowledge it addresses and what contribution it is able to make. Based on the review of the manufacturing planning decision making literature, in particular the aspects related to manufacturing flexibility, the following gaps are identified:

(1) In the current literature, multiple sources of flexibility to respond to demand uncertainty have been recognized (Jack and Raturi 2002). These include decisions made at different planning stages ranging from early planning decisions to those occurring during production. However, few quantitative models have considered multiple sources of flexibility in making strategic manufacturing planning decisions. Specifically, the strategic manufacturing planning decisions included in this thesis are the product to plant allocation and capacity investment decisions. This thesis also addresses operational flexibility, specifically decision during production concerning the use of overtime operations. Table 1 gives a summary of the literature reviewed

in this chapter and the decisions and flexibility types considered by each. Previous research either takes a deterministic approach and thus the value of flexibility under uncertainty is not appreciated (Bradley and Arntzen 1999; Inman and Gonsalvez 2001; Rajagopalan and Swaminathan 2001; Fleischmann et al. 2006) or only includes one or two of types of flexibility decisions when uncertainty is incorporated (Jordan and Gonsalvez 1990; Chandra et al. 2005; Francas et al. 2007). This thesis is an effort to take a more systematic approach in making strategic planning decisions by considering both the allocation and the capacity decisions, as well as the overtime operational decision for manufacturing systems. The interdependency between these decisions under demand uncertainty and the impact of taking a systematic approach are explored.

Table 1 Comparison between this research and closely related researches

	Allocation decision/process flexibility	Capacity decision	Overtime flexibility	Uncertainty incorporation
(Bradley and Arntzen 1999)		✓	✓	
(Rajagopalan and Swaminathan 2001)		✓	✓	
(Inman and Gonsalvez 2001)	✓		✓	
(Fleischmann et al. 2006)	✓	✓	✓	
(Jordan and Gonsalvez 1990)			✓	✓
(Chandra et al. 2005)		✓	✓	✓
(Francas et al. 2007)	✓			✓
This research	✓	✓	✓	✓

(2) The second gap relates to the computational challenge associated with using optimization methods for allocation, capacity and overtime production decisions, particularly when explicit consideration of demand uncertainty is included. When uncertainty is considered, stochastic optimization is often an approach used to identify optimal decisions in a large decision space. However, it becomes computationally challenging to solve the problem studied in this research. Several of the studies in Table 1 that make use of stochastic optimization are presented in Table 2. Aside from the specific strategic planning decisions and operational decisions considered in each study, characteristics of the stochastic optimization formulations, the size of the case studied and the computation time for each study are also listed. The model by Jordan and Gonsalvez (1990) evaluates the performance of a given allocation and capacity decision under demand uncertainty with overtime considered in operational decisions. This model is a linear stochastic optimization and takes only 45s to be solved for a problem with 7 products, 6 plants and 2 periods. However, it is not able to be used to search in the allocation and capacity decision space. Then in (Chandra et al. 2005), capacity decisions are included. The resulting model is also a linear stochastic optimization and is applied in a case with 8 products, 14 plants and 8 periods, which takes 15 hours to be finished. The product to plant allocation is given and thus cannot be solved with the model. Francas et al. (2007) considers product to plant allocation decisions with demand uncertainty, which makes the problem a mixed integer stochastic program. The authors studied a case with 4 plants, 4 products and 6 periods, commenting that "for larger problem instances, it is almost computationally intractable", and yet, the capacity decision is exogenous to this model. Although these studies may vary in terms of their specific formulations, parameters and constraints, which may affect the ease of solving the optimization problem, adding capacity and allocation decisions as variables into these problems causes major increases in computational time. This is discussed in details in Section 3.2. In practice, both allocation and

capacity decisions are unknown at the beginning of the planning stage and therefore need to be included in the problem formulation. This poses a computational challenge for searching for the optimal decision under demand uncertainty using stochastic optimization methods. In addressing this challenge, this research develops a method that is able to search large decision spaces that are otherwise computationally intractable in order to identify good strategic decision candidates.

Table 2 Computational challenge of using stochastic optimization for strategic planning decision makings under demand uncertainty

Study	**Components in Stochastic Optimization**				**Characteristics and size of Stochastic Optimization**					**Computational time**
	Allocation	Capacity	Overtime	Uncertainty	Linear	Integer	# of products	# of plants	# of periods	
Jordan and Gonsalvez (1990)			✓	✓	✓		7	6	2	45s
Chandar et al. (2005)		✓	✓	✓	✓		8	14	8	"tens of hours"
Francas et al. (2007)	✓			✓	✓	✓	4	4	6	"for larger problem instances computationally almost intractable"

3 Methods for decision making under uncertainty

This chapter discusses quantitative methods that can be used for decision making under uncertainty. Specifically, three groups of methods are reviewed: one group is the real options analysis method, which is used to examine and to evaluate decision alternatives under uncertainty; the second group and the third group are the optimization method and the Design of Experiments method respectively, both of which can be used to explore decision spaces and to select among decision alternatives. In each group, several quantitative methods and tools are reviewed with brief background introduction and discussion about the advantages and limitations of their applications to large complex engineering systems.

3.1 Real options analysis: evaluating decision alternatives under uncertainty

In planning and designing phase of a project, decision alternatives ought to be evaluated based on many criteria, such as economic impact, technical feasibility, etc., to make a decision. This thesis emphasizes on the evaluation of economic impact of decision alternatives. When a decision alternative's economic impact is evaluated, DCF (Discounted Cash Flow) analysis is the traditional approach widely accepted. It is calculated by summing up cash flow for every period of the project at a certain discount rate that accounts for the time value of money. However, when there exists uncertainty in the environment, DCF analysis has been criticized since it assumes uncertain factors to be constant and thus is not able to evaluate the value of flexibility in decisions (Kaplan 1986; Deaves and Krinsky 1998).

Real options analysis has been developed to address this issue. It explicitly considers uncertainty involved in a project, recognizes the value of flexibility that may exist in decision alternatives and provides a way to quantify it. Applying real options analysis helps people manage risks and uncertainties actively, not merely passively by perceiving the value of flexibility vaguely. Before we start a detailed discussion, let us define real options first.

3.1.1 What is "real options"

MIT professor Steward Myers (1984) first coined the term "real options":

"Strategic planning needs finance. Present value calculations are needed as a check on strategic analysis and vice versa. However, standard discounted cash flow techniques will tend to understate the option value attached to growing profitable lines of business. Corporate finance theory requires extension to deal with real options." (pp.136)

"Real options" has its root in financial derivatives, where an option is defined as a right, but not an obligation, to buy or sell an asset, at a pre-determined price, within a specified period of time. For example, one buys a call (European) option on a stock at a strike price of $50 within the expiration date of three months. The stock price at that time is $45. If the price after three months goes up to $60, then the owner can exercise this option by buying the stock at $50, $10 less than the market price. Then the owner can sell the stock at the market price $60. As such, he makes $10 on that stock from selling it the stock. If instead, after three months, the stock price is less than $50, the owner of this call option does not want and does not have to exercise this option.

Analogous to financial option, a real option is defined as: "the right, but not an obligation to do something at a certain cost within some specific time period". As compared to the definition of option, the difference here is that financial option is restricted to buying or selling an underlying asset while real option is something that is embedded in a real investment opportunity.

3.1.2 Real options "on" project and real options "in" project

Real options have been classified into two categories by de Neufville (2002) and Wang (2005). The distinction comes from the way that the technical design of an engineering system is treated during the analysis. Real options "on" projects mostly evaluate the management flexibility/options in investment while treating the engineering design as a black box. Trigeorgis (1993) provided some examples of real options "on" projects:

- The option to wait: Suppose a company can lease land and wait to see if the market price of real estate can justify to develop it or not.
- The option to abandon: if market conditions decline, the management can have the option to abandon current operations.
- The option to switch: management can switch to product that is favored by market by having a flexible production facility.

A number of books are dedicated to the exposition of this real options approach, including the ones by Amram and Kulatilaka (1999), Copeland and Antikarov (2001), Trigeorgis (1998), and Mun (2006). In the real options application in manufacturing systems, Nalin Kulatilaka is among the early researchers to use real options to analyze manufacturing flexibility. In (Kulatilaka 1988), he recognized the analogues between the operating flexibility of a flexible manufacturing system and the nested compounded financial option and presents a stochastic programming model which can capture the value of flexibility of a flexible manufacturing system. This method allows the incorporation of decisions on investment timing or the decision to temporarily shut down or to abandon the project entirely. In addition, Karsak and Ozogul (2002) developed a methodology based on the option approach for valuing expansion flexibility of flexible manufacturing systems. In all these analyses of real options "on" projects, the technical design of the system is not studied and changed.

However, real options "in" projects concern embedding flexibility into the design of the engineering systems. Real options "in" projects are of interest for engineering systems designers because it can provide a great value in addressing the intrinsic uncertainties that these systems operate in. Lin (2009) and Wang (2005) summarized some examples of real options “in” projects, including the parking garage (de Neufville et al. 2006), satellite systems (de Weck et al. 2004), water resource systems (Wang and de Neufville 2006), and petroleum exploration and production systems (Lin 2009). These examples are not be discussed in detail here, but as a summary, in all examples, real options analysis is applied to evaluate technical designs of large complex engineering systems and real options “in” projects leading to different technical design that greatly enhances the systems’ capability to deal with uncertainty.

Various valuation techniques have been developed to evaluate different options. But because of the distinctions between financial options, real options “on” project and real options “in” project, some valuation techniques may only apply for some types of options but not for the other. Thus, it is important to understand the assumptions that a valuation technique is based on and the advantages and limitations of each technique before applying them. Thus, the next section is going to discuss several valuation methods. Specifically, three valuation methods are discussed: Black-Scholes formula, binomial lattice model and simulation.

3.1.3 Black-Scholes model

The Black-Scholes model is discussed here because it is the cornerstone for option pricing theory and the foundation for other option valuation methods. It is a mathematical model of the market for an equity, in which the equity's price is a stochastic process. The option price derived from Black-Scholes model is given by a closed form formula:

$$C(S,t) = SN(d_1) - Ke^{-rT}N(d_2) \qquad (1)$$

Where N(x) denotes the standard normal cumulative distribution function for a variable that is normally distributed with a mean of 0 and standard deviation of 1.

$$d_1 = \frac{\ln(S/K) + (r + \sigma^2/2)(T-t)}{\sigma\sqrt{T-t}} \qquad (2)$$

$$d_2 = d_1 - \sigma\sqrt{T-t} \tag{3}$$

S is the price of the stock, K is the strike price of the option, r is the risk-free interest rate, T is the time to expire, μ is the annual drift rate of the price of the stock, and σ is the volatility of the stock.

However, there are important assumptions behind this formula: firstly, there must be a market in which the arbitrage can be made by buying or selling options and the replicating portfolios. Secondly, it is possible to create a portfolio which can replicate the payoff of the option. Thirdly, the uncertainty of the underlying assets is a Geometric Brownian Motion (GBM) process. If any of these assumptions is not met, this closed form formula cannot be applied. Unfortunately in the engineering world, these assumptions often do not hold. For example, there may not be a market for some technologies to be traded, so the arbitrage and the replication portfolio assumption are not valid. The GBM is commonly used to model the evolution of a stock price, but for uncertainties in engineering world, this stochastic process may not be the best model to fit the data. Thus, the application of Black-Scholes formula is very limited in real options "on" projects and real options "in" projects.

3.1.4 Binomial lattice model

The binomial lattice model is a discrete representation of the evolution of the underlying asset value. It was developed by Cox and Ross (1979). It models the uncertainty by using a lattice where each node represents a state of the underlying asset at a particular point of time. For each node, there are two states, up and down, with some probabilities at each stage. As Figure 14 shows, by recombination of states, the number of states increases linearly with the number of periods. Thus, this method reduces the size of the tree and therefore has the appealing feature of avoiding the "curse of dimensionality".

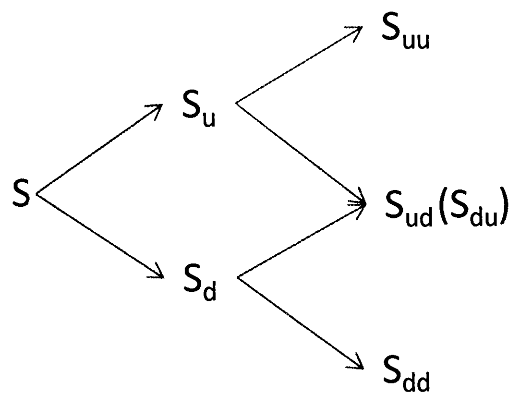

Figure 14 State evolution simulated by the binomial lattice model

After the uncertainty of the underlying asset is modeled by a lattice model, the valuation process is applied by starting at each final node, and then working backwards through the tree to the first node (valuation date), where the calculated result is the value of the option. Lattice model is flexible in that it can be combined with some efficient method such as dynamic programming to value the underlying real options.

However, there are also limitations of a binomial lattice model. Firstly, it assumes path independence, which means that the value at each node is only determined by its state, not by the path it used to arrive at the node. When there is path dependency, it is not appropriate to apply it. Secondly, usually binomial lattice model is applied for only one source of uncertainty. When there is more than one source of uncertainty, then the dimension of binomial lattice model has to increase also. For example, for two sources of uncertainty, it results in a trinomial lattice model. But when the number of sources of uncertainty grows, the computational appeal of this method disappears.

3.1.5 Simulation

Given the development of computer and computational techniques, another method for real options analysis, simulation, is increasingly used. Simulation generates thousands of possible paths of the evolution of the underlying system or asset over time given the specified parameters for the evolution process. With options exercise decision rules embedded in each of the paths, it computes values of each possible path. With commercial software such as Crystal Ball®, the generation of possible paths can be easily done within seconds.

The first advantage of simulation is that the uncertainties are not limited to a certain form of process, such as the GBM. The second advantage is that as with the binomial lattice model, it can be combined with other methods, such as optimization, to evaluate the value of real options. Another important advantage is that it can directly display many possible outcomes under uncertain environment. This is a very important aspect that distinguishes simulation from other valuation methods. While there is nothing preventing binomial lattice models from producing similar distributions, the details and resolutions that simulation can provide is much better than lattice models. The results from simulation can also be further summarized in various forms, such as probability distribution chart, that reveals more comprehensive information. Section 3.1.6 introduces one way to summarize and display results from simulation methods.

The early application of simulation to evaluate real options in manufacturing systems can be seen in Suresh's work. Suresh (1990) applied SIMSCRIPT II.5 to build a risk analysis simulation model of demand and compared the cumulative distributions of NPVs of system candidates with different flexibility. Jordan and Gonsalvez (1990) developed a CAPPLAN method based on simulation to analyze how uncertainty in product demand interacts with capacity and product assignment decisions to affect future sales and capacity utilization. Hauser and de Weck (2007) also present a framework to evaluate flexibility in component manufacturing systems by using a discrete time simulation. All of these works show that simulation is a helpful tool for analysis the problem related to uncertainty, such as flexibility.

However, there are also disadvantages with the simulation method. It can be computationally expensive to run, especially when decision space is large and many decision alternatives are available.

3.1.6 Value at Risk and Gain chart

As mentioned in previous section, results from simulation model can be summarized in various forms. This section introduces one way to summary results from simulation methods, which is the Value at Risk and Gain chart as an effective way to display the value of real options. The concept of Value at Risk has been originated and widely applied in financial industry. Value at Risk (VaR) is a measure of the risk of loss on a specific portfolio of financial assets. For a given portfolio, probability and time horizon, VaR is defined as a threshold value such that the probability that the loss on the portfolio over the given time horizon exceeds this value is the given probability level. For example, if a portfolio of stocks has a one-day 5% VaR of $1 million, there is a 5% probability that the portfolio will fall in value by more than $1 million over a one day period, assuming markets are normal and there is no trading.

Value-at-Risk has also been applied in areas beyond finance. One of these areas is flexibility in engineering systems. There it can be used as a way to measure the value of flexibility. For example, Hassan et al. (2005) presented a VaR-based real options analysis of satellite fleet design under demand uncertainty. VaR chart is applied to show the distribution of financial results of design alternatives, through which the value of flexibility was shown in that design alternatives with imbedded flexibility can reduce Value at Risk, and thus mitigate risks. Building on the concept of Value at Risk, Cardin and de Neufville (2007) constructed a counterpart concept, Value at Gain, to represent the upside potential of a project. It emphasizes that possible upside gain should also be a way to evaluate designs in engineering systems. Similar to VaR, Value at Gain (VaG) can be defined as a threshold value such that the probability that the gain of a system exceeds this value is the given probability level. By introducing the concept of VaG, the emphasis is to show the distribution of possible outcomes decisions makers can look at the whole spectrum of the results, including both the downside risk and upside risk and that the ultimate purpose of flexibility is to limit downside risk and to increase upside gain. Lin (2009) applied the Value at Risk and Gain chart in exploring flexibility in petroleum exploration and production systems. In the same stream, this research uses this chart as a way to display possible results of decision alternatives under demand uncertainty to comprehend the value of flexible system designs.

Figure 15 shows an example of VaRG chart with the cumulative distribution of NPVs of a project. The 5% VaR is -$110million and 5% VaG is $210 millions. It means that there is 5% probability that the loss of the project can be more than $110 million and there is 5% probability that the gain of the project can be more than $210 million. Other than VaR and VaG, this chart can provide other information to evaluate results of decision alternatives, such as expected value of NPV, minimum NPV and maximum NPV. It is also possible to calculate standard deviation of NPVs. Basically it provides the distribution of the outcomes with which a set of comprehensive information can be obtained, such as expected value, standard deviation, minimum, maximum, etc.

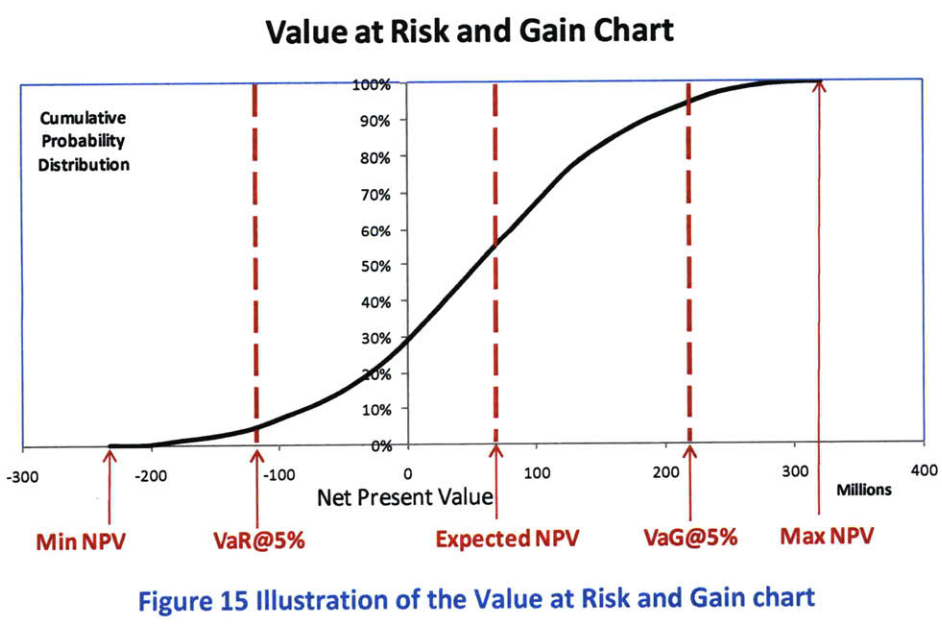

Figure 15 Illustration of the Value at Risk and Gain chart

This chart is also complemented by a table that summarizes key statistics of VaRG chart and other results of investment decisions, such as investment required of decision alternatives, Expected production and capacity utilization. These are important metrics that can influence investment decision makings.

3.1.7 Summary

Four methods are reviewed in this section, which provide tools and methods for evaluate the value of real options under uncertain environment. If used properly, it can provide great value and insights on real options evaluation. However, these methods all suffer from one drawback, which is that although it might be easy to calculate the value of each decision alternative, it is difficult to determine the optimal decision given the information available at the time the decisions are made. This may not be a big issue if the number of alternatives that can be evaluated is small. However, when the design space is very large, it is impossible to evaluate all possible decision alternatives for their values under uncertainty. Therefore, methods are needed to help explore the decision space and identify good options. The next two sections review two groups of methods in this regard. One is optimization; the other is Design of Experiments.

3.2 Optimization method: explore decision space under uncertainty

Optimization refers to the study of problems in which one seeks to minimize or maximize a real function by systematically choosing the values of real or integer variables from within an allowed set. Its extensive application was during World War II for military operations, but now has been extended to virtually all industries. It is a method widely applied in exploring decision spaces and helps in decision making. A wide range of methods and algorithms has been developed over time that can intelligently search a decision space.

Optimization has the following general form:

$$
\begin{aligned}
& \underset{x}{Max} \ \ or \ \ \underset{x}{Min}\, f(x) \\
& subject\ to: \\
& \qquad G_i(x) = 0 \quad i = 1,\ldots,m_e \\
& \qquad G_i(x) \leq 0 \ \ i = m_e + 1,\ldots,m
\end{aligned}
$$

where x is a decision variable, f(x) is the objective function, which returns a scalar value, and the vector function G(x) returns a vector of length m containing the values of the equality and inequality constraints evaluated at x.

Depending on particular forms of f(x) and G(x), there are many subfields in optimization, such as linear optimization, the most basic one with the f(x) and G(x) being linear, nonlinear optimization, which has f(x) and/or G(x) being nonlinear, and integer optimization, where decision variables x can only take integer values. Among many categories of optimization problems, stochastic optimization is a class of optimization that deals with decision making under uncertainty, which is the problem considered in this research. Thus, this section focuses on introducing and discussing stochastic optimization.

3.2.1 Introduction to stochastic optimization with recourse

Stochastic optimization, a.k.a. stochastic programming, deals with optimization problems in which some of data are uncertain. The uncertain data will be represented as random variables for which a probabilistic description is assumed available, under the form of probability distributions, densities, or, more generally, probability measures (Birge and Louveaux 1997). If some decisions can be taken after uncertainty is disclosed in a problem, it is referred as stochastic optimization with recourse.

Stochastic optimization with recourse typically incorporates two types of decisions: here-and-now and wait-and-see. Here-and-now decisions mean that decision makers have to make decisions before, or at least without the knowledge of, realizations of uncertainty. These decisions are called "first stage decisions"; in contrast, "wait-and-see" decisions mean decision-makers are assumed to be able to wait for the realization of the random variables. These decisions are called "second stage decisions".

If first stage decisions are represented by a vector x and second stage decisions are represented by vector y, a general formulation of a two-stage stochastic optimization with recourse is:

$$Min_x\, f(x)+Q(x,\xi) \qquad s.t. \quad g(x)\le 0 \tag{4}$$

Where

$$Q(x,\xi)=Min_y\; q(\omega,y) \qquad s.t. \quad h(\omega,y)\le 0 \tag{5}$$

Where ω is random variable representing uncertainty and $\xi=\xi(\omega)$, which represents the vector after ω is realized.

3.2.2 Application of stochastic optimization in manufacturing systems

Stochastic optimization has been widely used in exploring questions in manufacturing systems such as line design, production planning, capacity planning, technology selection, etc. The objective is to optimize the allocation of scarce resources and to efficiently contend with exogenous uncertain events. This section reviews the literature in this regard.

Kira et al. (1997) considers a production planning problem with multiple periods and multiple products while demands are uncertain. Decisions to be made for each period are the number of units of products to be produced, the number of units of products to be subcontracted, the number of units of inventory products, and regular and overtime hours. Demand is considered uncertain and modeled by a scenario based probabilistic distribution approach, in which typically less than five scenarios are assumed to represent uncertainty realization. The objective is to minimize total cost of production while meeting demand requirements. Overproduction and underproduction are penalized by being associated with penalty costs, which are included in the objective function. The model is a stochastic linear programming with simple recourse. A case study with 4 products, 3 periods and 4 scenarios probability distribution is illustrated, which shows superiority of the proposed model compared to deterministic approach with approximately 3% cost savings. Since all costs associated with production decisions are assumed to be linear, the problem remains computationally tractable.

Chen et al. (2002) applied stochastic programming in addressing the issue of technology and capacity planning in an environment characterized by multiple products, stochastic demands and technology alternatives distinguished by investment and operating costs. Technologies considered here are either "dedicated" so that only one type of product can be produced, or "flexible" to produce any type of product. This paper presented a generic model in which the objective is to minimize the total investment and operational costs comprising production and inventory carrying costs over the planning horizon. The Investment cost function is rather generic and allows incorporation of economies of scale. Capacities for technologies are determined during the beginning of each period for each product as demand is realized. The model is very generic so that it can have wide applications. A simplified version of the general model is applied on a new product introduction problem in the pharmaceutical industry based on the Eli Lilly case (Pisano and Rossi 1994).

Stochastic programming is also applied in (Chandra et al. 2005), which present a work closely related to the research in this thesis as mentioned in Chapter 2. A stochastic optimization model is developed that maximizes expected value of profits as a function of vehicle sales under demand uncertainty and expenses due to capacity investment and maintenances. This research takes a simulation-based approach to modeling demand uncertainty with samples generated by using Latin-hypercube methods. Genetic algorithm is used to optimize capacity planning decision based on expected value of profits of simulated demand samples for a given capacity planning decision.

Francas et al. (2007) studied benefits of strategic process flexibility in manufacturing systems with consideration of life cycle of products by using a stochastic optimization model. Product demand is assumed to be uncertain and normally distributed. The model considers product to plant allocation as the first stage decision and production decision in plants as the second stage decision. Since product to plant allocation decisions are modeled as a binary integer while production decision is a continuous variable, the model is a mixed integer linear program.

3.2.3 Computational challenge of stochastic optimization

The above section reviewed representative literature on application of stochastic optimization in planning and designing issues in manufacturing systems. However, although stochastic optimization has been widely applied, it has been indicated in various literature that it has become computationally challenging to solve large-scale problems efficiently:

In (Chen et al. 2002), although the generic model is formulated to explore technology selection decisions and capacity planning while allowing economies of scale in the investment function, as the authors pointed out, this results in "a large scale stochastic programming...even with a linear cost function, the resulting problems are not easy to solve using standard optimization packages". Particularly, the presence of nonanticipativity constraints prevents traditional method for large scale stochastic optimization models such as Dantzig–Wolfe (DW) decomposition from being applied effectively. In this paper, an algorithm is developed for problems with linear investment cost function, which is applied to cases with 2-3 products and 2 types of technology (flexible vs. dedicated) for periods between 5 and 8. For problems with concave costs and/or larger size, "optimal solution algorithms are likely to be time consuming, and heuristic procedures may have to be developed." (Chen et al. 2002).

The computational challenge is also mentioned by Chandra et al. (2005). The formulated stochastic optimization problem is a linear model with all variables being continuous. For the case presented in this paper with 8 plants and 14 vehicles, it takes 15 hours to run the model.

Their model does not consider economies of scale and production to plant allocation decision as this research attempts to address. The same challenge is mentioned in (Francas et al. 2007).

The challenges that are encountered in the literature are explained by Philpott (Philpott), who said that, in general, linear stochastic programming, when there are few random parameters and decision variables, can be solved quickly by use of some well-developed tools and theories in mathematical programming, such as duality theory and convexity analysis. For large scale linear stochastic programming, some decomposition methods have been developed to improve the computational efficiency. Then nonlinear stochastic programming adds complexity into the problem, but if the problem is still convex, decomposition techniques can still be applied to address large-scale nonlinear programming (Shastri and Diwekar 2006). However, when it comes to stochastic integer programming, where decision variables have to take integer values, problems arise in the loss of convexity, which makes the application of decomposition methods problematic. The size of the problem grows exponentially with the number of periods and the number of uncertainty sources. Especially when problems encompass integrality and nonlinearity, even the deterministic version of the problems is difficult to solve, let alone the stochastic optimization.

3.3 Design of Experiments methods

Design of Experiments (DOE), is another group of method that can be used to explore decision spaces and seek improvement of systems' performance. In general, it refers to the process of planning, designing and analyzing the experiment so that valid and objective conclusions can be drawn efficiently and effectively. (Antony 2003). The purpose is to understand an unknown system in terms of the relationship of variables and/or to seek an improvement on the system. This is contrasted with the optimization method. Optimization method requires the clear specification and formulation of the problem before any algorithm is applied and a solution is derived. Among many methods in Design of Experiments: two methods are used in this research and thus reviewed in this section. One method is Adaptive One-factor-at-a-time, which is reviewed in Section 3.3.1; the other is Response surface Methodology, which is reviewed in Section 3.3.2.

3.3.1 Adaptive one-factor-at-a-time (OFAT)

Adaptive one-factor-at-a-time (OFAT) is one of the adaptive Design of Experiment methods to explore the experimental space in seeking the improvement of the system. This section will first use a simple example to illustrate the idea about this method since it often is also a very informative and simple way for introduction. Then discussions in the literature about this method are reviewed.

The example is a system with three factors, each with two levels, -1 and +1. Figure 16 provides a schematic chart to illustrate the OFAT process as well.

First, an experiment is conducted at some baseline point in the design space. In Figure 16 this baseline point is A=-1, B=+1, C=+1.

Next, one of the factors is varied. For example, the factor A is varied from -1 to +1. Then another experiment is run based on the current system setting, which is A=+1, B=+1, and C=+1. If this setting leads to an improvement, then the change is retained.

Since there are only two levels for each factor, the exploration of the factor A is finished. Then, the next factor is changed. For example, the level of the factor C is changed from +1 to -1. Another experiment is conducted under the resulted new setting, which is A=+1, B=+1, and C=-1. Assume that this change does not lead to an improvement of the system's performance, this change is not retained so that the system's setting returns to A=+1, B=+1, and C=+1.

Then change the level of the factor B from +1 to -1, resulting the system's setting as A=+1, B=-1, and C=+1. Do the experiment under this setting. Assume that this change leads to a better performance, this changed is retained.

Since all factors are explored in the process, the OFAT process stops. As a result, the identified system setting is A=+1, B=-1 and C=+1.

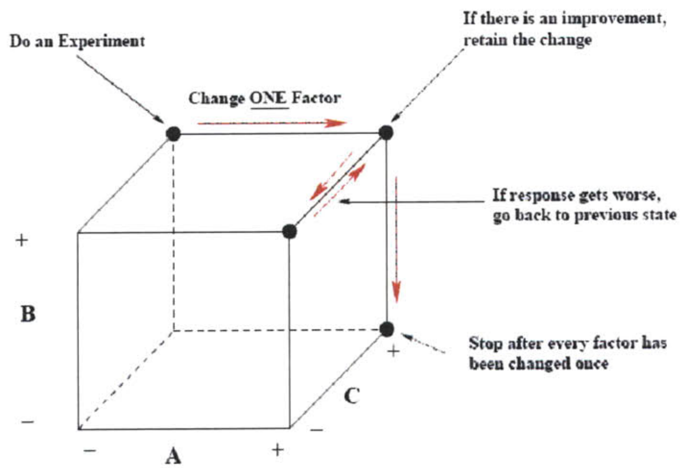

Figure 16 Illustration of the adaptive OFAT process applied to a system with three two-level factors adapted from (Wang 2007)

For more formal mathematically description of this method, the reader is referred to (Wang 2007). In brief, this process is conducted in the following two features:

(1) Each time only the level of one factor in the system is changed while the levels for all other factors are static;
(2) Whether to retain the change or not depends on the system's performance after this change as compared to before this change. If the system's performance after this change is better than the one before this change, then the change is retained.

This method had been criticized for several reasons, such as: it requires more runs for the same precision in effect estimation; it cannot estimate some interactions; and it can miss optimal settings of factors (Wang 2007). Although these cautions are valid, some statisticians also articulated a role for this method. Especially, some recent work by Frey and Wang (2006) provided a theoretical examination showing that when the experiment errors are small relative to main effects or when the interactions between factors in a system is strong relative to main effects, adaptive OFAT can perform better than Fractional Factorial Design with the same number of experiments.

Although the discussion regarding to the OFAT method remains an open topic, this method has several advantages that are more appealing than other methods for this research:

(1) Compared to Full Factorial Design, one advantage of the OFAT method is that it scales only linearly with the number of factors in a system, thus requiring shorter computational times. For example, for a system with m factors, each having 2 levels, a Full Factorial Design requires 2^m experiments while the OFAT method only requires $m+1$ experiments. The difference in the number of experiments between these two methods gets large when m gets large.

(2) As far as computational time or resource is concerned, the Fractional Factorial Design method is another alternative to seek systems' improvement. But the OFAT method has another advantage that makes it selected in this research: Instead of completely replacing optimization method, it can work with it in exploring a decision space. In this research, the optimization method is used to specify a starting point for the OFAT method, upon which the OFAT method can adaptively improve in searching the decision space. This will be further explained in this chapter and demonstrated in Chapter 6.

3.3.2 Response Surface Methodology (RSM)

Response Surface Methodology (RSM) is another experimental design scheme. It is a collection of mathematical and statistical techniques developed for modeling and analyzing problems of determining optimum operating points through a sequence of experiments. Pioneered by Box and Wilson (1951) in the field of experimental design and analysis, the RSM has been vastly studied and implemented in a wide range of fields, including robust parametric design and process optimization.

In the RSM, a group of design alternatives is first sampled based on some experimental design methods. Central Composite Design (CCD) is one such method often used and is also selected in this research. It consists of three distinct sets of experimental runs:

(1) A factorial (perhaps fractional) design in the factors studied, each having two levels[3] (-1 , +1);
(2) A set of center points, experimental runs whose values of each factor are the medians of the values used in the factorial portion. So if the two levels of each factor in the factorial design are -1 and +1, the center points take the value of 0 for each factor. This point is often replicated in order to improve the precision of the experiment.
(3) A set of axial points, experimental runs identical to the center points except for one factor, which will take on values both below and above the median of the two factorial levels, and typically both outside their range. So if the two levels of each factor in the factorial design is -1 and +1, the axial points take the level of either $-\alpha$ or $+\alpha$ for one factor while keeping the value of the other factor as 0. Here α is determined by the following formula:

$$\alpha = [\textit{number of factorial runs}]^{1/4}$$

As a result, the CCD design requires five levels for each factor. Figure 17 shows an example of central composite design for a system with 2 factors.

[3] Note that "level" here represents the relative value of each factor. It does not have actual physical meaning. In applying designed experiments to real problems, one needs to convert the levels to the actual quantity of factors according to specific contexts.

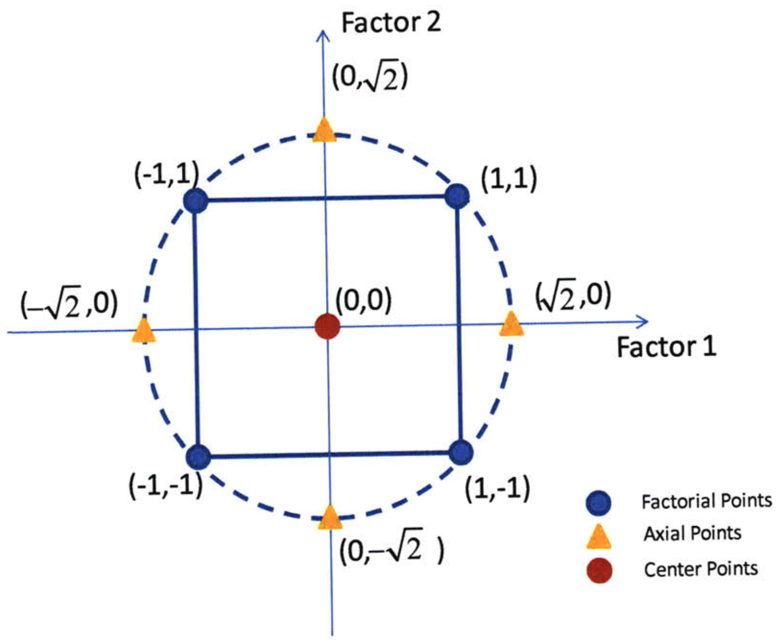

Figure 17 Example of Central Composite Design for a system with 2 factors.

Table 3 shows the resulting design of experiments:

Table 3 Experiments for a system with 2 factors with CCD method

No. of experiments	Factor 1	Factor 2
1	-1	-1
2	-1	1
3	1	-1
4	1	1
5	$-\sqrt{2}$	0
6	$\sqrt{2}$	0
7	0	$-\sqrt{2}$
8	0	$\sqrt{2}$
9	0	0

After experiments are designed, next step is to conduct all experiments designed and to get the responses. The response results are then regressed against some regression model, typically by least squares minimization. The regression model can be a simple function such as linear, quadratic function or sometimes cubic function depending on the property of the system under study. Equation (6) shows an example of a linear function for a system with 2 factors:

$$\Gamma = \lambda_0 + \lambda_1 y_1 + \lambda_2 y_2 + \varepsilon \tag{6}$$

where λs are coefficients that are obtained after the regression while y represents the design variables in the system that need to be optimized. ε is the error term that represents the distance from the true response to the estimated response by the regression model.

Optimization of the regression model with regard to y will lead to optimal response value at some design variables values. Since the regression model is mathematically tractable and is easy to be optimized, total computation cost can therefore be reduced. However, a model fit error ε has to be accepted.

The RSM is selected to explore the capacity decision space in this research because it is able to search in a continuous space with reduced computational cost. Capacity decision space is regarded as a continuous space with the range between zero and maximum of a plant's capacity. Methods such as the Factorial Design or the OFAT are not appropriate in exploring this space since the space must be discretized into levels first before experiments are conducted. If the intervals between levels are big, which leads to a low resolution of the exploration, completing all experiments will still leave a large space unexplored. If intervals between levels are small, the cost of conducting experiments will then become very expensive. On the contrary, for the RSM, although during experiment design phase, the decision space have to be discretized to get structured samples in the space, during the second phase optimization of regression model is conducted over the entire space without being constrained in the discrete space. Since the optimization is conducted upon some mathematically simple regression model, it takes less computational time than optimization on the original formulation. An issue though is that optimization is done with a model for which the coefficients are estimated, not known. Thus, an optimum value may only look optimal for the estimated response model, but be far from the truth because of variability in the coefficients. Nevertheless, when it is not feasible to find an optimal value with a complicated function, RSM provides a way of improving the response with reduced computational cost.

3.4 Summary

This chapter reviews relevant methods that can be used for decision making under uncertainty. Specifically, real options analysis is introduced as a group of methods to evaluate decision alternatives under uncertain environment. Four evaluation methods/tools in this group are discussed, including Black-Scholes model, binomial lattice model, simulation and Value at Risk and Gain chart. The advantages and disadvantages of each method are compared. Then in the group of optimization method, stochastic optimization method is reviewed as a method that can be used to search decision space under uncertain environment. Its computational challenge is discussed. Lastly, two methods in Design of Experiments field, including adaptive OFAT and Response Surface Methodology, are reviewed as another approach to explore decision space, which are used in this research for manufacturing planning decision making. The details of how they are applied in this research are described in Chapter 5.

4 Case study 1: A simple hypothetical case

This chapter, through a simple hypothetical case, investigates how strategic planning decisions should be explored. It focuses on addressing two questions posed in this research about strategic planning decision making for manufacturing systems: (1) What is the value of considering demand uncertainty on the strategic planning decision making and performances of manufacturing systems? (2) What is the value of considering operational flexibility on the strategic planning decision making and performances of manufacturing systems?

First, a general description of the case is provided, including the specific decisions considered and the assumptions taken in this study. Then a comparative analysis approach is used to demonstrate the impact of both uncertainty and operational flexibility on the early planning decision making stage. Specifically, four different decision approaches are taken to explore the strategic planning decision space, including (1) no consideration of demand uncertainty or operational flexibility, (2,3) consideration of only one of these and (4) simultaneous consideration of both concepts. The optimal decisions based on these four decision approaches are determined. Next, the performances of these decisions are evaluated and compared. The results are discussed and the benefits of considering uncertainty and operational flexibility are demonstrated based on the results. Then sensitivity analyses are performed to explore how the decisions are impacted by changes in some parameters. Finally, interactions between process flexibility and overtime flexibility are explored.

4.1 Case description

This simple case looks at a manufacturing planning problem that involves two products, denoted by A and B, and two available plants for production, denoted by plant 1 and plant 2. Variations in demand for each product are assumed to follow normal distributions characterized by a mean $\overline{d}$ and a standard deviation σ. The mean of annual demand for each product is assumed to be 200,000 units per year for five years. The standard deviation in the annual demand for each product is assumed to be 50,000 units. The variation in demand for the two products may be correlated, either positively or negatively or may exhibit not correlation at all. This correlation is represented by ρ, and is assumed to be 0 (no correlation) in the base case.

In order to produce these two products, the firm needs to make two strategic decisions one year prior to the production because it takes one year to acquire the required resources, such as equipment and tools, and to build the manufacturing system. These two strategic decisions are:

(1) Product to plant allocation decision

    Which product should be produced at which plant? There are many possible ways to allocate products to plants. Depending on the allocation decision, plants are designed and constructed differently. For example, each plant can be dedicated to a single product, both plants can be built to be flexible and able to make either product, or one plant can be flexible and able to produce both products while the other plant is dedicated to a single product. A flexible plant gives one the flexibility to adjust production between products that are allocated in that plant depending on the actual demands, but comes with a cost because it requires flexible tools that are more expensive than dedicated tools.

(2) Plant capacity decision

    The capacity, assuming no use of overtime, for each plant needs to be determined. This can be translated into the amount of equipment and tools and the expense for buildings that need to be acquired for each facility, which then determines the investment needed to purchase these resources. It is assumed that the plant's capacity cannot be downsized or expanded during the five years production period.

After these decisions are made, equipment and tools are invested and systems are built based on these decisions in a year. Then plants start production. During production, plant managers can decide production levels in each period depending on the actual demand for each product. If the demand exceeds the production quantities that can be produced during normal operating time, they can run overtime. However, there is a limit on the amount of overtime operation depending on the shift structure in a plant. In this case, it is assumed that the maximal ratio between overtime operation capacity to the normal time operation capacity is 0.15. Furthermore, the overall annual capacity of a plant cannot exceed 300,000, which is exogenously determined for technical reasons.

Variable costs are the only cost considered during production in this case. Furthermore, operation during overtime incurs higher variable cost than during normal operating time. No inventory cost is considered. This is reasonable given that each time period is one year so that production can be altered within the time period in order to satisfy as closely as possible the demand that is actually realized.

Manufactured products are then sold onto the market. Furthermore, the firm is a price taker in the market; all products are sold on the market at a specified price. Products that are more than market demand are not sold so that there is no incentive to produce more than market demands. On the other hand, unmet market demands are lost sales that lead to no revenue.

There are competing interests that complicate the decision makings regarding to the product to plant allocation and plant capacity at the planning stage. On the one hand, there is a desire to always be able to produce enough to fully capture demand even in cases with upswings in demand. On the other hand, building enough capacity to be able to satisfy demand even in extreme conditions is costly and can lead to very poor financial performance if demand is lower than anticipated. Further complicating the situation is the potential to need higher capacities for only one product thus creating an incentive to build flexible manufacturing facilities, but these also come with a cost of flexible tooling. What is also unclear is whether overtime flexibility during operational stage should be considered or not, since how much it is going to be used depends on how demands are realized and thus is unknown at this stage. In a word, the optimal decisions for plant capacities and product allocation should be impacted by the relative costs of each approach, the levels of demand and the anticipated variation, and the availability of operational flexibility in the form of overtime operations.

What this case study is going to show is how the optimal decision is impacted by decision approach taken during the early planning stage. Before the different decision approaches are explained, the next section will show the model used to calculate the economic impact of a given decision alternative.

4.2 Economic calculation model

First of all, the investment for building plants under a strategic decision alternative, including the product to plant allocation and plant capacity decision, needs to be calculated. The product to plant allocation decision is represented by a matrix X; the element in the matrix x_{ij} represents whether a product *i* is allocated to a plant *j*. In this case, this matrix is a 2 by 2 binary matrix. This decision determines the process flexibility of a plant. If only one product is allocated to a plant, then the plant is a dedicated plant; if both products are allocated to a plant, then the plant is a flexible plant. In the example shown in Figure 18, the matrix on the left corresponds to the allocation decision on the right. Under this allocation decision, the plant 1 is a dedicated plant since only product A is allocated to this plant while plant 2 represents a flexible plant since both product A and product B are allocated to this plant. A flexible plant requires flexible tooling with an upcharge cost β as compared to dedicated tooling.

Allocation matrix (X)

$$\begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \Longleftrightarrow$$

	Plant 1	Plant 2
Product A	1	1
Product B	0	1

Figure 18 An example of the product to plant allocation decision

The capacity for a plant is denoted by y_j. Then the investment cost of a decision alternative is calculated as:

$$INV = \sum_j \left(F_e + F_t \times \left(1+\beta_j\right) + F_b\right) \times \left(\frac{y_j}{100{,}000}\right)^{\alpha} \qquad (7)$$

Where INV represents investment, i is an index for product and j is an index for plant. Fe is the equipment cost per 100k unit production capacity. Ft is the tool cost per 100k unit production capacity for a dedicated process. Fb is the building cost per 100k unit production capacity. The values of these parameters are shown in Table 4.α represents economy of scale regarding to capacity, with 1 meaning there is no economy of scale. It is assumed to be 0.7 in this case. β_j represents upcharge cost of tools in a plant *j*. Its value depends on the allocation decision. If a plant is dedicated to only 1 product or does not produce any product, its value is 0; If a plant is flexible to produce both products, its value is β_0, which is bigger than 0. In this case, β_0 is assumed to be 20%.

$$\beta_j = \begin{cases} 0 & \sum_i x_{ij} < 2 \\ \beta_0 & \sum_i x_{ij} = 2 \end{cases} \qquad (8)$$

Then the economic model also includes variable costs occurred during production and the revenue from selling products, both of which are discounted to the time when strategic decision is made. The mathematical formulation is:

$$PV = \sum_t \frac{1}{(1+r)^t} \times \left(\sum_{ij} \left(p_i \left(w_{ijt} + z_{ijt}\right) - \left(vc_{mi} w_{ijt} + vc_{oi} z_{ijt}\right)\right)\right) \qquad (9)$$

Where r is the discount rate; t is the index for time periods. p_i is price of product i. VC_{ni} is the variable cost of producing product i during normal production time; VC_{oi} is the variable cost of producing product i during overtime production time. Variable costs are assumed to be \$100 during normal operation time and \$200 during overtime. Prices for both products are assumed to be \$600 each.

w_{ijt} is the production of product i in plant j during normal production time at time t; z_{ijt} is the production of product i in plant j during overtime production time at time t. These production decisions are made in each period with the objective to maximize the economic returns by best utilizing the available resources in response to demands in each period. In general, this process can be formulated as a linear optimization problem:

$$\underset{w,z}{Max} \quad \text{PV} \tag{10}$$

$$s.t. \quad w_{ijt} \leq H \times x_{ij} \qquad \forall i,j,t \tag{11}$$

$$z_{ijt} \leq H \times x_{ij} \qquad \forall i,j,t \tag{12}$$

$$\sum_j \left(w_{ijt} + z_{ijt} \right) \leq d_{it} \qquad \forall i,t \tag{13}$$

$$\sum_i w_{ijt} \leq y_j \qquad \forall i,j,t \tag{14}$$

$$\sum_i z_{ijt} \leq \theta y_j \qquad \forall i,j,t \tag{15}$$

$$\sum_i \left(w_{ijt} + z_{ijt} \right) \leq CAP_j \qquad \forall j,t \tag{16}$$

In Constraint (11) and Constraint (12), H is a big number that is used to specify the relationships for normal production and overtime production with allocation decision, meaning that if a product is not allocated to a plant, there cannot be a production in that plant for that product. This is a typically called the "Big M" technique. In Constraint(13), d_{it} is the demand for product i at time t; so Constraint (13) specifies that the total production for a product during normal time and overtime does not exceed the demand for this product. Constraint (14) indicates normal time production of all products in a plant cannot exceed the plant's normal time capacity. In Constraint(15), θ is a constant that represents the ratio of overtime production to the normal time production; so Constraint (15) indicates the overtime production of all products cannot exceed θ proportion of the normal time capacity. θ is assumed to be 0.15 in this case and is the same for both plants. In Constraint(16), CAP_j is the maximum of the overall capacity of a plant that may be imposed exogenously for technical reasons; so Constraint (16) specifies that the total production in a plant cannot exceed that maximal capacity. CAP is 300,000 for both plants in this case study.

Note that embedded in these decisions are two types of flexibility that is linked to the strategic allocation decision and the overtime flexibility at the operational level. If a plant is configured flexibly to be able to produce multiple products, then there exist operational flexibility options to balance production among products at a plant. Similarly, if a product can be produced at more than one plant, there exist operational options to balance productions between plants for a product. Having these types of flexibility during the operation stage require investing upfront on flexible processes in plants with a cost premium. Therefore, it is essentially like a real option that gives one the right, but not obligation to do something in the future. In addition, what is also embedded in the operation decisions is the overtime flexibility. It is independent of the allocation in that it does not require process to be flexible, but may be interacting with the process flexibility, which will be studied in this chapter.

Finally, the economic performance of a strategic decision alternative, represented by allocation decision X and capacity decision y, is measured by Equation (17) as follows:

$$NPV(X,y) = \arg\max PV(X,y,d) - INV(X,y) \tag{17}$$

Table 4 Summary of values of the parameters in the simple case

Symbol	Meaning	Value
$\bar{d}$	Expected value of annual demands for both products	200,000
σ	Standard deviation of annual demands for both products	50,000
F_e	Equipment cost per 100k unit of capacity	$80 million
F_t	Dedicated tool cost per 100k unit of capacity	$50 million
F_b	Building cost per 100k unit of capacity	$20 million
α	Economy of scale	0.7
β_0	Tool upcharge in a plant	20%
r	Discount rate	12%
VC_n	Variable cost during normal operating time	$100
VC_o	Variable cost during over time	$200
θ	Maximum Proportion of overtime capacity to normal time capacity	0.15
CAP	Maximum overall capacity of a plant, including normal time and over time capacity	300,000

4.3 Different decision approaches to explore the decision space

As mentioned before, a comparative analysis approach is used to demonstrate the value of considering demand uncertainty and operational flexibility during the early planning stage. Strategic planning decisions can be made under four different decision approaches as listed below in terms of whether demand uncertainty is considered and whether operational flexibility is considered during early planning stage. It should be noted that while uncertainty and operational flexibility are not considered in some of these decision making approaches, they still exist and are considered when evaluating the resulting decisions.

Decision Approach 1 (DA1): Under this approach, planning decisions are based on the demand forecasts, the expected value of demand for each product. Overtime operational flexibility is not considered at the planning stage.

Decision Approach 2 (DA2): Decisions are still made based on the demand forecasts, but overtime operational flexibility is considered at the planning stage.

Decision Approach 3 (DA3): Decision makers recognize that the future demand is uncertain, and therefore consider a distribution of possible demands for each product when making decisions. Overtime flexibility is not considered at this stage.

Decision Approach 4 (DA4): Decision makers recognize both the uncertainty of the future demand and the opportunities to use overtime flexibility in the form of overtime production.

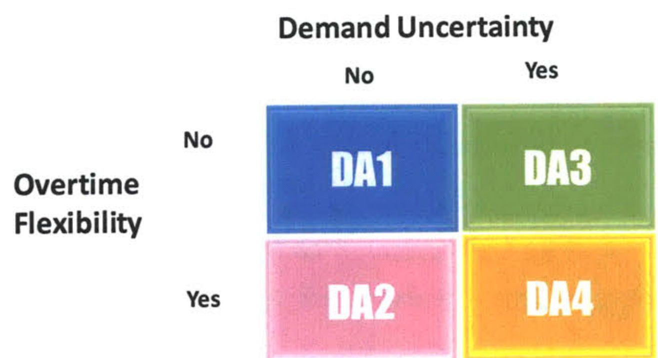

Figure 19 Schematic view of the four decision approaches

Both DA1 and DA2 do not consider demand uncertainty at the strategic planning stage. The difference between DA1 and DA2 is the way that overtime flexibility is taken into account. DA1 represents a "decoupled" view that leaves the overtime flexibility out of the strategic decision making process. DA2 represents a coupled view between strategic and operational levels of flexibility by considering the potential to run overtime production when making the capacity and allocation decisions. Thus, through comparison of results from these two approaches, one can see the impact of the consideration of overtime flexibility on strategic decision making and the resulting performance of the system assuming demand uncertainty is not considered.

On the other hand, both DA3 and DA4 consider demand uncertainty at strategic planning stage. Again these approaches differ in the way that overtime flexibility is taken into account, and are precisely parallel with approaches DA1 and DA2 in this regard. As such, the difference between decision approaches DA3 and DA4 reflects the impact of consideration of overtime flexibility on strategic decision making and the resulting performance of the system when uncertain demand is considered.

To reflect these different decision approaches, variants of the metric indicated in Formula (17) to measure economic performance of a strategic decision alternative are developed, which are then compared to select the "optimal" decision alternatives under decision approaches respectively. These variants are:

Under DA1 and DA2, for a given strategic decision set with an allocation decision *X* and a capacity decision *y*, since no demand uncertainty is considered, the metric is NPV:

$$NPV(X,y) = \arg\max PV\left(X,y,\overline{d}\right) - INV(X,y) \tag{18}$$

Where $\overline{d}$ is a vector that represents the expected values of the product demands over periods. $\arg\max PV\left(\overline{d}\right)$ represents the present value of the future cash flows under the best operation decision with the expected values of demands. The best operation plan is determined by solving the linear programming problem formulated in Formulation (10)- (16) with the d_{it} in Constraint (13) being changed to be $\overline{d}_{it}$, which means the expected value of demand for product *i* at time *t*.

In addition, since no overtime flexibility is considered under DA1, the variable *z* is fixed as 0 while only w is optimized to obtain the best PV while both w and z are variable under DA2 due to the consideration of overtime flexibility.

Under DA3 and DA4, to implement demand uncertainty, Monte Carlo simulation is used to simulate the uncertain demand, and ENPV is used to as the metric to measure strategic alternatives as follows:

$$ENPV(X,y) = E(\arg\max PV(X,y,d_s)) - INV(X,y) \tag{19}$$

Where d_s represents one scenario of products demands over t periods and $\arg\max PV(d_s)$ represents the present value of the future cash flows under the best operation decision under the demand scenario s. The best operational decision here is determined by the linear programming problem formulated in Formulation (10)- (16) except that the d_{it} in Constraint (13) is changed to be d_{ist}, which is a simulated demand scenario s for product *i* at time *t*.

As for the overtime flexibility, since DA3 does not consider overtime flexibility, *z* is fixed at 0 while both *w* and *z* are decision variables to be optimized under DA4.

The next section will introduce how these decision approaches are applied and will identify the "optimal" allocation and capacity decisions under each decision approach. Note that each "optimal" decision is only optimal for the corresponding decision approach. Whether it is actually the optimal decision or how it compares with other decisions will be discussed in detail in Section 4.5, where all "optimal" decisions are evaluated and compared.

4.4 Decisions under different decision approaches

No matter which decision approach is considered, the objective is to find the optimal strategic decision in the decision space that gives the best performance. Although many different ways can be used to find the optimal strategic decision, this case study uses an exhaustive search method to find the optimal strategic decision in the decision space. This is feasible because the size of the decision space is relatively small as the system only includes 2 products and 2 plants.

By the exhaustively search method, 16 allocation decisions are explored for a system with 2 products and 2 plants. Then to explore the plant capacity decision space under each allocation decision, the exhaustive search method theoretically is not feasible because the capacity of a plant is continuous and can be any number from 0 to 300,000. But it can be simplified by discretizing the capacity decision space with a specified interval, thus allowing the use of the exhaustive search method to search the space. More specifically, a gridded exhaustive search is used in this case study, which is illustrated in Figure 20:

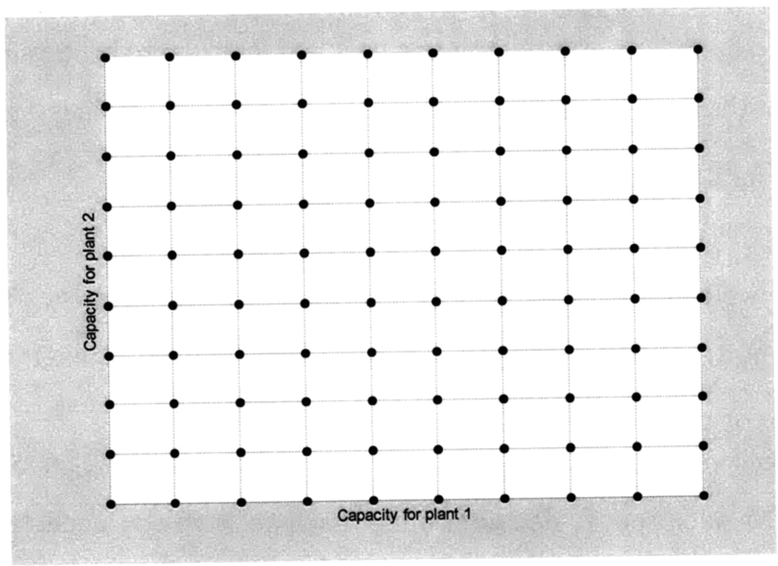

Figure 20 Illustration of the gridded capacity decision space

Each point on this gridded space represents an alternative for plants' capacity decision. Each point contains capacities for two plants. The interval between two points can be expressed as:

$$\delta_j = \frac{UB_j - LB_j}{N} \tag{20}$$

Where UB_j represents the upper bound for a plant j's capacity, LB_j represents the lower bound of a plant j's capacity; δ_j is the interval between two capacity levels under examination. N represents the total number of capacity levels examined for a plant.

In this case, a coarse-to-fine gridded search approach is taken, which is described as follows:

Step 1: $UB_1=UB_2=300{,}000$, $LB_1=LB_2=0$, N=10. As a result, $\delta_1=\delta_2=30{,}000$.

Then the NPV or ENPV, depending on different decision approaches, of the points defined by this grid are calculated and compared. The one that gives the highest NPV or ENPV is identified as the optimal point for this step;

Step 2: After an optimal point is found based on the grid defined by Step 1, denoted by C_j^1

Then $UB_j= C_j^1+50000$, $LB_j=$ MAX $(C_j^1-50000, 0)$, N=10. As a result, $\delta_1=\delta_2=10{,}000$. Similar to Step 1, the optimal point on the grid defined by this step is obtained;

Step 3: After an optimal point is found based on the grid defined by Step 2, denoted by C_j^2

Then $UB_j= C_j^2+10000$, $LB_j=$ MAX $(C_j^2-10000, 0)$, N=10. As a result, $\delta_1=\delta_2=2{,}000$. Finally, the optimal point is found based on the grid defined by Step 3, denoted by C_j.

Note that this gridded search method is sensitive to the granularity used in defining the grids. However, computational experiments indicate that a grid interval of 2000 provides a result with reasonable fidelity. Employing a smaller interval with greater granularity only leads to about a 0.5% difference in ENPV, which is much smaller than the difference between the decisions under different approaches.

As a result of the gridded exhaustive search, the following "optimal" decisions under four decision approaches are derived. They are also shown in Table 5.

Decision under DA1 (S1): Two dedicated plants are built for each product. Plant capacities are set 200,000 for both plants, corresponding exactly to the expected demand of each product. This decision alternative is denoted as ***2 dedicated-200k*** in the last column in Table 5.

Decision under DA 2(S2): Two dedicated plants are built for each product. But decision makers take a more conservative view on investments and build plants with capacities of 174,000 each. This is because operational flexibility in the form of overtime production can be used to make up the difference with the expected value of demand. This decision alternative is denoted as ***2 dedicated-174k*** in Table 5.

Decision under DA 3(S3): One flexible plant is built to produce both products. The capacity is set at the maximum 300,000 units a year. This decision alternative is denoted as ***1 flexible-300k*** in Table 5.

Decision under DA 4(S4): One flexible plant is built to produce both products. The capacity is set smaller than DA3, at 262,000 units a year. This decision alternative is denoted as ***1 flexible-262k*** in Table 5.

Decision Approach	Considers Demand Uncertainty?	Considers Overtime Flexibility?	Allocation Decision	Capacity Decision	Decision Characteristics
DA1	*No*	*No*	Product A → Plant 1 Product B → Plant 2	200k 200k	***S1**:(2 Dedicated-200k)*
DA2	*No*	*Yes*	Product A → Plant 1 Product B → Plant 2	174k 174k	***S2**:(2 Dedicated-174k)*
DA3	*Yes*	*No*	Product A → Plant 1 Product B → Plant 1 Plant 2	300k	***S3:**(1 Flexible-300k)*
DA4	*Yes*	*Yes*	Product A → Plant 1 Product B → Plant 1 Plant 2	262k	***S4:**(1 Flexible-262k)*

Table 5 Four decision candidates identified by four different decision approaches

4.5 Evaluation of decision alternatives

In this section, the identified decision candidates are evaluated. Firstly, they are evaluated under deterministic demands, which are the expected values of the product demands. Then they are evaluated under uncertain demands. The difference between these two evaluation ways also demonstrates the value of using the evaluation model proposed in this research.

4.5.1 Results under deterministic demands

Table 6 shows the results of the four "optimal" decisions under deterministic demands at the assumed expected values. Most items under evaluation in columns are self-explaining while the calculations for Average Capacity Utilization and for Returns on Investment are shown below:

$$\text{Average Capacity Utilization} = \frac{\text{Total Production} / \text{Total Periods}}{\text{Total Capacity}} \tag{21}$$

$$\text{Returns on Investment} = \frac{\text{NPV or ENPV}}{\text{Investment}} \tag{22}$$

Here Average Capacity Utilization is the capacity utilization of the system, consisting two or one plant depending on what the strategic planning decision is, over production periods. It does not include overtime capacity.

One can see that, under deterministic demands, the decision under DA2, which is to build two plants at capacity of 174,000 units each, has the highest NPV among all decisions. Furthermore, it has the lowest lost sales, 0, and very high Average Capacity Utilization 114%. Although it requires more investment than two other decision alternatives, its high NPV, high capital utilization and zero lost sales seem to provide good justifications for it.

Table 6 Evaluation results under deterministic demands

Decision alternatives	Considers demand uncertainty?	Considers overtime flexibility?	INV. (million $)	NPV (million $)	Returns on Investment	Average Capacity Utilization	Total prod. (million units)	Total lost sales (million units)
DA1 (2 Dedicated-200k)	No	No	487	233	47.8%	100%	***2***	***0***
DA2 (2 Dedicated-174k)	No	Yes	442	***260***	***58.8%***	***114%***	***2***	***0***
DA3 (1 Flexible-300k)	Yes	No	345	195	56.5%	100%	1.5	0.5
DA4 (1 Flexible-262k)	Yes	Yes	***314***	213	***67.8%***	***115%***	1.5	0.5

4.5.2 Results under uncertain demands

Then this section evaluates the performance of the four "optimal" decisions shown in Table 5 under uncertain demands. The evaluation model shown in Figure 21 is used. In this model, Monte Carlo simulation method is used to simulate demand uncertainty and the linear programming model is used to mimic the operational decision making in respond to realized demand scenarios. Both methods are indifferent from the ones used under DA4. However, instead of getting the expected values of all NPVs, this evaluation model summarizes all the NPVs in the Value at Risk and Gain Chart, which is described in Section 3.1.6, to allow more extensive examination of the decision alternatives.

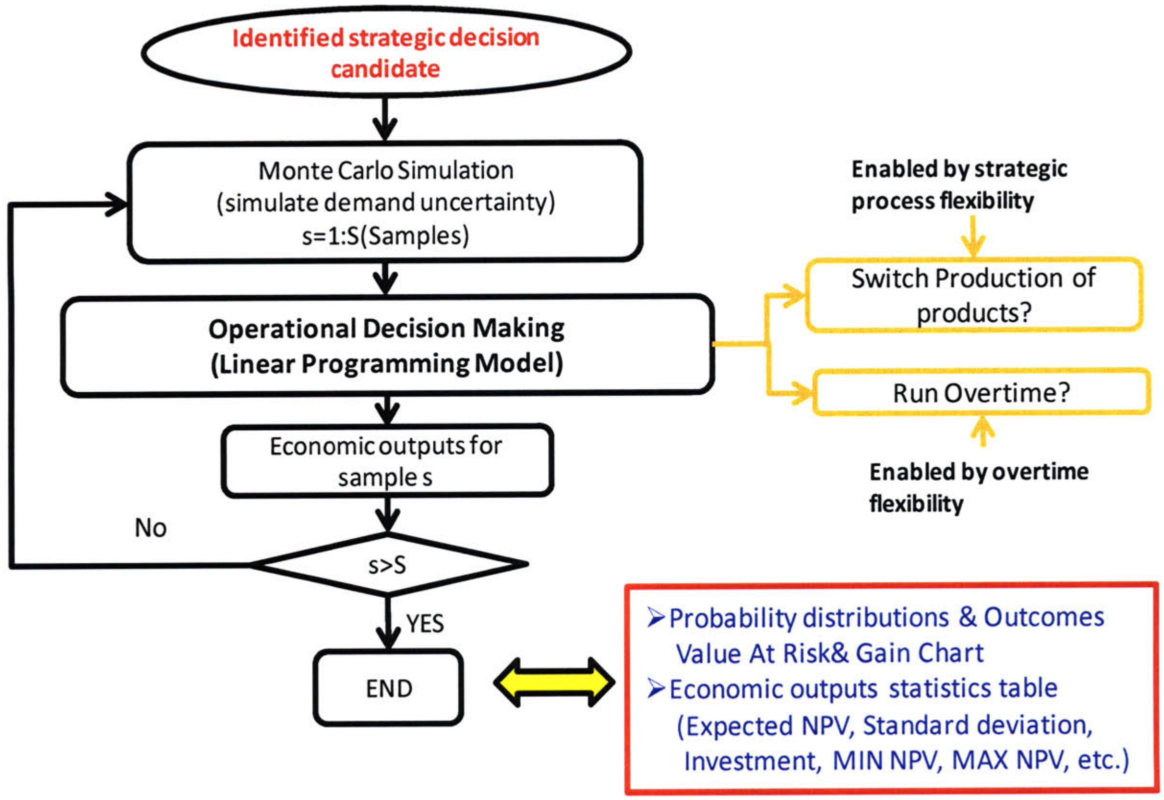

Figure 21 Logic flow chart for the evaluation model

Figure 22 shows the VaRG chart for results of these decisions and Table 7 provides the summary table for key statistics of the results as a complementary.

4.5.2.1 The flaw of averages

First of all, if one compares the NPV under deterministic demands in Table 6, and the expected value of NPVs under uncertain demands in Table 7, it can be found that they are not equal; in fact, for all decisions:

$$\text{Expected NPVs} < \text{NPV under expected demands}$$

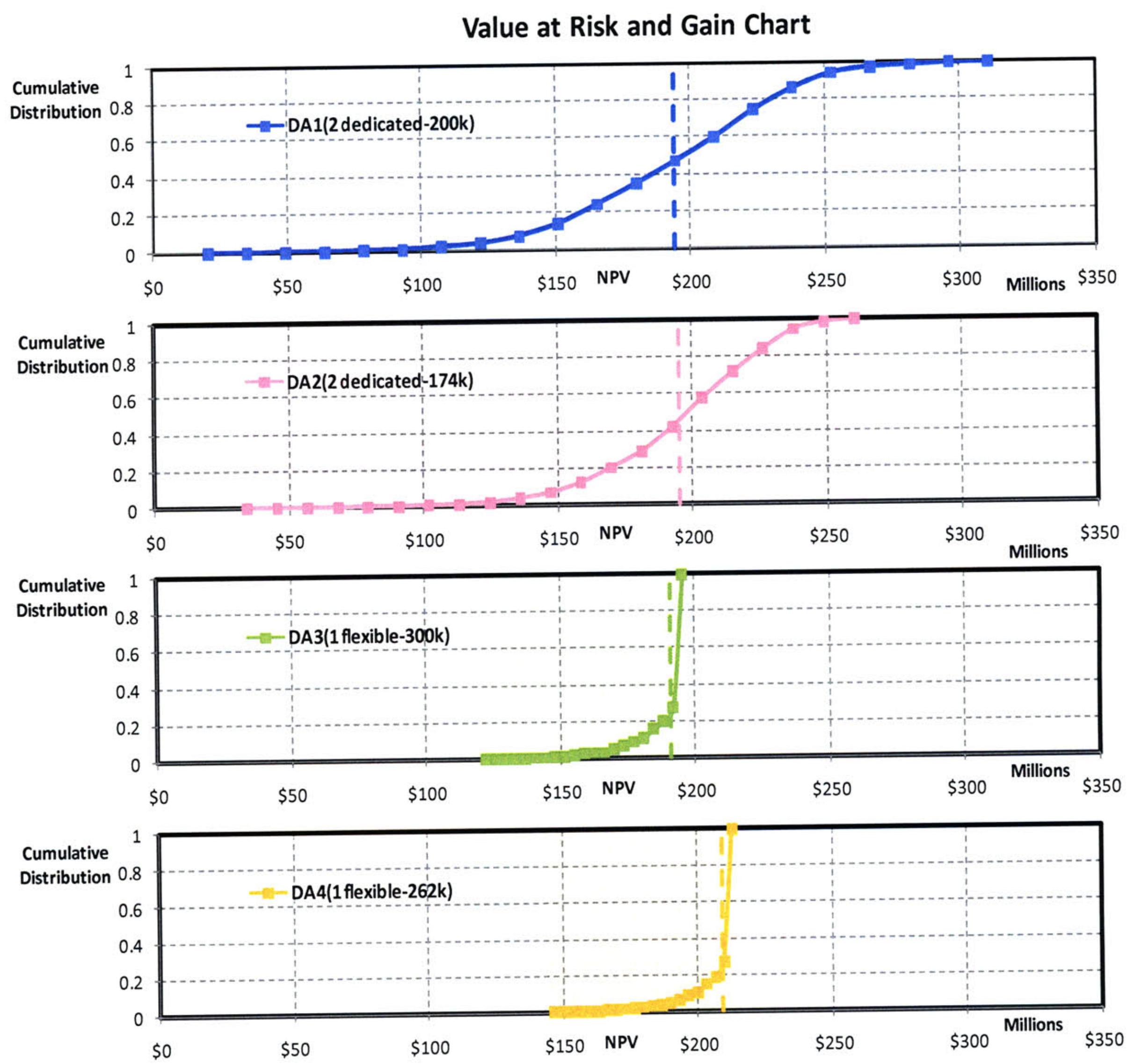

Figure 22 VaRG chart for decision alternatives under uncertain demands

Table 7 Summary table for decision alternatives under uncertain demands

Decisions	Considers demand uncertainty?	Considers overtime flexibility?	Investment (Million $)	NPV						Returns on Investment	Average Capacity Utilization	Expected Production (million units)	Expected Lost Sales (million units)
				ENPV (million $)	MIN (million $)	MAX (million $)	SD (million $)	VaR@5% (million $)	VaG@5% (million $)				
DA1 (2 dedicated-200k)	No	No	487	194	20	***311***	42	122	***252***	39.8%	96%	***1.91***	***0.09***
DA2 (2 dedicated-174k)	No	Yes	442	195	34	260	32	136	238	44.1%	104%	1.8	0.2
DA3 (1 flexible-300k)	Yes	No	345	191	122	195	10	169	195	55.4%	99%	1.49	0.51
DA4 (1 flexible-262k)	Yes	Yes	***314***	***208***	***145***	213	***9***	***190***	213	***66.2%***	***113%***	1.48	0.51

Table 8 lists the specific results for a better contrast:

Table 8 Comparison of NPV under expected value of demands and expected value of NPVs

Decisions	NPV under Expected demands (Million $)	Expected value of NPVs (Million $)
DA1(2 dedicated-200k)	233	194
DA2(2 dedicated-174k)	260	195
DA3(1 flexible-300k)	195	191
DA4(1 flexible-260k)	213	208

This is known as the "the flaw of averages" (Savage 2009). Figure 23 explains how this concept is embodied in the context of the case studied here. The red solid line is the simulated demand for a product with expected value of 200,000 and standard deviation of 50,000. The upper red dotted line represents expected value of demand. Blue solid line represents production if this product is produced at a plant with capacity 200,000 and blue dotted line represents expected value of productions at the planned plant capacity 200,000. If results are evaluated under expected value of demands, when capacity is at the same level of expected value of demand 200,000, then the production is expected to be at 200,000. However, when demands are uncertain, for situations when the demand actually is lower than expected value, the production is the actual demand; and for situations when the demand is higher than expected value, the production is capped by the capacity. As a result, the expected value of productions is lower than the expected value of demands, which finally leads to a lower expected value of NPVs than the NPV under expected value of demands.

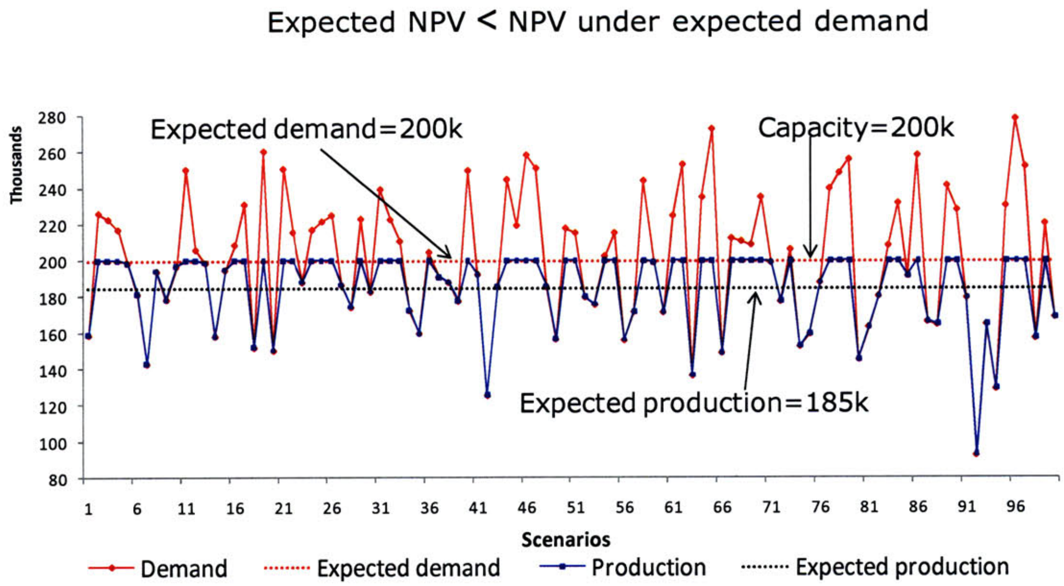

Figure 23 the flaw of averages: Expected value of NPVs is not equal to NPV under expected demand

4.5.2.2 Discussion of results under uncertain demands

Then one can see that, VaRG chart provided in Figure 22 reveals more and critical information about performances of decisions as compared to Table 6. Instead of a single NPV, it allows one to see the whole spectrum of possible NPVs under simulated demand uncertainty, For example, NPV of the decision under DA1, which neither considers demand uncertainty nor operational flexibility during early planning stage, is $233 million if evaluated at expected value of demands as shown in Table 6. However, when examined with demand uncertainty, its performance can have very big variations: it could have profit as big as $311 million, or could only be $20 million. This piece of information can be very important to influence firms' decision making because it informs one the potential risks associated with decisions under demand uncertainty.

From the VaRG chart and the summary table, one can see that the superiority of decisions has changed from what's shown in Table 6. Instead of the decision under DA2, the decision under DA4 now outperforms other decisions in many aspects. It has the highest ENPV, the highest minimal NPV, the highest average capacity utilization and the smallest standard deviation. All of these mean that the decision under DA4 has a much more stable and better performance than the other decisions under uncertain demands. Furthermore, all of these gains do not require additional investment. Instead, the investment is the least one. Thus, it has the highest Returns on Investment. In a word, the DA4 leads to a system design with reduced investment, improved upside gain and reduced downside risks.

This change of optimal decision is due to the following reasons: (1) the consideration of demand uncertainty allows one to recognize the value of process flexibility that would not have been recognized under deterministic demands. (2) Building one big flexible plant as supposed to two smaller plants allows the system to take advantage of the economies of scale. (3) Instead of building one plant at 300k annual capacity, which is the decision under DA3, the decision under DA4 builds a smaller plant at 262k annual capacity because of the consideration of overtime flexibility, which further saves the required upfront investment. This indicates that considering overtime flexibility further enhanced the value of process flexibility. Overall, the result has clearly demonstrated the value of considering demand uncertainty and operational flexibility during strategic planning stage.

However, this decision does not win in all aspects. In fact, one can see that both the decisions under DA3 and DA4 lead to a narrower range of cash flow outcomes (with a range the does not become negative), but also consistently lead to lower expected unit production and more expected lost sales than the decisions under DA1 and DA2. This implies that although this kind of risk containment can be very valuable, it requires accepting that there will be lower average production of products, which may compromise other components of firm strategy, but these are outside the scope of this analysis. The notion is that firms must be prepared to accept strategies that sacrifice maximizing expected production and sales in exchange for a more stable cash flow.

4.6 Sensitivity analysis

This section is going to discuss the results of two sensitivity analyses. The first is how the product to plant allocation decision is sensitive to the process flexibility upcharge, and the second is how the capacity decision is sensitive to the overtime upcharge.

4.6.1 Sensitivity to process flexibility upcharge

Table 9 shows the sensitivity of the optimal product to plant allocation decision to process flexibility upcharge in terms of ENPV. First of all, the second column shows that if one makes the strategic planning decisions under deterministic demands, the best decision is always going to be building two dedicated plants no matter how much the process flexibility upcharge is. However, if demand uncertainty is considered, then the production to plant allocation decision becomes sensitive to the process flexibility upcharge. The base case, which is analyzed previously in this chapter, is the case with process flexibility upcharge 20%. The decision is to build one flexible plant, indicated by Italianized and blue font in the table. Under the same demand uncertainty, this decision of flexible process is unchanged with less expensive flexibility upcharge. This is reasonable because as process flexibility costs less, the flexible plant becomes more favorable. But when the process flexibility upcharge increases to 35%, then building two dedicated plants will have better ENPV. This shows the trade-off between the benefit and cost of the flexible process.

It should be noted that the result here only shows the comparison of ENPVs between different levels of process flexibility. For more effective decision making, other criteria such as the ones discussed in the previous section should be considered all together.

Table 9 Sensitivity of the product to plant allocation decision to process flexibility upcharge

Process Flexibility Upcharge	Deterministic	Uncertain
15%	Dedicated	Flexible

20%	Dedicated	*Flexible(base case)*
25%	Dedicated	Flexible
30%	Dedicated	Flexible
35%	Dedicated	Dedicated
40%	Dedicated	Dedicated
45%	Dedicated	Dedicated

4.6.2 Sensitivity to overtime upcharge

This section shows another sensitivity analysis, which is how the optimal capacity decision is sensitive to the overtime upcharge. The overtime upcharge here means the extra cost to produce a product during overtime as compared to during normal time. Table 10 shows the results. It can be seen that as the overtime flexibility gets more expensive, the optimal decision is to build a larger plant. This demonstrates the trade-off between building a bigger capacity and using overtime flexibility, to deal with demand uncertainty.

Table 10 Sensitivity analysis of the plant capacity decision to overtime upcharge

Overtime upcharge	Capacity for plant 1	Capacity for plant 2
$50	262,000	0
$100 (base case)	*262,000*	*0*
$200	262,000	0
$340	286,000	0
$350	300,000	0

4.7 Interactions between process flexibility and operational flexibility

One interesting question is how each type of flexibility contributes to the system's ability to respond to demand uncertainty and whether they have interactions with each other. This section is going to analyze the interaction between process flexibility and operational flexibility through a comparison between two alternatives: one is a flexible plant at annual capacity of 260k, the other is 2 dedicated plants at annual capacity of 130k each. So the total capacity of the dedicated plants is 260k, which is equal to the flexible plant. In this way, the value of these two types of flexibility can be studied without being affected by different capacities. For these two alternatives, there are two scenarios to be contrasted: one is to assume that there is no overtime flexibility available to the system; the other is to allow overtime flexibility available to the system. Expected production is calculated for each decision under each scenario, which generates four results as shown in Table 11.

Table 11 Values of process and overtime flexibility, and their synergies

The value of overtime flexibility

	Expected Production without overtime *(Million units)*	Expected Production with overtime *(Million units)*	Difference between (with overtime) and (w/o overtime) *(Million units)*
Product A → Plant 1 @Capacity 130k Product B → Plant 2 @Capacity 130k	1.28	1.45	0.17
Product A → Plant 1 @Capacity 260k Product B → Plant 1 @Capacity 260k Plant 2 (No production)	1.30	1.48	0.18
Difference between dedicated process and flexible process	0.02	0.03	0.01

The value of process flexibility

Synergy between process and overtime flexibility

Firstly, looking at the table row-wise, one can get the answer to the question about the value of overtime flexibility for each process by the difference of the expected productions between with overtime and without overtime. For the *2 dedicated plants* case, the value of overtime flexibility is 0.17 million units. For the *1 flexible plant* case, the value of overtime flexibility is 0.18 million units.

Secondly, looking at the table column-wise, one can get the answer to the question about value of process flexibility for the with-overtime scenario and the without-overtime scenario. When there is no overtime available, the value of process flexibility is 0.02 million; when there is overtime available, the value of process flexibility is 0.03 million.

Thus, an interesting result is derived from the above results: when the process is flexible, the value of overtime flexibility, measured by the increase of expected production, is more than the one when process is dedicated. Similarly, when there is overtime available, the value of process flexibility, measured by the increase of expected production, is more than the one when there is no overtime available. Clearly this indicates that there is a synergy between process flexibility and overtime flexibility, which is that the value of one type of flexibility is more when the other type of flexibility is at present.

Notably, this synergy will be affected by other parameters in the system. Among all the parameters, two specific parameters are of the interest here and are explored by sensitivity analysis. One is to demand correlation; the other is to standard deviation of demand uncertainty.

Figure 24 shows the sensitivity of the synergy between process flexibility and overtime flexibility to demand correlation. It indicates that the synergy becomes stronger when the demand correlation is more negative and weaker when the demand correlation is more positive. When the demand is perfectly correlated, there is no synergy. This is reasonable because process flexibility is at best addressing the demand correlation. When demand is more positively correlated, the value of process flexibility is reduced. But what's unintuitive and is often missed is that, even under positively correlated demands, there is still a synergy between process flexibility and overtime flexibility; it is just that synergy is less than the one under more negative correlation.

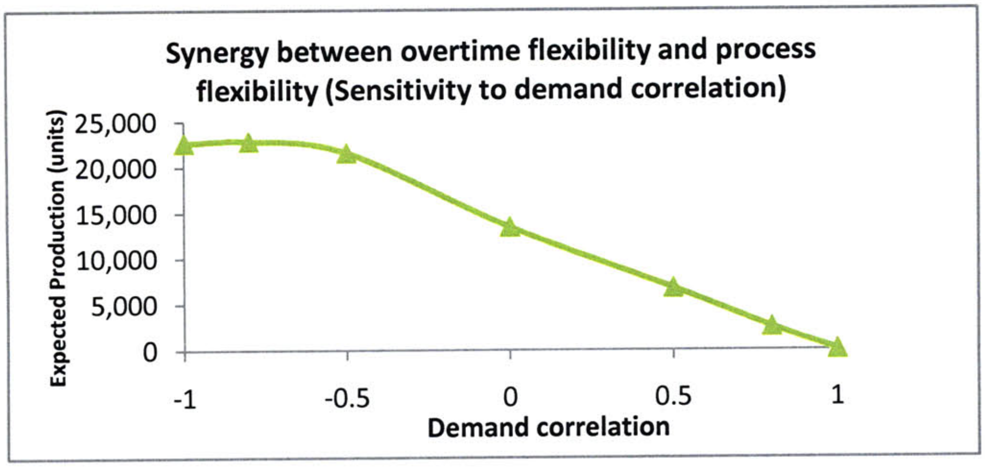

Figure 24 Sensitivity of the synergy between overtime flexibility and process flexibility to demand correlation

Figure 25 shows the sensitivity of the synergy between overtime flexibility and process flexibility to standard deviation. It shows that the synergy is stronger when the demands are more uncertain. There is no synergy when there is no demand uncertainty. This can be explained by the reason that overtime flexibility is at best to address the demand variation. When demand is less uncertain, the value of overtime flexibility is reduced, thus the synergy becomes less.

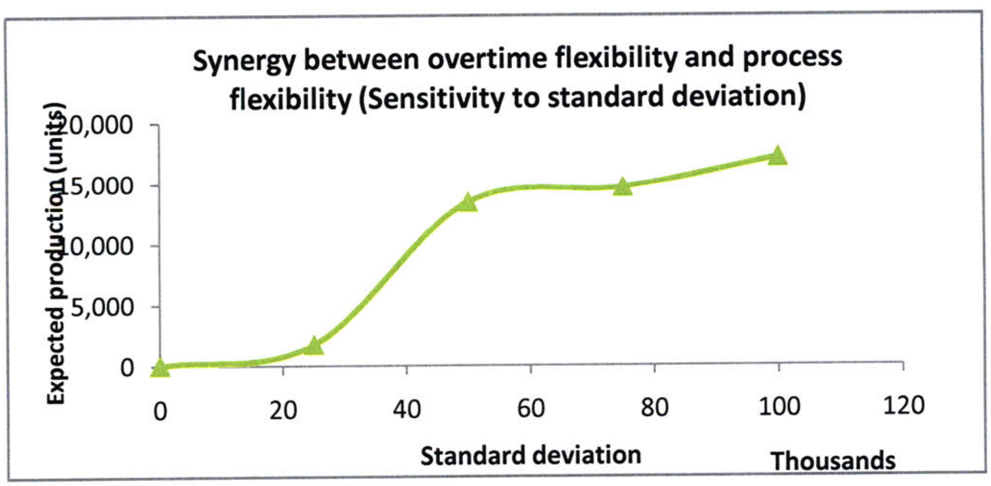

Figure 25 Sensitivity of the synergy between overtime flexibility and process flexibility to standard deviation

4.8 Summary

In this chapter, a simple and hypothetical case with 2 products and 2 plants is used to demonstrate the value of considering demand uncertainty and operational flexibility in improving strategic decision making. To achieve this purpose, a comparative analysis approach is taken in that: the problem in the case is solved by different decision approaches in terms of whether uncertainty is considered and whether operational flexibility is considered. Solving all four formulated problems lead to four different "optimal" decisions. These strategic decision alternatives are evaluated under the developed evaluation model.

Based on the evaluation result, it has been shown that: (1) Consideration of demand uncertainty allows one to recognize the value of flexible process design as compared to a deterministic approach. (2) Consideration of overtime flexibility enhances the value of strategic process flexibility by reducing investment cost, reducing downside risks and improving upside gain. Then sensitivity analyses are done to test how strategic decisions change regarding to process flexibility upcharge and overtime flexibility upcharge. As process flexibility upcharge goes up, the more dedicated process leads to higher expected value of NPV. As overtime flexibility upcharge increases, plant capacities increases, which reflects the trade-off between using bigger capacity to respond to demand uncertainty and using overtime operational flexibility. Finally, the interaction between process flexibility and overtime flexibility is studied. The results show that there is a synergy between overtime flexibility and process flexibility, even under positive demand correlation. The synergy is stronger under more negative correlation and higher standard deviation of demand uncertainty.

5 Proposed framework

The preceding chapter presents a simple and hypothetical problem to demonstrate the value of considering demand uncertainty and operational flexibility during the strategic planning stage. Although analytically interesting, it is not very realistic because the real problem in practice is normally larger than that as more products and more plants need to be considered in a manufacturing system, which constitutes a large decision space that is computational intractable for the exhaustive search method to identify the best decision candidate with considering demand uncertainty and operational flexibility. Stochastic optimization is another method that is often used to identify optimal decision under demand uncertainty. However, as discussed in Chapter 3 and will be shown in Chapter 7, it also becomes computationally challenging for problems with even moderately larger sizes. As such, this research develops a new method to address this computational challenge. It is a computationally practical way to explore large decision spaces and to identify good decision alternatives. Then it is coupled with an evaluation model that provides a means to more comprehensively evaluate decision alternatives. Overall, the framework that consists of both parts is illustrated in Figure 26 and further explained as follows:

(1) A screening model that efficiently explores the decision space to identify good candidates.

Designing and operating complex engineering systems involves making many decisions over long time periods, which constitutes a large decision space. The existence of uncertainties further impedes an efficient search in this large decision space. While the computational cost of using optimization approach to obtain a globally optimal decision in such a large and complex decision space can be prohibitively high, an alternative approach is to identify not necessarily the best decision, but good ones that are promising to provide plausible performance. The screening model developed in this research is one way of achieving this: It identifies good decision candidates by using an

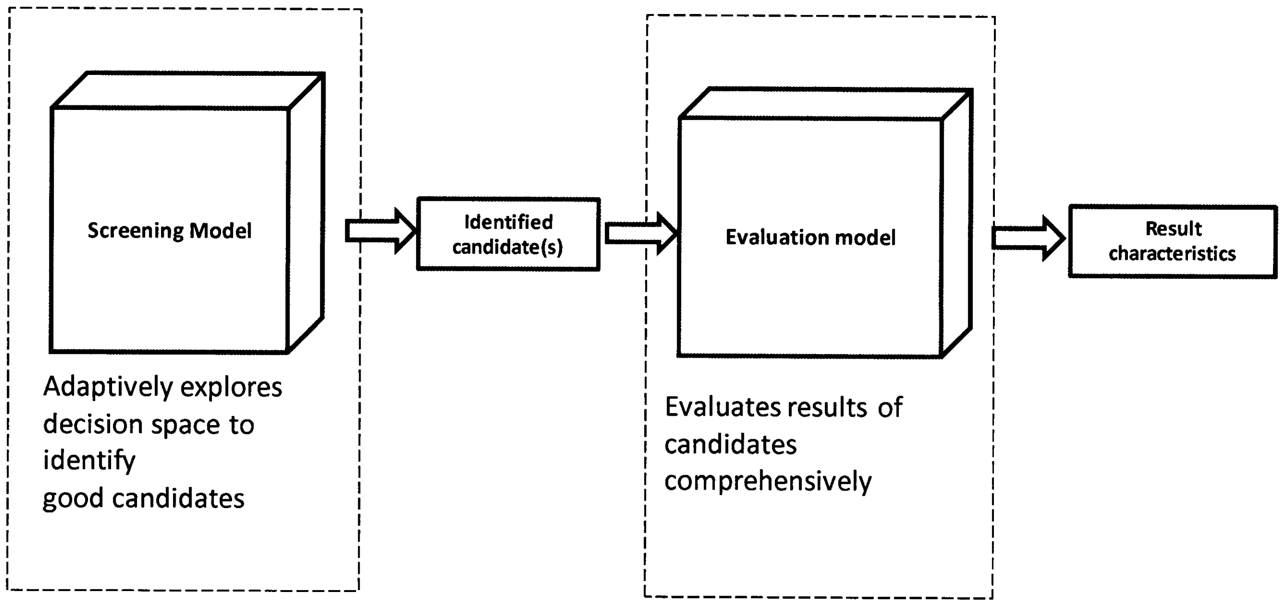

Figure 26 The proposed framework: a screening model that adaptively explores the decision space to identify good candidates and an evaluation model that evaluates results of candidates more comprehensively

adaptive process to search the decision space. It is a simplified model of the system and the decision space in two aspects:

- Instead of exhaustively searching all possible points in the decision space, it selects search paths in the decision space and adaptively searches for continued improvement.
- It forms a simplified representation of the decision space, within which it is easier to find good decision candidates than in the original decision space.

This screening model is composed of two methods in the field of Design of Experiments: the Adaptive one-factor-at-a-time (OFAT) to explore the product to plant allocation decisions space and the Response Surface Methodology (RSM) to explore the capacity decision space, and the method of Simulation-based Linear Programming (SLP) to explore the operation decision space. The details are elaborated in the next section.

(2) An evaluation model that helps to evaluate results of candidates more comprehensively. The purpose of an evaluation model is to examine, characterize and display results of identified decision candidates. Such results provide decision makers with more comprehensive information than what screening models can provide. Especially with regard to uncertainty, it displays the distribution of all possible outcomes for a decision candidate under assumed uncertainty. Furthermore, it is complemented by a summary table which summarizes key statistics of the distributions, such as expected value, standard deviation and other metrics that may be of interest of decision makers, such as investment, return on investment, production, etc. In the evaluation model, a simulation method is used to simulate demand uncertainty. Under each simulated demand scenario, a decision candidate, which includes a set of strategic decisions, is executed and decisions at the operational level are made in response to the realized demand scenario. Performances of the system will be obtained under different demand scenarios for a given decision alternative, which are plotted on a Value at Risk and Gain (VaRG) chart.

Since the evaluation model is the same as what is used in case study 1, it is not explained again here. The rest of this chapter will focus on describing the screening model that is developed in this research. Firstly, the concept of screening model and the relevant research in the literature are reviewed in Section 5.1; then the screening model developed in this research is introduced in Section 5.2 and Section 5.3. Section 5.2 focuses on the general structure of the screening model and Section 5.3 focuses on the detailed mathematical description of the methods in the screening model.

5.1 The concept of screening model

The concept of screening model has long been used in system design and analysis. Jacoby and Loucks (1972) first proposed the idea of a "screening model" in water resource planning. More applications in this area were done by Chaturvedi and Srivastava (1985), Karamouz et al.(1992)

and Srivastava and Patel (1992). Wang and de Neufville (2004; 2006) extended the use of screening model in flexibility of systems design. Lin et al. (2009) provide a recent work that uses screening model to examine multi-levels of flexibility in offshore petroleum exploration and production systems. In these researches, a screening model is developed as an approach to identifying promising design alternatives in the designing and planning of large-scale complex engineering systems. It is a step to identify, or to screen, the set of possible plans that are worthy of more comprehensive exploration, as illustrated in Figure 27.

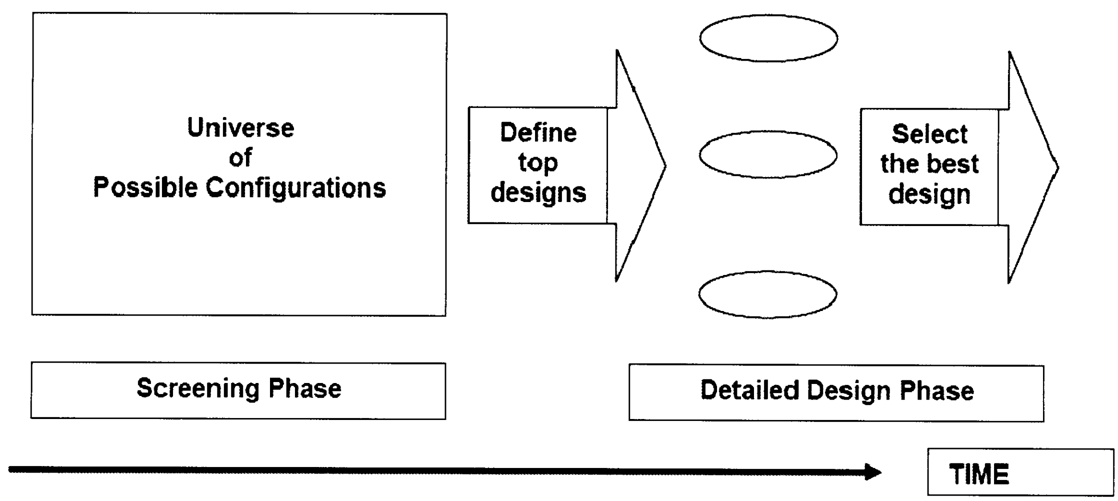

Figure 27 Screening models help define top designs for detailed analysis and design, adopted from (de Neufville et al. 2009)

The following discusses some examples in literature with the purpose to show how screening models are developed and applied in addressing various problems in engineering systems designing and planning:

Jacoby and Loucks (1972) considers a system that includes 35 reservoirs, 9 run-of-rivers, 12 variable head hydroelectric sites, and 5 major water supply areas in the Delaware river basin. The stream flow horizon under planning consideration is 50 years of monthly stream flow data. For a system with this scale and this time duration, it is not practical to either build an optimization model to obtain an optimal solution, or to use a simulation model to explore every possible design alternative to find optimal solution. Therefore, in the screening process, the problem is simplified by reducing time frequency and possible stream flow scenarios and linearizing of cost functions. After the simplification, a stochastic linear optimization model is developed and solved to obtain design candidates that are further examined in the simulation model.

Wang (2005) applies the concept of screening model and extends the use of it to flexibility of engineering systems. It used a screening model to identify options "in" projects, after which the value of these options are evaluated. With simplified low-fidelity cost functions, shortened time periods and no uncertainty, the screening model, which is a deterministic mixed integer program, can be efficiently solved to get an optimal solution. Solving the model with changed value of parameters that are uncertain results in different solutions, which are then evaluated by the simulation model.

Lin (2009) presents another screening model that can be used to explore flexible strategies in offshore oilfield production systems. A model is developed to integrate physical, logical, and financial relationships for offshore petroleum exploration and production systems at mid-level detail. It is not an optimization model, but the simplification of the relationships made it possible to be run very efficiently so that it can be combined with simulation model to examine some design alternatives.

In summary, common characteristics of screening models include:

(1) It is a simplification of the system in some way. Complexity of large-scale systems results in a computationally intractable space, which makes infeasible to find the optimal solution through optimization approach. Thus, a screening model has to simplify the real system in some way to become practical. Table 12 summarizes the simplifications made in screening models in the literature mentioned above and in this research.

Table 12 Summary of screening models in the literature

	Title	Domain	Simplifications	Characteristics of screening model
(Jacoby and Loucks 1972):	Combined Use of Optimization and simulation model in River Basin Planning	River basin	Linearization of cost functions ;Reduced time frequency each year; limited scenarios of possible stream flow for each period at each gage site	static and dynamic stochastic linear optimization approach
(Wang 2005)	Real Options "in" projects and systems design-identification of options and solutions for path dependency	River basin	Simplified economic relationships; Reduced time duration; Simplified uncertainty to be deterministic	deterministic optimization approach
(Lin et al. 2009)	Exploring Flexible Strategies in Engineering Systems Using Screening Models: Applications to Offshore Petroleum Projects	Offshore petroleum exploration and production system	Simplify physical, logical, and financial relationships;	not an optimization approach, but is an integrated, simplified and flexible model that can perform a quick survey of alternative designs
This research	Exploring manufacturing planning decisions in consideration of multi-level flexibility in automotive industry	Automotive manufacturing system	Simplify relationships between components; Simulate response surface; reduce combinatorial space	not optimization approach, but an adaptive searching method in use of Design of Experiments methods

(2) It must be computationally efficient to run screening models to examine decision alternatives. A screening model is used to screen out inferior alternatives and to identify good ones as a preliminary step. The purpose is to reduce the space for more comprehensive examination. Thus, it needs to be computationally feasible to run for large systems.
(3) Its results need to be further examined more comprehensively. Because a screening model has to make simplifications, after decision candidates are identified, it may not provide the true or the complete result of decision candidates. Thus, it is necessary to examine them in a more comprehensive way.

5.2 General description of the screening model developed in this research

The screening model developed in this research is a variant of the screening model described above. What is novel about the screening model developed in this research is that it applies a new set of methodologies to explore the decision space. Furthermore, the application of DOE methods does not prevent one from using traditional optimization method as part of screening model. It can be combined with traditional optimization method to identify good decision candidates. This section describes the screening model developed in this research at the structural level. Details and mathematical representation of the screening model are discussed in the next section.

The screening model is composed of three methods: Adaptive one-factor-at-a-time (OFAT), Response Surface Methodology (RSM), and Simulation-based Linear Programming (SLP). Each is used to explore one dimension in the decision space. OFAT explores the product to plant allocation decision space, RSM explores the plant capacity decision space, and SLP is used to explore the operation decision space. These three methods are integrated together to search the decision space and to identify promising decision candidates.

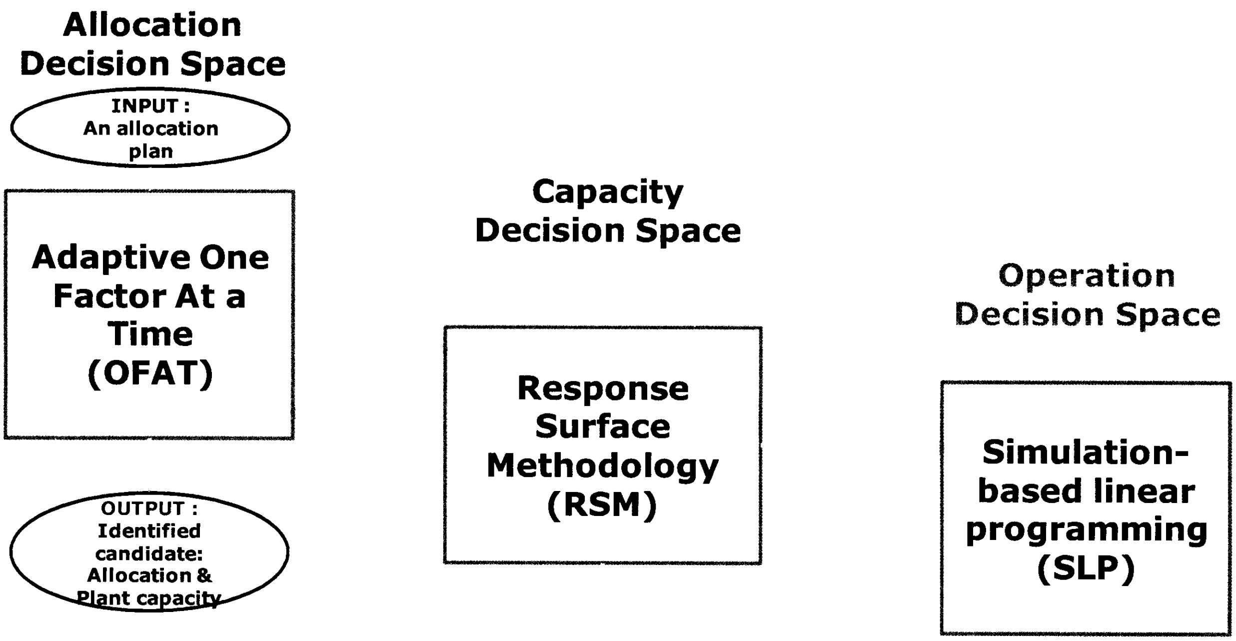

Figure 28 General view of the integrated screening model to explore the decision space

5.2.1 Adaptive One-factor-at-a-time (OFAT): the allocation decision space

In this research, OFAT is selected as a method to explore the product to plant allocation decision space. The product to plant allocation decision space is a discrete space with decision variable values being either 0 or 1. Values of decision variables are considered as two levels for each factor in the OFAT process. If we denote n products as A, B, ..., N, and m plants as 1,2,..., M, the allocation decision can be denoted by a matrix X as follows:

$$X = \begin{bmatrix} x_{A1} & x_{B1} & \cdots & x_{N1} \\ x_{A2} & x_{B2} & \cdots & x_{N2} \\ \cdots & \cdots & \cdots & \cdots \\ x_{AM} & x_{BM} & \cdots & x_{NM} \end{bmatrix}_{n\times m}$$

$$x_{ij} \in (0,1)$$

x_{ij} represents the decision of allocating product i to plant j or not. It can take the value of 0 or 1. 1 means that product i is allocated to plant j while 1 means that it is not. Each row represents allocations of *a given product* to plants while each column represents allocations of products to *a given plant*.

Factors in the OFAT experiment are elements in this allocation matrix while levels are the values of the elements, taking the value of either 0 or 1. In conducting experiments in the OFAT process, one experiment means one alternative to allocate all products to all plants, characterized by the elements in the matrix X taking value of either 0 or 1. The allocation decision space is explored by changing one factor, which is one element in the allocation matrix, at a time. For a problem with n products and m plants, total number of elements in the matrix is $n \times m$, which is also the number of factors to be explored in the OFAT process. Since each factor has two levels, 0 and 1, the total number of experiments conducted in the OFAT process is 2nm+1. As a comparison, if a full factorial design is used, the total number of experiments is $2^{(n*m)}$. The larger n and m, the more computational cost the OFAT method saves.

When applied in this research, the OFAT process starts with a specified allocation plan input by users. The specification of starting point is very flexible. It can be a random guess, or can be based on expertise and knowledge about the system, or can be derived from other methods that can give a viable solution.

With a starting point, the OFAT process can be initiated. Each time a factor is changed, if it leads to an improvement of the system's response, the change is retained. Otherwise, the change is not retained and the process starts to explore the next factor. The process of applying the OFAT process in exploring the allocation decision space is described in detail in Section 5.3.1.

However, there is one question that remains unexplained in the above descriptions, which is how to get response for an allocation plan with which the OFAT process can compare. This is explained in the next section.

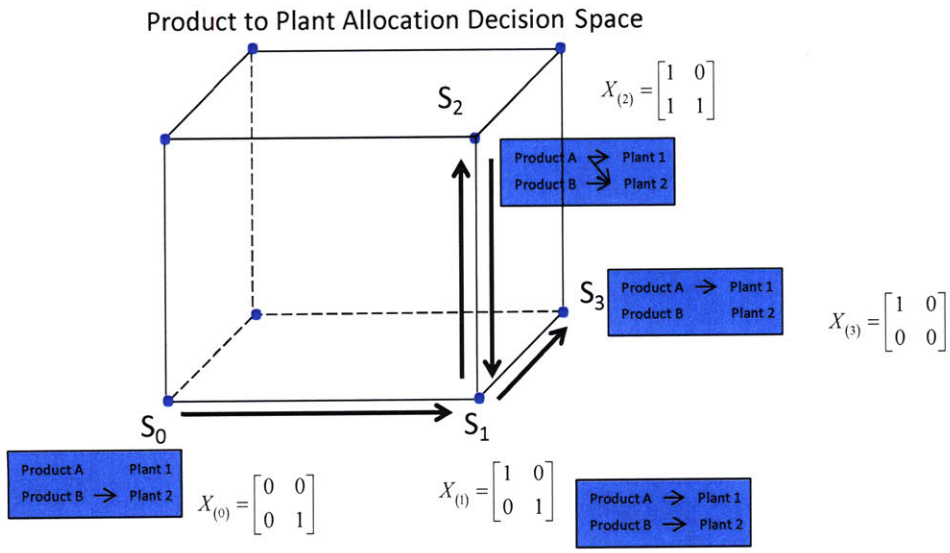

Figure 29 Schematic view of using the OFAT method to explore the product to plant allocation decision space

5.2.2 Response Surface Methodology (RSM): the plant capacity decision space

The response of a manufacturing system does not only depend on the product to plant allocation decision, but also depends on the plant capacity decision. Thus, even under the same allocation plan, there can still be many different responses. However, the OFAT process requires defining one response that is compared between two experiments. One natural way to resolve this issue is to get the optimal response among all possible capacity decisions. But for a large-scale and complex system, it can still be computationally challenging to find the optimal capacity decision under an allocation plan. Thus, in the screening model developed in this research, Response Surface Methodology (RSM) is used to as a method to efficiently explore the plant capacity decision space with reduced computational cost.

In applying the RSM in this research, the Central Composite Design (CCD) method is used to generate designs of experiments. Factors in design of experiments refer to plant capacities and levels correspond to different capacity values for a plant. Each experiment specifies the values of capacities for all plants in the system. Together with the allocation plan specified in the OFAT process, a strategic planning decision, including product to plant allocation decision and plant capacity decision, is conceived. Then one can do the experiment and obtain the response of the system by using the Simulation-based Linear Programming (SLP) model, which is introduced in Section 5.2.3.

After obtaining the responses for all the experiments designed by the CCD method, they can be regressed against some regression model. Instead of a linear function, a quadratic function is used in this research for the regression model as shown in Equation(23):

$$\Gamma = \lambda_0 + \sum_{i=1}^{k} \lambda_i y_i + \sum_{i=1}^{k} \lambda_{ii} y_i^2 + \sum_{i<j=2}^{k} \lambda_{ij} y_i y_j + \varepsilon \tag{23}$$

Coefficients λs are derived as a result of the regression. y represents plant capacity. Γ is the response of the system. ε is the error terms.

The model includes, from left to right, an intercept, linear terms, quadratic interaction terms, and squared terms. As such, it is able to explore the interactions between plant capacities. This regression model is then optimized with regard to plant capacity. As a result, the optimal plant capacities and the optimal corresponding response for this regression model are obtained.

However, this regression model has a model fit error, which means that the optimal decision and response may not be the true optimal for the real system. This leads to an additional step before passing the response to the OFAT process. The step is to compare the obtained optimal response for the regression model with the responses that are obtained when conducting experiments designed under the CCD method and get the best one as the response to be passed to the OFAT process. Doing this step does not add additional computational cost because all the responses are already available, but it helps to identify better response for the OFAT process.

5.2.3 Simulation-based Linear Programming (SLP): the operational decision space

In the RSM model, each experiment implies a strategic plan that includes a plant capacity decision and a product to plant allocation decision that is carried from the OFAT process. The SLP model is developed in this research to get the best expected net present value for this strategic plan under demand uncertainty by exploring the operational decision space.

There are several different approaches to dealing with operation decisions under uncertainty. Wang (2005) used Decision Tree Analysis to deploy contingency plans in satellite communication systems. Decision Tree Analysis has been a standard system analysis and scenario planning tool under uncertainty. In general, uncertainties are discretized into several scenarios and contingency plans are provided as operation strategies to be selected to respond to uncertainty. Lin (2009) employed a simulation based approach to exploring operation strategies. Multiple sources of uncertainties are simulated in various simulation models by a large number of scenarios. Then decision rules are prescribed that specify what actions are to be taken as certain conditions are encountered. Although this approach is different from Decision Tree Analysis in Wang (2005), what is common in both is that decision rules or contingency plans are predefined before uncertainties unfold as options to respond to uncertainties. They are not necessarily the optimal operation strategies that can lead to optimal performance of the system. However, given complexity and uncertainties in large-scale engineering systems, it is very difficult to find the optimal operations strategy, especially when there is path dependency existing between decisions made over periods. Thus the approach of "decision rules" provides an alternative to tackle the problem. In Lin's work, this is remedied by fine tuning decision rules with some trial-and-error experiments and sensitivity analysis.

Operation decisions considered in this research during each period of production are concerned about the production quantities of products in plants under consideration. More specifically, each plant manager needs to decide how much the plant should produce a given product during normal production time and during overtime. If realized demands of products in a plant are less than the normal time capacity of the plant, normal production time will have to be reduced; if realized demands of products in a plant exceed total capacity of normal production time at a plant, the plant can run overtime by having workers work for longer durations.

Such operation decisions are complicated given the complexity of a production system network. Particularly it is difficult to predefine a set of decision rules before uncertainty is realized and before product to plant allocation decisions are made. Fortunately, since there is no significant fixed cost involved in making these decisions and there are only variable costs associated with them, operation decisions over periods are path independent. Furthermore, it is reasonable to model these decisions as continuous variables. Analysis of the structure and characteristics of the problem leads to the use of a linear optimization method to deal with the operation decision space. By formulating the operation decisions as a linear optimization problem, the large decision space can then be efficiently explored.

In addition, simulation is taken as an approach to simulating demand uncertainty. Specifically, Monte Carlo simulation is employed. Under each simulated demand scenario, linear optimization is used to optimize normal time production and overtime production decisions. Details are presented in Section 5.2.3.

5.3 Mathematical description of the screening model

A screening model integrates methods discussed above, the OFAT, the RSM and the Simulation-based LP, to achieve the purpose of identifying promising decision alternatives. This section mathematically describes how this is implemented in this research. Figure 30 provides an overview of the flow chart of the screening model.

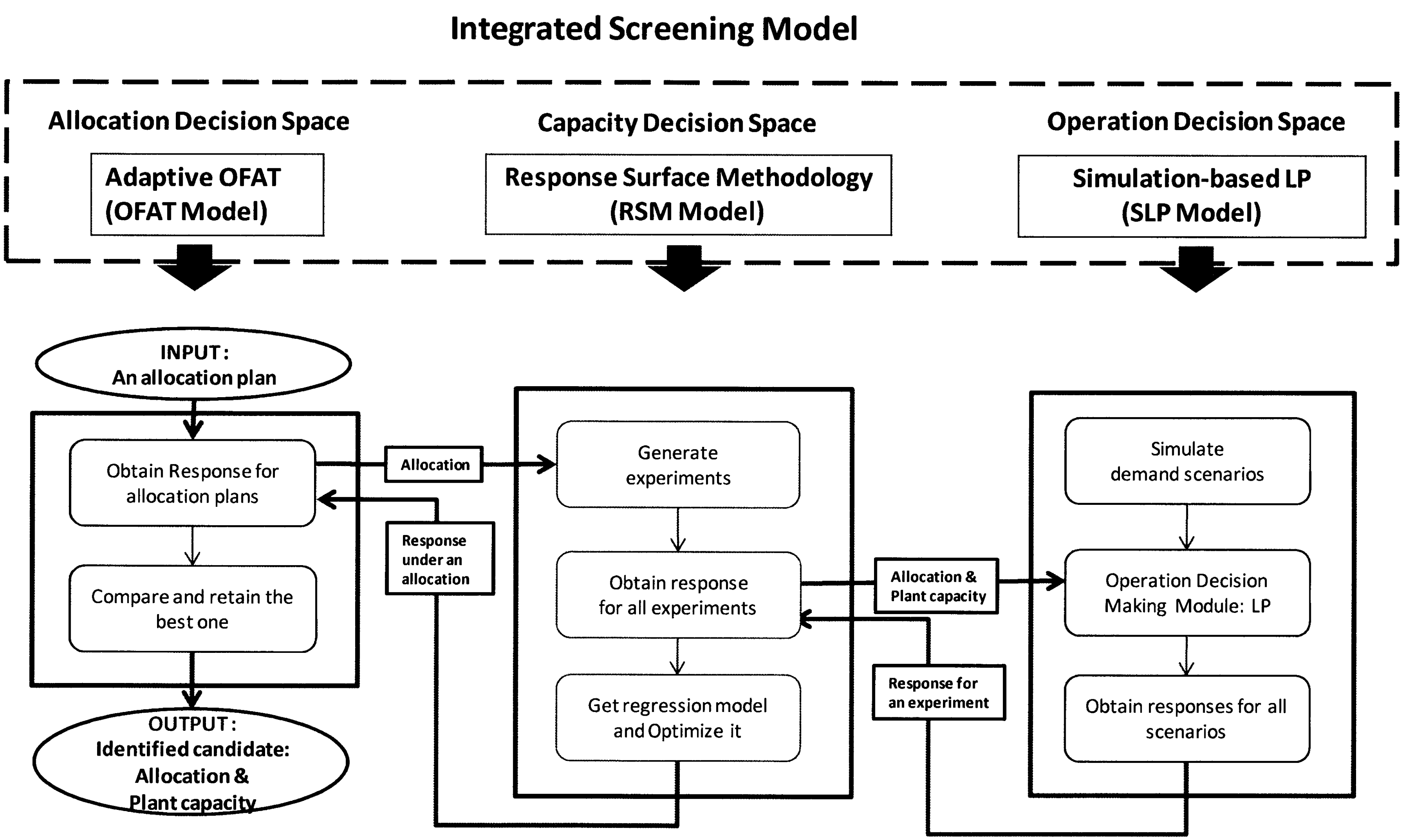

Figure 30 General overview of the screening model

5.3.1 The OFAT model to explore the allocation decision space

The screening model starts with a product to plant allocation decision, which needs to be specified by users. It can be a randomly selected allocation decision plan if users have no good knowledge about the system, or an educated guess if users know the systems. Since the OFAT process makes improvement based on this point, it is preferred that the starting point have good response.

- ***OFAT STEP*** ***1:*** User specifies the starting point.

The starting point at least should be an allocation plan. If users also have a reason for which capacity plan under the specified allocation plan is preferred, he or she can specify the capacity plan as well. Otherwise, simply specifying an allocation plan is enough for the screening model to get initiated.

Assume the specified input allocation plan is represented by matrix $X_{(0)}$ [4]:

$$X_{(0)} = \begin{bmatrix} x_{A1}^{(0)} & x_{B1}^{(0)} & \dots & x_{N1}^{(0)} \\ x_{A2}^{(0)} & x_{B2}^{(0)} & \dots & x_{N2}^{(0)} \\ \dots & \dots & \dots & \dots \\ x_{AM}^{(0)} & x_{BM}^{(0)} & \dots & x_{NM}^{(0)} \end{bmatrix}_{n \times m}$$

n is the number of products and m is the number of plants.

- ***OFAT STEP*** ***2:*** Obtain response for an allocation plan

[4] Denotation rules in description of the screening model: subscription in bracket indices an allocation plan explored in the OFAT model; superscription indices an experiment in RSM model that contains a set of capacity plans for plants; subscription without bracket indices a plant's capacity.

The response under the allocation plan $X_{(0)}$, denoted by $\Gamma_{(0)}$, is then obtained by using Response Surface Methodology (RSM) model, which is described in 5.3.2. What is also obtained from RSM model is the capacity decision that leads to $\Gamma_{(0)}$, denoted by $y_{(0)}$. Use $\Gamma_{(*)}$ to represent the lower bound of response during the search process and $X_{(*)}$ and $y_{(*)}$ to represent the corresponding allocation plan and capacity decision through OFAT process, then let:

$\Gamma_{(*)}=\Gamma_{(0)}$;

$X_{(*)}=X_{(0)}$;

$y_{(*)}=y_{(0)}$.

The lower bound $\Gamma_{(*)}$,together with $X_{(*)}$ and $y_{(*)}$, is updated later on in the search process once there is a new allocation plan that leads to a better response.

- ***OFAT Step 3:*** Change one element at time in the allocation matrix.

There can be many paths in which the element can be changed in the allocation matrix. For example, the elements can be changed from the first row to the second, and so on, and from the left to the right. It can also be changed from the first column to the second column, and so on, and from the top to the bottom. Section 6.5 describes some examples of paths and examines how different paths can lead to identification of different decision candidates.

No matter what path is taken, in the OFAT process, only one element is changed at a time. Since each element in the allocation matrix X can only take two values, either 0 or 1, the change will be toggling an element from 0 to 1 or from 1 to 0. Then go back to OFAT step 2 with the new allocation plan and repeat the same process to obtain the response for this new allocation plan. If the new allocation plan leads to a better response than $X_{(*)}$, then the change is retained. The corresponding response replaces the value of $\Gamma_{(*)}$ as the benchmark that next allocation plan is compared with. Otherwise, the next element is changed. The process repeats until all elements are explored.

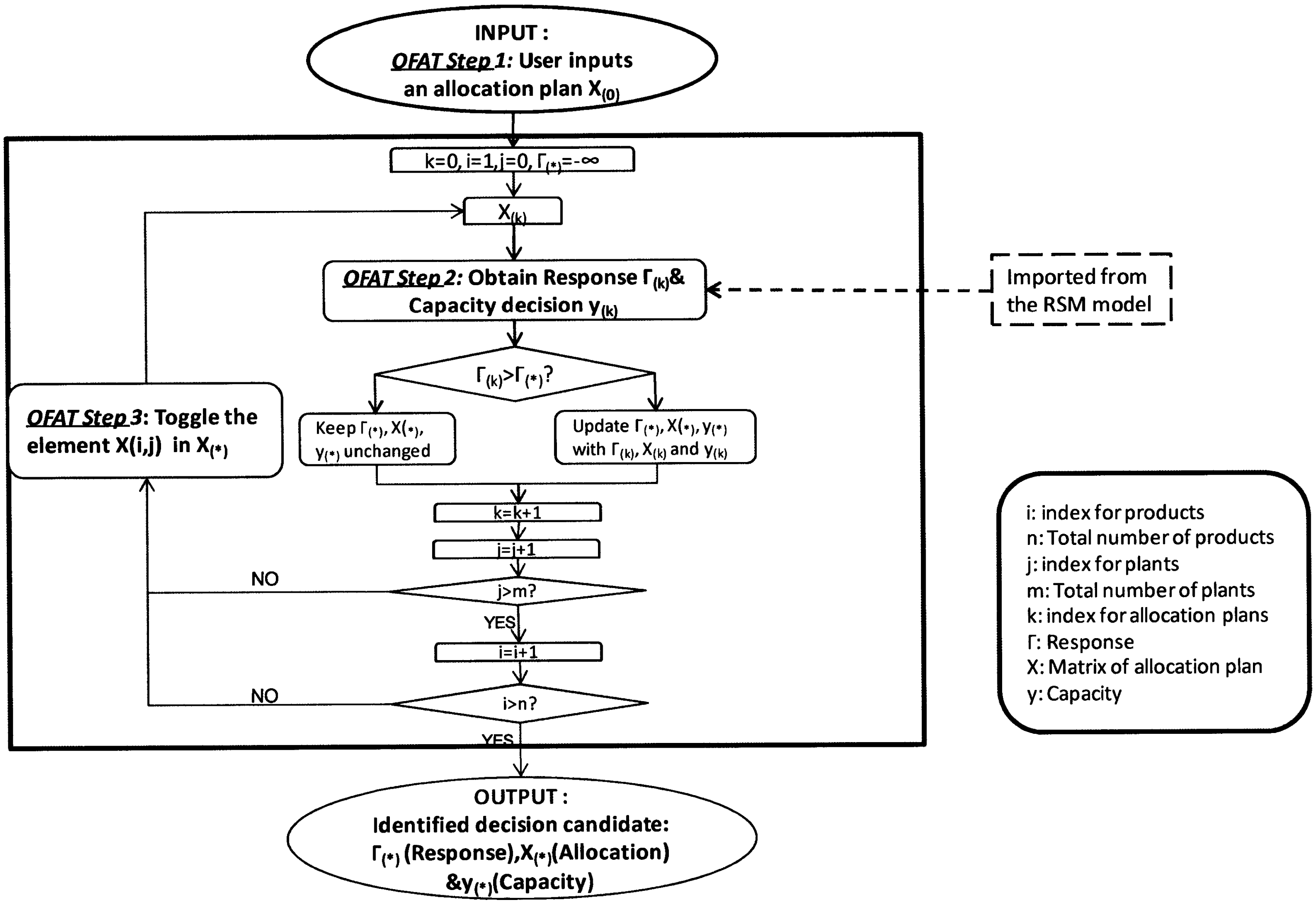

Figure 31 Logic flow chart of the OFAT model that explores the allocation decision space

Figure 31 schematically shows how this process is operationalized with one kind search path, which is to change factors starting from the upper left corner to the lower right corner in a row by row order. This process can also be described by the loop as follows:

<u>OFAT Step</u> 1: input an allocation plan and/or a capacity decision

k=0

For i=1 to n

    For j=0 to m

        Denote the matrix as $X_{(k)}$;

        <u>OFAT Step</u> 2: Use the RSM model to obtain response for $X_{(k)}$, record $\Gamma_{(k)}$ and $y_{(k)}$;

        If $\Gamma_{(k)} > \Gamma_{(*)}$

            Update $\Gamma_{(*)}$ with $\Gamma_{(k)}$: $\Gamma_{(*)}=\Gamma_{(k)}$;

            Update $X_{(*)}$ with $X_{(k)}$: $X_{(*)}=X_{(k)}$;

            Update $y_{(*)}$ with $y_{(k)}$: $y_{(*)}=y_{(k)}$;

        End if

        k=k+1

        j=j+1

        <u>OFAT Step</u> 3: Change the element X(i,j) in $X_{(*)}$ (if it is 0, change it to 1; if it is 1, change it to 0);

    End

    i=i+1

End

As a result, $X_{(*)}$,and $y_{(*)}$ at the end of this process are identified as strategy set, including product to plant allocation decision and capacity decision, that is further examined and characterized in the evaluation model.

5.3.2 The RSM model to explore the plant capacity decision space

As discussed before, the objective of Response Surface Methodology model is to obtain a response under an allocation plan. However, there can still be many possibilities for capacity decisions under an allocation plan, all of which have different responses. It is not trivial to find the optimal response among all capacity decisions under a given allocation plan because of the nonlinearity of the investment function and scaling problem caused by demand uncertainty. This problem is addressed in this research by using Response Surface Methodology. Based on some structure samples, this method generates a response surface that can be easily optimized; in this way, the computational cost to search for good responses and decisions is greatly reduced. The implementation is explained in detail as follows.

- *RSM Step 1:* generate design of experiments

Use Central Composite Design to generate experiments in exploring capacity decision space. This can be generated by using the defined MATLAB function ccdesign. Note that in the classic Central Composite Design, the center points are replicated to estimate the experiment error in the system. When applied in this research, the experiment error can be regarded as very small. This is because the response is the expected net present value, which is the average of a large number of scenarios, the variation between ENPV for different runs is relatively small. Thus, the center runs are not replicated. For each generated experiment in design matrix DM, capacities for plants are denoted by using a vector y^q where q represents the No. of experiment and the element in this vector is y_j^q representing the capacity for a plant j.

$$DM = [y^1, y^2, ..., y^q]^T$$
$$y^q = [y_1^q, y_2^q, ..., y_m^q]$$

There are five levels involved in each factor/plant, two levels are for factorial designs, two levels are for axial designs, and one level is central points. Denoted these five levels as:

l_1, l_2, l_3, l_4, l_5 and $l_1 > l_2 > l_3 > l_4 > l_5$

To run these designed experiments, one needs to translate different levels to values of factors in a system. Since the axial designs require factor settings to be outside the range of the factors in the factorial designs, factor normalization needs to ensure that each coded factor corresponds to feasible (reasonable) levels before starting a factorial experiment. This is done in this research by using the following formula:

$$y_J(l_\vartheta) = \frac{(CAP_J + 0)}{2} \times \left(1 + \frac{l_\vartheta}{l_1}\right) \quad (24)$$

where ϑ represents levels of factors in design matrix. This formula guarantees that (1) the minimum level is always corresponding to the minimal capacity of a plant, which is 0, and thus, does not go to negative, which will be meaningless for the problem here. (2) the maximal level is always corresponding to the maximal capacity of a plant, which will also be meaningless otherwise.

- *RSM Step 2:* Conduct all the experiments and obtain responses for the experiments.

Each experiment designed in The RSM Step 1 is a strategy set that contains a plan for plant capacities under an allocation plan that is carried from OFAT model. Then responses for all of these experiments can be obtained by using Simulation-based Linear Program (SLP) model that optimizes the operational decision for realized demands over periods. The detail is discussed in the next section.

- *RSM Step 3:* Obtain regression model for the response surface

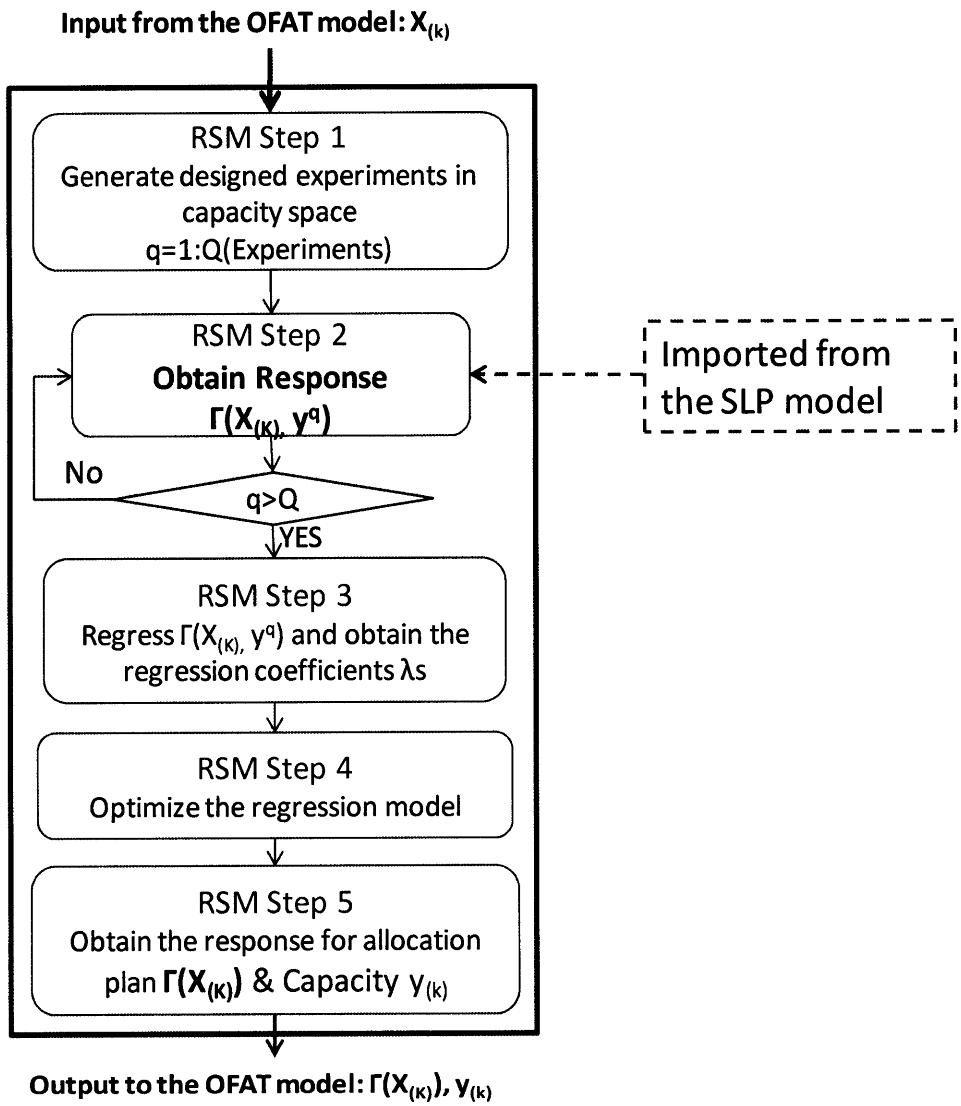

Figure 32 Logic flow chart of the RSM model that explores the capacity decision space

Denote the responses for experiments obtained from the SLP model $\Gamma\left(X_{(k)}, y^q\right)$, q=1…Q, where Q is the total number of designed experiments. Then fit the values y^q and $\Gamma\left(X_{(k)}, y^q\right)$ to a quadratic linear regression model as shown in Equation (25) by doing least square regression between y^q and $\Gamma\left(X_{(k)}, y^q\right)$. As a result, estimators for coefficients λs in the regression model are obtained:

$$\Gamma = \lambda_0 + \sum_{i=1}^{k} \lambda_i y_i + \sum_{i=1}^{k} \lambda_{ii} y_i^2 + \sum_{i<j=2}^{k} \lambda_{ij} y_i y_j + \varepsilon \tag{25}$$

- *RSM Step 4:* Optimize the obtained response surface model:

$$\max_{y} \quad \Gamma = \lambda_0 + \sum_{i=1}^{k} \lambda_i y_i + \sum_{i=1}^{k} \lambda_{ii} y_i^2 + \sum_{i<j=2}^{k} \lambda_{ij} y_i y_j \tag{26}$$

$$s.t. \quad y_j \le H \times \sum_{i=1}^{I} x_{ij}^q \tag{27}$$

Then the optimal capacity for this regression model is obtained, denoted as $y'_{(k)}$, as well as an optimal objective function at this capacity. However, because the regression model may have regression error, the true response may not be the same as the optimal objective function in Formula (26). Thus, the response at $y'_{(k)}$ is obtained by running the SLP model in the same way as the experiments in the design matrix are conducted. This response is denoted as $\Gamma'_{(k)}$.

- *RSM Step 5:* Obtain the response for the allocation plan and the capacity decision.

As discussed in Section 5.2.2, although solving the problem in the RSM Step 4 leads to an optimal solution and an optimal capacity decision for the regression model(25), it may not necessarily be the true optimal solution. Thus, this step compares all the points in the capacity decision space that have responses available and get the best response as the final response for an allocation plan in the OFAT process. These points include the "optimal" point identified by optimizing the regression model, all the points in the design matrix of experiments, and if any, user-specified points. The best response and the corresponding capacity plan among all the points is denoted as $\Gamma_{(k)}$ and $y_{(k)}$ respectively and are output to the OFAT model as the response for an allocation plan.

5.3.3 The SLP model to explore the operational decision space

This section explains how the response is obtained for an experiment specified in the RSM Step *2*. Under the specified capacity and allocation plan, the system is then put into production. As a response to realized demands for products, operational decisions are made in an attempt to optimize the net present value with the available resources. Then the expected value of the NPVs of simulated demand scenarios is used to characterize the performance of the system under uncertain demands. This is illustrated in Figure 33 and described as follows:

- *SLP Step 1:* Generate demand scenarios based on demand uncertainty distributions and parameters. Demand realizations are modeled by Monte Carlo simulation, which is implemented by using Crystal Ball® as an add-in to Microsoft Excel®. Each demand scenario includes a demand realization for all products in the system over the periods under consideration.

- *SLP Step 2*: Obtain the response of the system defined by the allocation and capacity decision under the simulated demand scenario $\Gamma\left(X_{(k)}, y^q, d_s\right)$. The response is characterized by NPV and comprised of two parts: One part is the investment cost determined by the allocation decision $X_{(k)}$ and capacity decision y^q at the strategic planning stage, which is denoted as INV. The other part is the future revenue and expense incurred over production periods, which is discounted to the time that strategic decisions are made, denoted as PV (Present Value). Revenue is the income from selling produced products and expense is the operating cost or incoming materials associated with producing products. Both revenue and expense depend on the actual production quantities during the operational stage, which are decided with the objective to best utilize the available resources in response to the realized demand scenario, including exercising the strategic process flexibility and using overtime flexibility if necessary. This is formulated as follows:

$$\underset{w,z}{Max} \quad \mathrm{PV}\left(X_{(k)}, y^q, d_s\right) \tag{28}$$

$$s.t. \qquad w_{ijt} \leq H \times x_{ij}^{(k)} \qquad \forall i, j, t \tag{29}$$

$$z_{ijt} \leq H \times x_{ij}^{(k)} \qquad \forall i, j, t \tag{30}$$

$$\sum_{i} w_{ijt} \leq y_j^q \qquad \forall i, j, t \tag{31}$$

$$\sum_{i} z_{ijt} \leq \theta y_j^q \qquad \forall i, j, t \tag{32}$$

$$\sum_{j} \left(w_{ijt} + z_{ijt}\right) \leq d_{ist} \qquad \forall i, t \tag{33}$$

$$\sum_{i} \left(w_{ijt} + z_{ijt}\right) \leq CAP_j \quad \forall j, t \tag{34}$$

The meanings of these symbols are similar to the ones in Equation (10)-(16) and therefore are not repeated here. The only exception is d_{it} in Constraint (13) is changed to be d_{ist}, which is a simulated demand scenario s for product *i* at time *t*.

Hence, $\Gamma\left(X_{(k)}, y^q, d_s\right) = -INV\left(X_{(k)}, y^q\right) + \arg\max PV\left(X_{(k)}, y^q, d_s\right)$ (35)

where $\arg\max PV\left(X_{(k)}, y^q, d_s\right)$ represent the present value of future revenue minus expense based on the optimal production plan in response to the realized demand scenario d_s under the given allocation decision $X_{(k)}$ and capacity decision y^q.

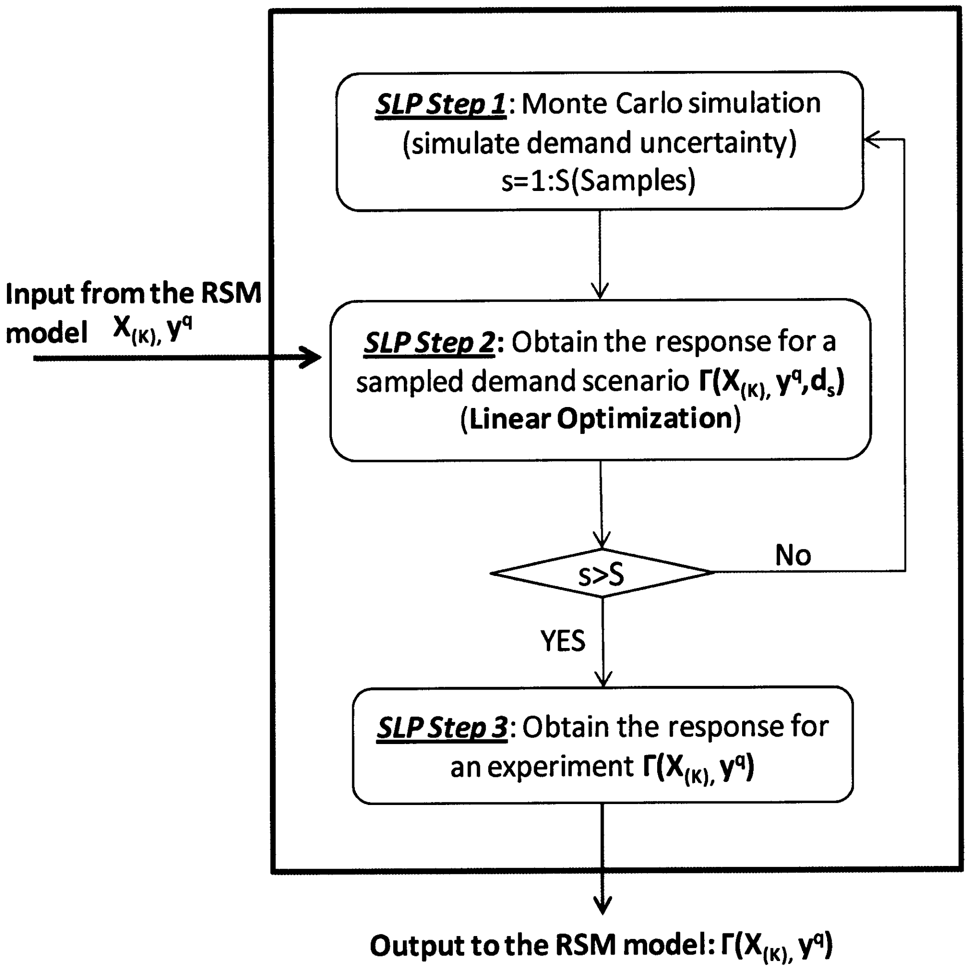

Figure 33 Logic flow chart of the SLP model that explores the operational decision space

- *SLP Step 3*: Take the expected value of optimal NPVs as the response for an experiment in the RSM Step 2, denoted as $\Gamma\left(X_{(k)}, y^q\right) = E\left(\Gamma\left(X_{(k)}, y^q, d_s\right)\right)$.

5.4 Illustration of the screening model in the simple case

This section will illustrate how the screening model can be applied to explore the decision space by applying it on the simple case presented in the preceding chapter. It should be noted that the screening model is developed to address the computational challenge that is encounter for large-scale complex systems, so it is not necessary to use the screening model to explore the decision space for the simple case, which can be explored by the exhaustive search method as described in that chapter to find the optimal decision within a reasonable amount of time. But since the case is small, it is clear to see the whole process of the screening model and to visualize the decision space, so it is used as an example only for illustration purpose. Chapter 6 presents a bigger case where the screening model is really needed and brings value to.

The process of using the screening model in this simple case is as follows:

- ***OFAT Step 1***: First, input a random initial allocation variable matrix for the OFAT model as:

$$X_{(0)} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

- ***OFAT Step 2:*** Under this allocation matrix, run the RSM model to obtain the response value for $X_{(0)}$:
  - *RSM Step* 1: Generate design of experiments by using the CCD method. In the case of 2 plants, the designed experiments are:

Table 13 Designed experiments under Central Composite Design method for 2 factors

No. of experiments	F1	F2
1	-1	-1
2	-1	1
3	1	-1
4	1	1
5	$-\sqrt{2}$	0
6	$\sqrt{2}$	0
7	0	$-\sqrt{2}$
8	0	$\sqrt{2}$
9	0	0

Graphically, it is shown in Figure 34. The first 4 designs are two level factorial designs, which are followed by a 4 axial designs and 1 center runs. F_1 and F_2 represent factors in this design, which correspond to plants. In this case, $l_1=\sqrt{2}$, $l_2=1$, $l_3=0$,$l_4=-1$,$l_5=-\sqrt{2}$

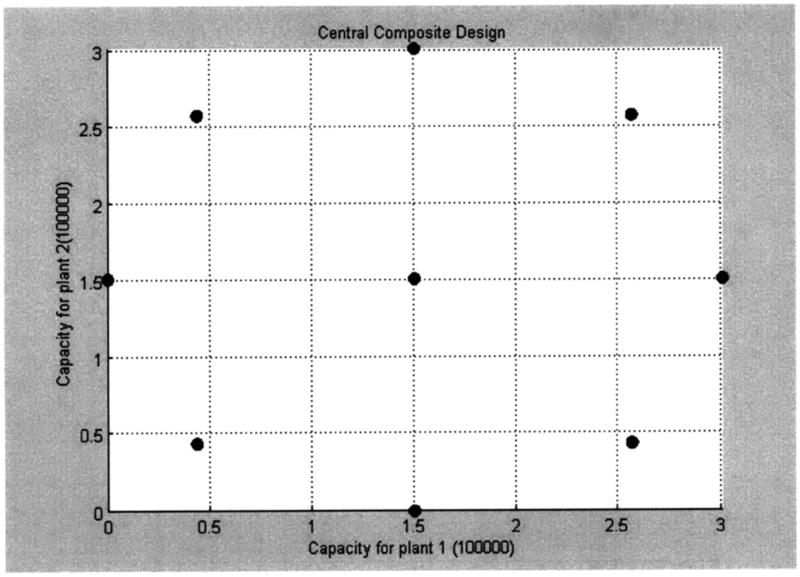

Figure 34 Graphic view of sample points determined by Central Composite Design

- ***RSM Step*** **2: Conduct experiments and obtain the following results.**

  First, this requires converting the input levels to capacities of plants: Based on formula (24), the corresponding capacities of plants in experiments are:

$$y_j(l_1) = \frac{(300,000+0)}{2} \times \left(1+\frac{l_1}{l_1}\right) = 150,000 \times \left(1+\frac{\sqrt{2}}{\sqrt{2}}\right) = 300,000$$

$$y_j(l_2) = \frac{(300,000+0)}{2} \times \left(1+\frac{l_2}{l_1}\right) = 150,000 \times \left(1+\frac{1}{\sqrt{2}}\right) \approx 256,000$$

$$y_j(l_3) = \frac{(300,000+0)}{2} \times \left(1+\frac{l_3}{l_1}\right) = 150,000 \times \left(1+\frac{0}{\sqrt{2}}\right) = 150,000$$

$$y_j(l_4) = \frac{(300,000+0)}{2} \times \left(1+\frac{l_4}{l_1}\right) = 150,000 \times \left(1+\frac{-1}{\sqrt{2}}\right) \approx 44,000$$

$$y_j(l_5) = \frac{(300,000+0)}{2} \times \left(1+\frac{l_5}{l_1}\right) = 150,000 \times \left(1+\frac{-\sqrt{2}}{\sqrt{2}}\right) = 0$$

Thus the design matrix becomes:

Table 14 Central Composite Design of experiments for a system with 2 products and 2 plants

No. of experiments	F1	F2	y_1	y_2
1	-1	-1	44,000	44,000
2	-1	1	44,000	256,000
3	1	-1	256,000	44,000
4	1	1	256,000	256,000
5	$-\sqrt{2}$	0	0	150,000
6	$\sqrt{2}$	0	300,000	150,000
7	0	$-\sqrt{2}$	150,000	0
8	0	$\sqrt{2}$	150,000	300,000
9	0	0	150,000	150,000

Then each experiment is conducted with the specified plant capacities. The response under each experiment is obtained through the SLP model. The Experiment 8 is taken as an example to demonstrate how this is done:

- *SLP Step* 1: generate demand scenarios. In this case, 500 demand scenarios are generated to simulate demand uncertainty. For conciseness, not all 500 scenarios will be listed here except for the first one:

Table 15 One scenario generated by Monte Carlo simulation

	Year1	Year2	Year3	Year4	Year5
A	186,372	263,047	196,520	122,686	251,695
B	229,284	224,640	260,959	197,639	108,673

- *SLP Step* 2: Obtain response of the system under this scenario. The linear optimization problem formulated in Equation (28)- (34) is solved, which leads to the following contingency plan:

Table 16 Normal time production decision made under one demand scenario

Product	Plant	Normal time	Year1	Year2	Year3	Year4	Year5

		production					
A	1	w_{11}	150,000	150,000	150,000	122,686	150,000
A	2	w_{12}	0	0	0	0	0
B	1	w_{21}	0	0	0	0	0
B	2	w_{22}	229,284	224,640	260,959	197,639	108,673

Table 17 Overtime production decision made under one demand scenario

Over time production	Year1	Year2	Year3	Year4	Year5
z_{11}	22,500	22,500	22,500	0	22,500
z_{12}	0	0	0	0	0
z_{21}	0	0	0	0	0
z_{22}	0	0	0	0	0

The same step is repeated for all the 500 scenarios. For different scenarios, production decisions will be different, which lead to different NPVs.

- *SLP Step* 3: Then the expected value of the 500 NPVs is calculated. In this case, it is equal to \$124,170,432, which is the result for $\Gamma\left(X_{(0)}, y^{8}\right)$ in Table 14.

Other experiments are carried out in the same manner. Thus, the following result is obtained:

Table 18 Results for all designed experiments

Exp. No.	F_1	F_2	y_1	y_2	$\Gamma\left(X_{(k)}, y^{q}\right)$
1	$-\sqrt{2}$	0	0	150,000	\$88,867,215
2	-1	-1	44,000	44,000	\$8,606,739
3	-1	1	44,000	256,000	\$72,907,903
4	0	$-\sqrt{2}$	150,000	0	\$88,237,523
5	0	0	150,000	150,000	\$177,104,739
6	0	$\sqrt{2}$	150,000	300,000	\$124,170,432
7	1	-1	256,000	44,000	\$72,117,437
8	1	1	256,000	256,000	\$136,418,602
9	$\sqrt{2}$	0	300,000	150,000	\$123,981,966

- *RSM Step* 3: Fit the results to the quadratic linear regression model (25) and get the values of coefficient λs:

  $\lambda_0 = -0.61 \times 10^8$
  $\lambda_1 = 1.3760 \times 10^8$
  $\lambda_2 = 1.3821 \times 10^8$
  $\lambda_{11} = 0$
  $\lambda_{22} = -0.3892 \times 10^8$
  $\lambda_{12} = -0.3902 \times 10^8$

  Thus, the regression model is:

  $$\hat{\Gamma} = 10^8 \times \left(-0.61 + 1.3760 y_1 + 1.3821 y_2 - 0.3892 y_2^2 - 0.3902 y_1 y_2\right)$$

  R^2=0.80, which indicates that the regression model fits pretty well with the experimental data. The response surface determined by this regression model is shown in Figure 35. In this figure, red dots represent the sample points in capacity decision space and dark dots represent response obtained for the sample points.

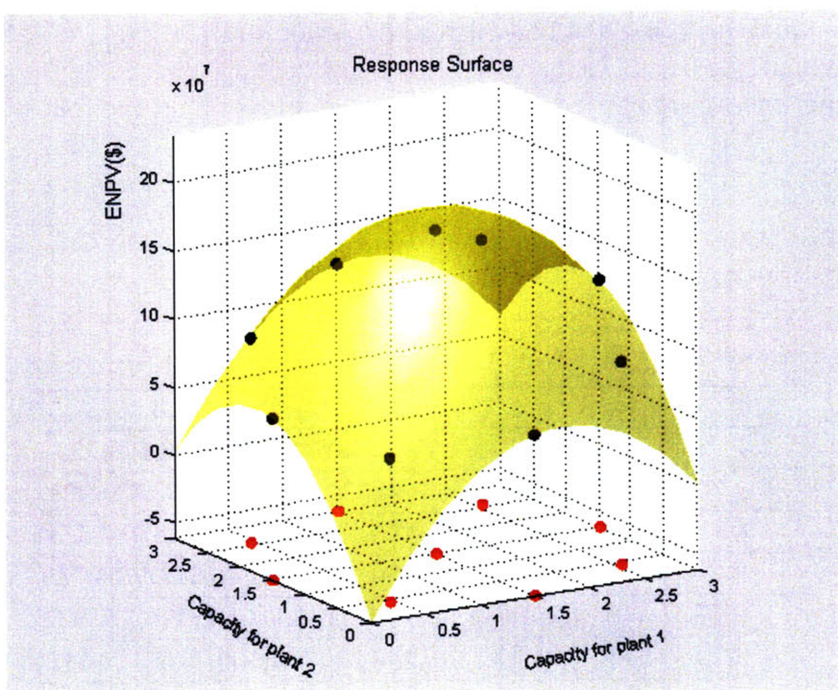

Figure 35 Response surface determined by a regression model

- *RSM Step* 4: Optimize the regressed model to get the optimal response value for $X_{(0)}$:

  $y'_{(0)}$=[176746, 177093], $\Gamma'_{(0)}$=$195,970,046

- *RSM Step* 5: Obtain the response for the allocation decision in the OFAT process

  By comparing the optimal response for the regression model and the responses in Table 18, the best one is the one by the regression model. Thus,

  $y_{(0)}$=[176746, 177093], $\Gamma_{(0)}$=$195,970,046

➢ ***OFAT Step 3***: Then do the next round of OFAT by changing only the first factor in the allocation matrix such that the allocation matrix will be:

$$X_{(1)} = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$$

➢ Go back to OFAT Step 2 and repreat RSM Step 1 through 5 and get the following results:

$y_{(1)}$=[0, 178792], $\Gamma_{(1)}$=$98,414,126

➢ Since $\Gamma_{(1)} < \Gamma_{(0)}$, thus $X_{(0)}$ is retained and the next OFAT allocation input level changes the second variable in $X_{(0)}$. Thus, the third OFAT allocation input is:

$$X_{(2)} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}$$

Similarly, the result is:

$y_{(2)}$=[98564, 269545], $\Gamma_{(2)}$= $201,954,148

➢ Since $\Gamma_{(2)} > \Gamma_{(0)}$, thus $X_{(2)}$ is retained and the next OFAT allocation input level changes the third variable in $X_{(2)}$. Thus, the third OFAT allocation input is:

$$X_{(3)} = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}$$

The result is:

$y_{(3)}$=[44000, 256000], $\Gamma_{(3)}$= $192,441,934

- Since $\Gamma_{(3)} < \Gamma_{(2)}$, thus $X_{(2)}$ is retained and the next OFAT allocation input level changes the fourth variable in $X_{(2)}$. Thus, the fourth OFAT allocation input is:

  $$X_{(4)} = \begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix}$$

  The result is:

  $y_{(4)}=[0, 0]$, $\Gamma_{(4)}=\$0$

- Since $\Gamma_{(4)} < \Gamma_{(2)}$, thus $X_{(2)}$ is retained. Since all the variables in the input matrix are explored, the OFAT process ends here. The final result of the OFAT process is thus:

  $$X_{(OFAT)} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}$$

  $y_{OFAT}=[98564, 269545]$, $\Gamma_{OFAT}=\$201{,}954{,}148$

Thus, the identified design alternative is to allocate product A to plant 1 and plant 2 and to allocate product B to plant 2 only.

If we compare the planning decision identified by the screening model and the one identified by the exhaustive search method, we can see that these two decisions are not the same. The strategic planning decision identified by the exhaustive search method is to build 1 plant at an annual capacity of 262k. This is not unexpected because the screening model only explores part of the allocation decision space and using response surface methodology to explore the capacity decision space has regression error. These two reasons can cause the screening model not necessarily to obtain the true optimum. However, this does not mean that the screening model has no value. The screening model is valuable when it is computational too expensive or intractable to use other methods, such as the exhaustive search method and stochastic optimization method, to search the decision space. In that case, the screening model can search in the decision space and lead to improvement as compared to the deterministic approach. As shown in this case, it leads to 8 million of improvement in ENPV ($202 million versus $194 million). This value of the screening model is further demonstrated in Case study 2 in Chapter 6.

6 Case study 2: Automotive body shop assembly system planning

This chapter is going to demonstrate how the screening model developed in this research can be applied in a manufacturing planning problem in the context of automotive industry and its value. Manufacturing systems concerned here is automotive body shop assembly system. The same as the simple case, this case considers product to plant allocation decision and plants' capacity decision at strategic planning stage and normal time production and overtime production as the operational decisions. But it extends to a larger size of a problem with 6 products and 3 plants. While in practice, the size of the problem that firms need to deal with is likely to be bigger, the intention here is to demonstrate the value of the screening model, not its computational efficiency, which will be studied in Chapter 7. Furthermore, as will be shown in Chapter 7, the problem with this size has already constituted a large and complex decision space that is computationally expensive or intractable for the exhaustive search method and stochastic optimization method. But the screening model provides a means to explore this space and leads to improvement of the system's performance under demand uncertainty.

Other than having a problem with bigger size than the simple case, this case study also links to product platform strategy which adds another complexity as compared to the simple case. Product platform strategy is a widely used as product development strategy in automotive industry. It affects the investment cost and process flexibility upcharge in automotive manufacturing systems. Section 6.1 will introduce this strategy in the automotive industry and discuss how it adds the complexity to the problem. Section 6.2 describes the case studied in this chapter, including the assumptions taken in the study. Then Section 6.3 demonstrates how the screening model is applied to identify good decision is demonstrated for one of the decision approaches. Section 6.4 discusses the results to show the value of the screening model. Lastly Section 6.5 discusses the convergence of the screening model for different exploration paths.

6.1 Product platform strategy in the automotive industry

Product platform strategy, combined with the flexible manufacturing strategy, is developed in many industries in response to more profit proliferations and shorter product life cycle. It refers to "the set of common components, modules, or parts from which a stream of derivative products can be efficiently developed and launched" (Meyer and Lehnerd 1997). In the case of automotive industry, an automotive platform normally includes underbody and suspensions (with axles), where the underbody is made of front floor, underfloor, engine compartment and frame (reinforcement of underbody)(Muffatto 1999). Figure 36 provides a picture of a vehicle platform.

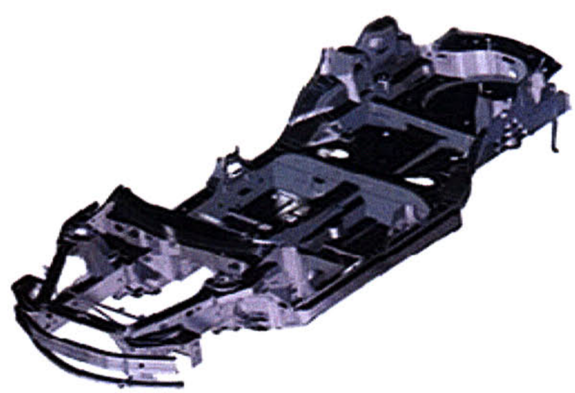

Figure 36 Picture of a vehicle platform

From product development point of view, platform strategy reduces product development costs; from manufacturing point of view, it can lead to cost reduction by reducing changeover times, improving responsiveness to market, and exploiting economies of scale with sharing components and production processes across a platform of products. However, product platform can lead to loss of product variant performance and distinctiveness due to component sharing, which could potentially lead to a loss of market share. In this aspect, flexible manufacturing strategy is complementary with platform strategy to retain product differentiation that otherwise will be too costly.

Since product platforms determine commonality between products, they affect cost of producing different products on the same process. Vehicles with similar platforms require less flexibility upcharge in tools as compared to vehicles with different platforms. A such, the flexibility upcharge for a flexible process that produces multiple different products depends not only on the number of types of vehicles produced one the process, but also on how the number of types of platforms on the process, as well as the difference between the platforms. How this relationship is captured in this case study is further discussed in Section 6.2.2. As product platforms affect tool investment costs on manufacturing processes, it ultimately influences product to plant allocation decision since if it is too costly to produce products on the same process in a plant, it may be better to produce them on the separated processes of plants.

6.2 Case description

In this case study, 6 different vehicles and 3 plants are under consideration. These six vehicles are designed based on three platforms: Delta, Epsilon and Theta. Epsilon represents a platform for compact cars, Epsilon represents a platform for mid-size car and Theta represents a platform for crossover SUV. Each platform has two variances or styles, labeled as Small 1, Small 2, Middle 1, Middle 2, SUV 1 and SUV 2, respectively, as shown in Figure 37.

Manufacturing these vehicles involves many steps. Generally it includes part production, chassis production, body shop assembly, general assembly, and paint shop. Body shop assembly system is the assembly system that assembles car body sheet metal (including doors, hoods, and deck lids) has been assembled or designed but before the components (chassis, motor) and trim (windshields, seats, upholstery, electronics, etc.) have been added, which is done in General assembly. The product of body shop assembly system is referred as body in white (BIW).

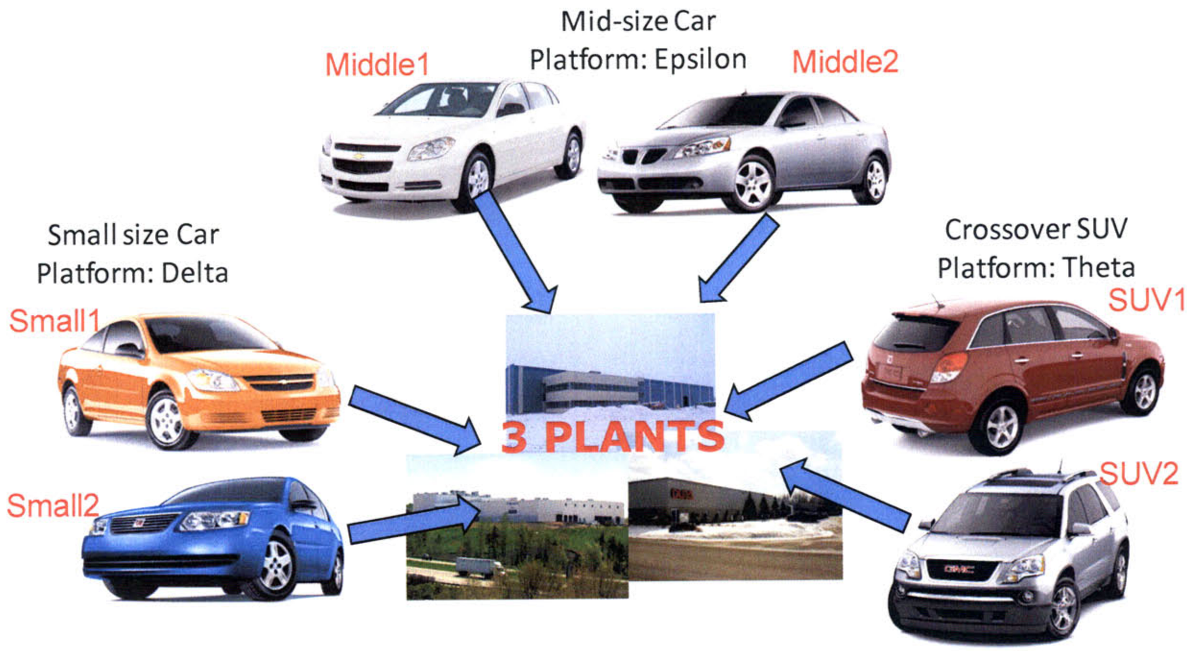

Figure 37 Case study 2: 6 vehicles and 3 plants.

Typically, body shop assembly, general assembly and paint shop are included in one assembly plant and a product goes through the three steps in the plant before put onto the market. Manufacturing planning decisions are based on a complete system with these three processes. However, this requires information about all three processes, such as investments cost of processes, variable costs of processes, and technical constraints. Obtaining the information requires a significant amount of time, efforts, and resources, which are not available at the time of this research. However, previous work in Materials Systems Laboratory at MIT has accumulated the information and knowledge regarding to the BIW assembly system. Thus, this research is going to focus on only the body shop assembly system. Nevertheless, Body shop assembly system is the most interesting system for manufacturing flexibility question during manufacturing planning stage. First of all, body shop assembly system plays a very important role in manufacturing planning decisions because it is very capital intensive. In North America, the investment for a dedicated body shop assembly process is well above two hundreds of millions dollars. Secondly, process flexibility in body shop assembly system has big impact on capital investment as compared to other parts of the manufacturing system. Body shop assembly line employs a large amount of robots and automated equipment. Thus, making a flexible body shop line will entail a great level of engineering changes on equipments and tools in the system. As a comparison, general assembly is more labor intensive and thus building a flexible line does not have as much extra cost as body shop assembly system does. In addition, the framework developed in this research is readily applicable to more extended systems such as general assembly and paint shop.

6.2.1 Assumption about vehicle demands

Demands for vehicles are assumed to follow the normal distribution characterized by expected values and standard deviations. The evolution of the demand over periods and the relationship among products demands are characterized as follows:

$$d_{it} \sim N\left(\bar{d}_{it}, \sigma_{it}\right) \quad where \quad \begin{aligned} \bar{d}_{it} &= \bar{d}_{it-1} \bullet (1 - v_i t) \\ \sigma_{it} &= \sigma_{it-1} \bullet (1 + \eta_i t) \\ \rho_{ij} &= corr\left(d_i, d_j\right) \end{aligned}$$

By which, expected values of vehicle demands are assumed to be decreasing at a rate *v* each year as compared to the previous year. This is consistent with general market trend for a vehicle model in reality that new models are more popular than subsequent ones. Assumptions about the first year demands are shown in Table 19. Annual decreasing rate v is assumed to be 4% each year. In addition, standard deviations for demands are assumed to be increasing over years at a rate η, reflecting the fact that uncertainty grows overtime. η is assumed to be 5% each year. The first year standard deviations for all vehicles are assumed to be 17%. Finally, it is assumed that demands of products have a certain correlation, represented by ρ, which value is indicated in Table 22. In general, it is assumed SUVs have negative correlation with compact car and mid-size car, possibly due to the impact of fuel prices; the correlation between compact car and mid-size car and the one within market segments are more positively correlated.[5]

Table 19 Expected values of product demands in the starting year

Product	Small 1	Small 2	Middle 1	Middle 2	SUV 1	SUV 2
Platform	Delta	Delta	Epsilon	Epsilon	Theta	Theta
Demand	260,000	200,000	150,000	200,000	140,000	130,000

Table 20 Demand decrease rates over years

Year 1	Year 2	Year 3	Year 4	Year 5
0	4%	8%	12%	16%

Table 21 Ratios between standard deviations to expected values of demands over years

Year 1	Year 2	Year 3	Year 4	Year 5
17%	23%	29%	35%	40%

Table 22 Demand correlation between products

Product	Small 1	Small 2	Middle 1	Middle 2	SUV 1	SUV 2
Platform	Delta	Delta	Epsilon	Epsilon	Theta	Theta
Small 1	1	0.8	0.84	0.84	-0.11	-0.11
Small 2	N/A	1	0	0.84	-0.11	-0.11
Middle 1	N/A	N/A	1	0.8	-0.15	-0.15
Middle 2	N/A	N/A	N/A	1	-0.15	-0.15
SUV 1	N/A	N/A	N/A	N/A	1	0.8
SUV 2	N/A	N/A	N/A	N/A	N/A	1

[5] These values are developed based on the combination of the market uncertainty model result in Cirincione, R. J. (2008). A Study of Optimal Automotive Materials Choice Given Market and Regulatory Uncertainty. Engineering Systems Division. MIT, **M.S.:** 185, Cambridge, MA., actual market data and intuition. This may be improved by further modeling and analysis with more market data, which is not the focus of this research.

6.2.2 Body shop assembly investment cost

It is assumed that investment decision has to be made at one year before production and it takes one year to implement the decision to build the plant and process. Investment includes the investment on equipment, tools and buildings. The investment function is:

$$INV = \sum_{j} \left(F_e + F_t \times \left(1 + \beta_j\right) + F_b \right) \times \left(\frac{y_j}{200{,}000} \right)^{\alpha} \tag{36}$$

α represents the effect of economy of scale, F_e is the investment cost for equipment per 200k unit of capacity, F_t is the investment cost for tools per 200k unit of capacity, and F_b is the investment for building per 200k unit of capacity.

β_j is the flexibility upcharge for tools for a plant j. As discussed in 6.1, due to the product platform strategy, the value of this upcharge is very scenario dependent. Equation (37) shows the formula used in this research to capture the relationship between the upcharge β and three factors that affects it: the number of styles produced on a line, the number of platforms produced on a line and the difference/similarity between platforms.

$$\beta = \beta_0 \times \left(\#of\ \ styles - 1\right) + \beta_1 \times \left(\#of\ \ platforms - 1\right) + \beta_2 \times \left(difference\ \ between\ \ platforms\right) \tag{37}$$

β_0 is the basic flexibility upcharge of a flexible process with 1 platform and 2 styles. β_1 represents the additional upcharge for having a different platform to the upcharge of an additional style. β_2 represents the additional upcharge for difference between platforms. The values of the parameters in Formula (36) and Formula (37) and are derived by regressing results from a Process-based cost model that Material Systems Laboratory at MIT that was developed by the author, as shown in Table 23.

Table 23 Values of the investment parameters in Case 2

Symbol	Meaning	Value
F_e	Equipment cost per 200k unit of capacity	\$30 million

F_t	Tool cost per 200k unit of capacity	\$66 million
F_b	Building cost per 200k unit of capacity	\$20 million
α	Economies of scale	0.6
β_0	Base flexible tool upcharge per additional style in a plant	0.2
β_1	Flexibility tool upcharge per additional platform in a plant	0.02
β_2	Flexibility upcharge for tools for difference between platforms	0.11

6.2.3 Body shop assembly variable cost

Variable cost for a BIW includes parts cost and various costs during assembly process that are paid over time, including materials, energy, maintenance, labor cost, and overhead cost. The values of these parameters are also derived based on Process-Based Cost Model that is developed by Material Systems Lab at MIT and relevant research that was done based on this model (Kelcar 2001). In addition, the same as the simple case, the maximum of the plant capacities are assumed to be 300,000 units and the maximum proportion of overtime capacity to normal time capacity is assumed to be 0.15.

Table 24 Variable costs during production (Units: \$)

Product	Small 1	Small 2	Middle 1	Middle 2	SUV 1	SUV 2
Platform	Delta	Delta	Epsilon	Epsilon	Theta	Theta
Purchased parts unit cost	600	610	830	800	1,760	1,860
Assembly variable cost during normal time	200	200	220	220	400	400
Total variable cost during normal time (VC_n)	800	810	1,050	1,020	2,160	2,260
Assembly variable cost during over time	300	300	320	320	500	500
Total variable cost during over time(VC_o)	900	910	1,150	1,120	2,160	2,360

Lastly, Table 25 shows assumptions about prices of products, which is BIW in this case (obviously they are less than typical sale prices of products). Revenue from selling vehicles is discounted at a rate r to the time that the strategic decision is made, which is assumed to be one year before production. The discount rate is assumed to be 10% in this case.

Table 25 Prices of products (Units: $)

Product	Small 1	Small 2	Middle 1	Middle 2	SUV 1	SUV 2
Platform	Delta	Delta	Epsilon	Epsilon	Theta	Theta
Price(p)	955	980	1,255	1,205	2,385	2,495

The present value of the future revenue and expense is calculated in the same way as in the case study 1:

$$PV = \sum_t \frac{1}{(1+r)^t} \times \left(\sum_{ij} \left(p_i \left(w_{ijt} + z_{ijt} \right) - \left(vc_{ni} w_{ijt} + vc_{oi} z_{ijt} \right) \right) \right) \tag{38}$$

Where the meanings of the symbols are the same as in case study 1, so are not repeated here.

6.3 Application of the screening model

The case described above is computationally very challenging to find the optimal decision by the exhaustive search method and stochastic optimization method, as will be shown in Chapter 7. In particular, the following four aspects make stochastic optimization limited to solve the problem in this case:

(1) Demand uncertainty. Incorporation of demand uncertainty makes the computational time of optimization scale quickly with the size of the problem. Especially many products considered in the system constitute many sources of uncertainty so that the size of the stochastic optimization problem grows exponentially.

(2) Integerality of allocation decision variable. Allocation decision variable is modeled as a binary integer. This makes the problem lose the property of convexity and thus prevents efficient algorithms to be applied to solve this large scale stochastic optimization problem.

(3) Scenario-dependence of flexibility upcharge β. As indicated by Equation(37), it depends on three factors: the number of styles, the number of platforms and the difference between platforms. This makes the problem very hard to be formulated into an objective function. Although some form of treatment might be possible to convert this relationship, there is no readily available technique that can be used.

(4) Economy of scale. Investment in body shop assembly system has the effect of economy of scale, which means α is bigger than 0 and smaller than 1. This adds nonlinearity to the optimization problem so that it increases the computational time to solve it.

The development of the screening model in this research is an effort to address this computational challenge. This section describes how the screening model developed in this research is applied in this case.

6.3.1 Specification of a starting point

To apply the screening model, an allocation plan needs to be specified as a starting point for the OFAT process. It can be a random assigned decision, an educated guess based on expertise and experience of the system, or derived by using some formal method. In this case study, a model based on optimization method is used to identify the starting point for two reasons. One reason is that it will give one a better starting point than a random guess. The other reason is that it can provide a base point so that one can see the improvement of the screening model upon the traditional optimization approach.

To make optimization problem solvable within a reasonable amount of time, several simplifications are made for the optimization model:

(1) No demand uncertainty.

Because incorporation of demand uncertainty makes the computational time of optimization scale quickly with the size of the problem, the optimization method used to identify starting point is based on deterministic demand, which is the expected value of demand.

(2) Simplified flexibility upcharge relationship.

The scenario-dependence of flexibility upcharge makes the problem very hard to be formulated into an objective function. As such, in this case study, this relationship is simplified to be:

$$\beta = \beta_0 \times (\# \ of \ styles - 1) \tag{39}$$

This equation implies that the difference between platforms and styles is not considered so that the additional investment cost for producing multiple styles is the same as the one for multiple platforms. In this regard, the process flexibility cost is underestimated for the case of multiple platforms.

(3) No economies of scale.

Economies of scale add nonlinearity to the optimization problem so that it increases the computational time to solve it. Thus, this is assumed to be 1 in the optimization model used to identify a starting point.

Based on these simplifications, the problem is formulated into an optimization problem as shown in Appendix A. The allocation and plant capacity decision obtained by solving this optimization problem is selected as the starting point for the screening model. Note that even with these simplifications, it still takes 3 hours to solve the optimization problem.

Figure 38 shows the solution given by the two deterministic decision approaches. Under DA1, both Small1 and Small2 are not produced. For the other four vehicles, the allocation decision is to allocate Middle1 to plant 1 at a capacity of 176k, to allocate SUV1 and SUV2 plant 2 at a capacity of 231k, making plant 2 with 1 platform and 2 styles; and to allocate Middle2 to plant 3 at a capacity of 132k. Under DA4, allocation decisions are the same, but the capacities for all plants are smaller: plant 1 is at a capacity of 160k, plant 2 is at a capacity of 215k, and plant 3 is at a capacity of 125k.

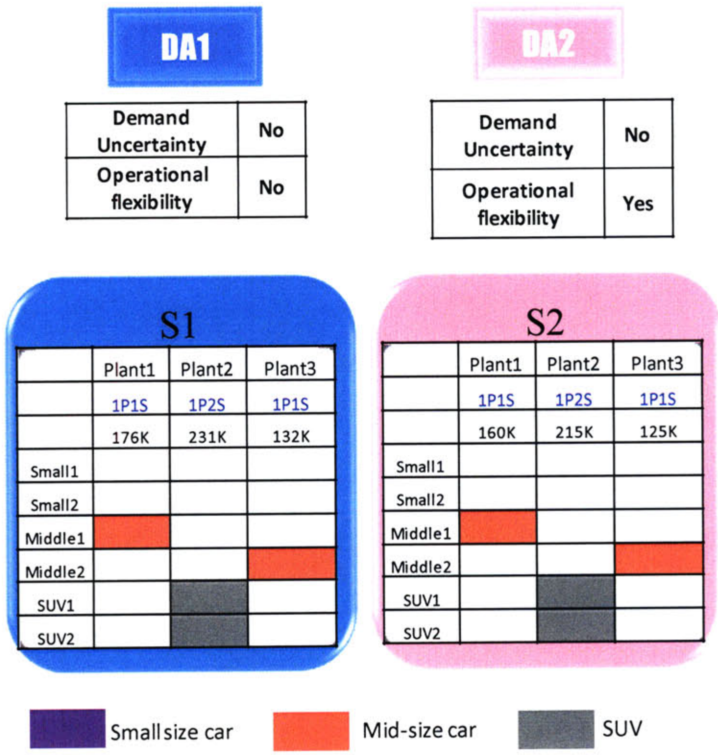

Figure 38 Solutions from deterministic and simplified optimization model under DA1 and DA2, which serves as the starting point for the screening model

6.3.2 Running the screening model

Then with the solution of the optimization model described in the preceding section as the starting point, the screening model is run based on DA3 and DA4 respectively. DA3 is to only consider demand uncertainty during early planning stage, but not the overtime flexibility over periods while DA4 is to consider both demand uncertainty and overtime flexibility. For conciseness purpose, only the process for DA4 is shown here since the process is identical for DA3, but the results for both decision approaches are shown in the end of this section.

Note that when running the screening model under one decision approach, even with the same allocation plan as the starting point, there are many different paths to explore the allocation decision space in OFAT. In this case study, among many other paths that can be used, four different paths are explored. However, this section will only show the result of using the screening model to explore decision space with the path that led to the identification of the best decision candidate under both decision approaches while the different results from different paths are shown and discussed in Section 6.5. This path is illustrated in Figure 39:

$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{bmatrix}$$

Figure 39 The path that leads to the best decision candidate among four paths explored in the case study 2

This path refers to the path that the elements are changed from the lower right corner of the allocation matrix to upper left corner in a column-wise direction. The exploration under this path, together with other intermediate results of running the screening model, is illustrated as follows.

- ***<u>OFAT Step</u> 1:*** Starting with the starting point, which is the allocation plan determined by simplified deterministic optimization model, as shown in Figure 38 above. It is represented by the following matrix $X_{(0)}$:

$$X_0 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{bmatrix}$$

➢ ***OFAT Step 2:*** get response for this allocation plan by using the RSM model:

- *RSM Step 1:* Generate design of experiments:

Table 26 Design of experiments for case study 2

Experiment	Plant 1	Plant 2	Plant 3
1	0	150,000	150,000
2	61,000	61,000	61,000
3	61,000	61,000	240,000
4	61,000	240,000	61,000
5	61,000	240,000	240,000
6	150,000	0	150,000
7	150,000	150,000	0
8	150,000	150,000	150,000
9	150,000	150,000	300,000
10	150,000	300,000	150,000
11	240,000	61,000	61,000
12	240,000	61,000	240,000
13	240,000	240,000	61,000
14	240,000	240,000	240,000
15	300,000	150,000	150,000

- *RSM Step 2:* Conduct all the experiments to obtain responses

For Experiment No.1: y^1=[0 150,000 150,000], which means capacity for plant 1 is 0, capacity for plant 2 is 150,000, and capacity for plant 3 is 150,000.

- *SLP Step 1:* Generate demand scenarios. In this case, 500 demand scenarios are generated. Table 27 shows an example of one generated demand scenario.

Table 27 Example of a generated demand scenario

	Year1	Year2	Year3	Year4	Year5
Small 1	206,619	202,143	181,296	240,377	219,740
Small 2	180,146	180,155	151,499	221,966	74,514
Middle 1	130,772	128,394	144,861	143,875	118,232
Middle 2	190,706	173,999	182,385	216,512	83,305
SUV 1	127,138	146,413	83,141	79,276	194,262
SUV 2	118,552	139,473	59,656	85,242	210,168

- *SLP Step 2:* Solve optimization problem Equation (28)- (34) and get response under this demand scenario:

  $\Gamma\left(X_{(0)}, y^1, 1\right)$ = \$36,222,518

  The optimal production plans with this realized demand scenario over years are shown in from Table 28 to Table 32:

Table 28 Production plan for Year 1 under demand scenario 1

	Plant 1		Plant 2		Plant 3	
	Capacity: 0		Capacity: 150,000		Capacity: 150,000	
	Normal time	Over time	Normal time	Over time	Normal time	Over time
Small 1	-	-	-	-	-	-
Small 2	-	-	-	-	-	-
Middle 1	-	-	-	-	131,077	0
Middle 2	-	-	-	-	-	-
SUV 1	-	-	31,448	22,500	-	-
SUV 2	-	-	118,552	0	-	-

Table 29 Production plan for Year 2 under demand scenario 1

	Plant 1		Plant 2		Plant 3	
	Capacity: 0		Capacity: 150,000		Capacity: 150,000	
	Normal time	Over time	Norma l time	Over time	Normal time	Over time
Small 1	-	-	-	-	-	-
Small 2	-	-	-	-	-	-
Middle 1	-	-	-	-	128,394	0
Middle 2	-	-	-	-	-	-
SUV 1	-	-	10,527	22,500	-	-
SUV 2	-	-	139,473	0	-	-

Table 30 Production plan for Year 3 under demand scenario 1

	Plant 1		Plant 2		Plant 3	
	Capacity: 0		Capacity: 150,000		Capacity: 150,000	
	Normal time	Over time	Norma l time	Over time	Normal time	Over time
Small 1	-	-	-	-	-	-
Small 2	-	-	-	-	-	-
Middle 1	-	-	-	-	144,861	0
Middle 2	-	-	-	-	-	-
SUV 1	-	-	83,141	0	-	-
SUV 2	-	-	59,656	0	-	-

Table 31 Production plan for Year 4 under demand scenario 1

	Plant 1		Plant 2		Plant 3	
	Capacity: 0		Capacity: 150,000		Capacity: 150,000	
	Normal time	Over time	Norma l time	Over time	Normal time	Over time
Small 1	-	-	-	-	-	-
Small 2	-	-	-	-	-	-
Middle 1	-	-	-	-	143,875	0
Middle 2	-	-	-	-	-	-
SUV 1	-	-	65,758	15,000	-	-
SUV 2	-	-	85,242	0	-	-

Table 32 Production plan for Year 5 under demand scenario 1

	Plant 1		Plant 2		Plant 3	
	Capacity: 0		Capacity: 150,000		Capacity: 150,000	
	Normal time	Over time	Norma l time	Over time	Normal time	Over time
Small 1	-	-	-	-	-	-
Small 2	-	-	-	-	-	-
Middle 1	-	-	-	-	118,232	0
Middle 2	-	-	-	-	-	-
SUV 1	-	-	0	0	-	-
SUV 2	-	-	150,000	23,000	-	-

Repeat SLP step 1&2 until the number of scenarios is reached; in this case, the number of simulated demand scenarios is set as 500.

- *SLP Step 3:* Take the expected value of the NPVs above as the response for experiment 1:

$$\Gamma\left(X_{(0)}, y^{1}\right) = \frac{1}{500} \times \sum_{s=1}^{500} \Gamma\left(X_{(0)}, y^{1}, s\right) = \$35{,}695{,}291$$

Repeat SLP Step 1 through 3 for other experiments in Table 26, the following results are obtained:

Table 33 Results of designed experiments

Experiment	Plant 1	Plant 2	Plant 3	Response($\Gamma(X_{(k)})$
1	0	150,000	150,000	$ 35,695,291
2	61,000	61,000	61,000	$ (22,691,443)
3	61,000	61,000	240,000	$ (37,072,273)
4	61,000	240,000	61,000	$ 35,142,276
5	61,000	240,000	240,000	$ 20,761,446
6	150,000	0	150,000	$ 12,128,503
7	150,000	150,000	0	$ 37,649,663
8	150,000	150,000	150,000	$ 42,736,729
9	150,000	150,000	300,000	$ (2,043,183)

10	150,000	300,000	150,000	$	56,924,487
11	240,000	61,000	61,000	$	(11,713,801)
12	240,000	61,000	240,000	$	(26,094,632)
13	240,000	240,000	61,000	$	46,119,918
14	240,000	240,000	240,000	$	31,739,087
15	300,000	150,000	150,000	$	17,815,088

- *RSM Step 3:* Obtain the regression model

  $$\Gamma\left(X_{(0)}\right)=10^7\times\left(-7.35+4.33y_1+5.70y_2+4.39y_3-1.41y_1y_2-1.06y_2y_3-1.80y_1y_3\right)$$

  In this case, the R-Square is 0.78, which indicates the regression model fits pretty well with the experimental data.

- *RSM Step* 4: Optimize the regression model to obtain the optimal capacity

  The optimal capacity is $y'_{(0)}$=[154,040 268,690 121,720]; run the SLP Step 1 through 3 to obtain the true response under the identified optimal capacity $\Gamma'_{(0)}$ =$65,355,537.

- *RSM Step* 5: Compare this response with responses with other points available under this allocation plan and get the best one. Other points include all the tested points in RSM experiments and the starting point. In this case, the best response is the starting point specified from the deterministic and linearization optimization model, which is $68,430,666, so the lower bound for OFAT process is now:

  $\Gamma_{(0)}=\Gamma_{(*)}$ =$68,430,666

  $y_{(0)}=y_{(*)}$= [175,643 237,118 131,732]

  $$X_{(0)}=X_{(*)}=\begin{bmatrix}0&0&0\\0&0&0\\0&0&1\\1&0&0\\0&1&0\\0&1&0\end{bmatrix}$$

➤ ***<u>OFAT Step</u> 3:*** Change one factor in allocation matrix. This case demonstrates a row-wise exploration path from the lower right corner to upper left corner. So change the X(6, 3) from 0 to 1 and thus the allocation matrix becomes:

$$X_{(1)} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & \mathit{1} \end{bmatrix}$$

Then repeat the same process in the OFAT Step 2 with only slight difference in the RSM Step 4. The difference is because the starting point is the solution of the simplified deterministic optimization model, so it is specified with allocation plan and capacity decision, with which response can be calculated. For other allocation plan explored in the process, only allocation plan is specified, thus the optimal response will be the response with the regressed optimal capacity, without being compared with other point in the space.

The response for this allocation plan is:

$\Gamma_{(1)}$= $55,278,695

$y_{(1)}$=[154,146   181,450   154,763]

Since $\Gamma_{(1)} < \Gamma_{(*)}$, this change of factor is not retained. Then the next allocation plan to be explored is

$$X_{(2)} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & \mathit{0} & 0 \end{bmatrix}$$

Repeat the same process in The OFAT Step 3 until all factors in allocation matrix is explored. The process is abbreviated due to the repetition of the process, but the evolution of allocation plans explored in the OFAT model is shown in Appendix C.

The same process can be repeated for DA3. As a result, two decision candidates are identified for DA3 and DA4 respectively as shown in Figure 40. Under DA3, instead of three plants, the decision is to build two plants. One plant is to produce 2 platforms with 3 styles, including Small 2, SUV 1 and SUV 2, at a capacity of 300,000; the other plant is to produce 1 platform with 2 styles, including Middle 1 and Middle 2 at a capacity of 300k. Under DA4, the allocation decision is the same, but the capacity for plant 2 is 260,000 instead of 300,000. Comparing these two decisions with decisions made under deterministic approaches, one can see that one big difference is that less, but more flexible plants are required. The financial impact of the change of strategic decisions are shown and discussed in the next section.

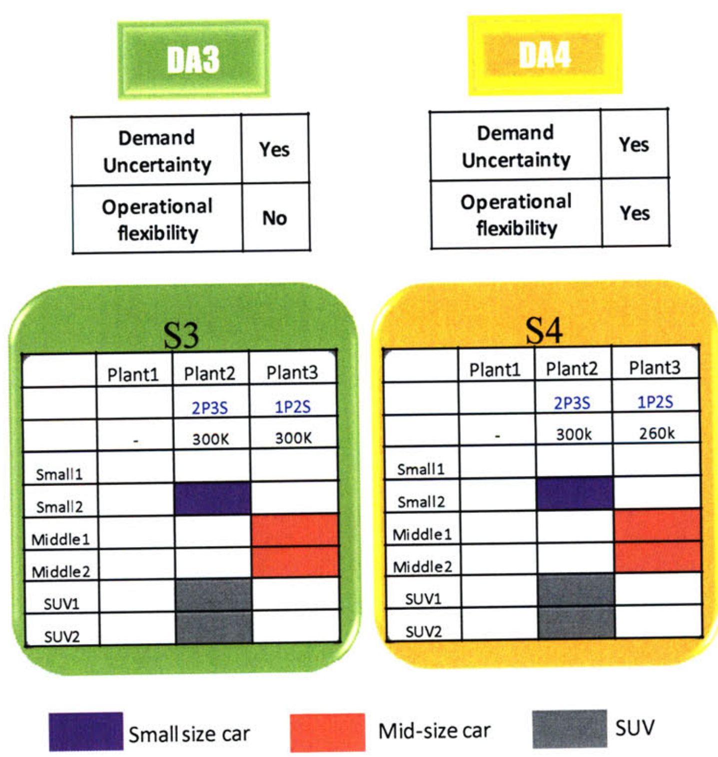

Figure 40 Solutions under DA3 and DA4 with the screening model

6.4 Result discussion

Figure 41 shows the VaRG curve for the four decisions under different decision approaches and Table 34 summarizes the key statistics. One can see that the decisions identified by the screening model under DA3 and DA4 outperform the decisions made under deterministic approaches DA1 and DA2. The expected NPV is improved from around \$65-\$68 million to \$91-\$94 million, representing almost 40% improvement. The minimal NPV is reduced from loss of \$4-10 millions to around \$20 million, and the maximal NPV is increased to be \$120 million or so from \$102-117 million. VaR@ 5% is increased from \$25 million to \$60 million or so, and VaG@5% is increased from \$95 million or so to \$115 million or so. The Returns on Investment is also higher than the ones by the optimization method. Overall, the decisions identified by the screening model achieve more stable and better performances than the decisions identified by deterministic approaches in that they have improved ENPV, reduced downside risks, and increased upside gains. This is similar to the result in Case study 1. What is different is that this case also leads to increased expected production because it allows 1 more product to be produced.

Then compare DA3 and DA4, we have similar conclusion to the conclusion in simple case, which is that considering operational flexibility further enhanced the value of process flexibility and thus improves the strategic planning decision making. The ENPV is further improved from \$91 million to \$93 million and the downside risk is reduced with minimal NPV increasing from \$20 million to \$26 million; furthermore, these do not come at the expense of investment increase. The required investment is reduced from \$359 to \$346 by having a small plant. The result clearly shows the value of the proposed systematic framework for making strategic planning decisions and the value of the screening model for identifying good decision candidates that improve the system's performance.

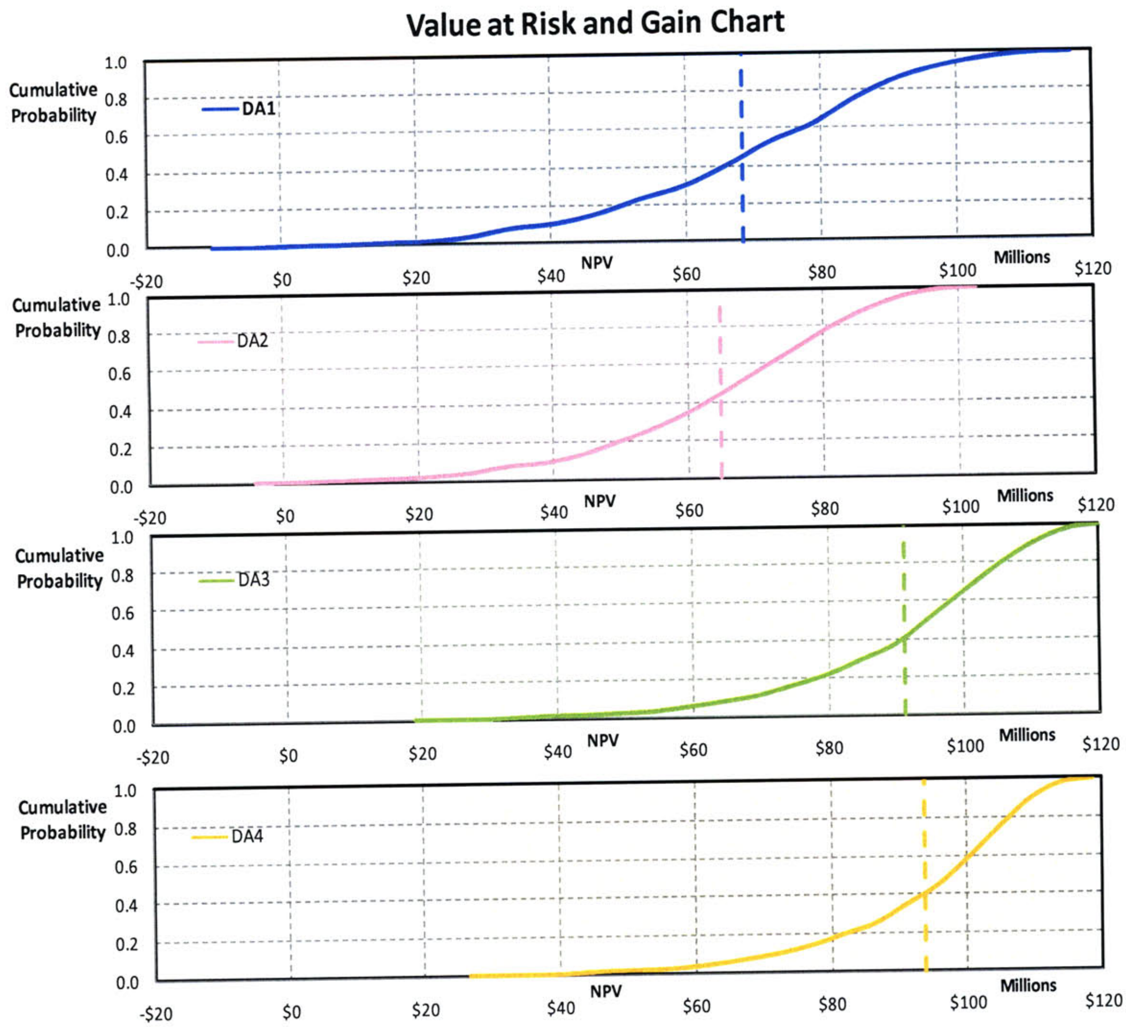

Figure 41 VaRG chart for different decisions under different decision approaches

Table 34 Summary table for four decisions under four decision approaches

Decision Approaches	Considers demand uncertainty?	Considers overtime flexibility?	Investment (Million $)	NPV						Returns on Investment	Average Capacity Utilization	Expected Production (million units)
				ENPV (million $)	MIN (million $)	MAX (million $)	SD (million $)	VaR@5% (million $)	VaG@5% (million $)			
DA1	No	No	340	68.4	(10.3)	117	22	28	***98***	20.1%	98%	26.49
DA2	No	Yes	324	64.8	(4)	102	19	27	92	20%	101%	25.35
DA3	Yes	No	359	91.3	20	***120***	17	60	***115***	25.4%	95%	28.55
DA4	Yes	Yes	***346***	***93.8***	***26***	118	***15***	***64***	114	***27.1%***	***102%***	28.52

6.5 Convergence of the screening model

As discussed before, even with the same starting point, there are many different paths to explore the allocation decision space in the OFAT process. The preceding section has shown the result of one path, which is the path that has led to the best result among four paths explored in this case. This section will show the results for other three paths and discuss the convergence of the screening model under different exploration paths in allocation decision space.

Specifically, four different paths that are explored in this case study are shown in Figure 42.

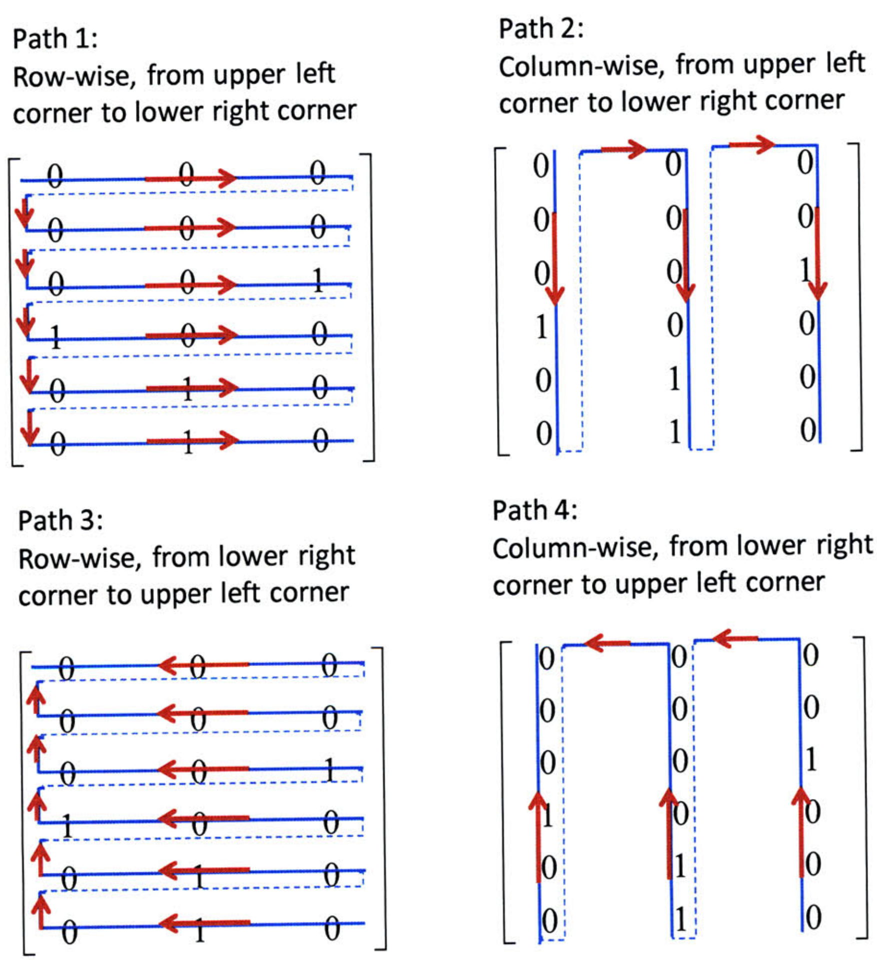

Figure 42 Four different paths to explore the allocation decision space

Path 1 represents a search path starting from the element on the upper left corner in the allocation matrix. It changes one element at a time in a row-wise way and from the left to the right. So the elements are changed in the following order:

$$x(1,1) \to x(1,2) \to x(1,3) \to x(2,1) \to x(2,2) \to x(2,3) \ldots \to x(6,1) \to x(6,2) \to x(6,3)$$

Path 2 represents a search path starting also from the element on the upper left corner in the matrix. It changes one element at a time in a column-wise way and from the left to the right. So the elements are changed in the following order:

$$x(1,1) \to x(2,1) \ldots \to x(6,1) \to x(1,2) \to x(2,2) \ldots \to x(6,2) \ldots \to x(1,3) \to x(2,3) \ldots \to x(6,3)$$

Path 3 represents a search path starting from the element on the lower right corner in the matrix. It changes one element at a time in a row-wise way and from the right to the left. So the elements are changed in the following order:

$$x(6,3) \to x(6,2) \to x(6,1) \to x(5,3) \to x(5,2) \to x(5,1) \ldots \to x(1,3) \to x(1,2) \to x(1,1)$$

Path 4 represents a search path starting also from the element on the lower right corner in the matrix. It changes one element at a time in a column-wise way and from the right to the left. So the elements are changed in the following order:

$$x(6,3) \to x(5,3) \ldots \to x(1,3) \to x(6,2) \to x(5,2) \ldots \to x(1,2) \ldots \to x(6,1) \to x(5,1) \ldots \to x(1,1)$$

With the specified path and the starting point, the screening model can be run in the same manner as shown in the preceding section. Finally, each path will finally identify its decision candidate under a decision approach. This applies to both DA3 and DA4. Since the result for DA3 has the similar pattern to the result for DA4, this section is only going to show the result for DA4. The specific decisions identified under DA4 through these four paths are shown in Figure 43 and their performances characterized by VaRG chart are shown in Figure 44.

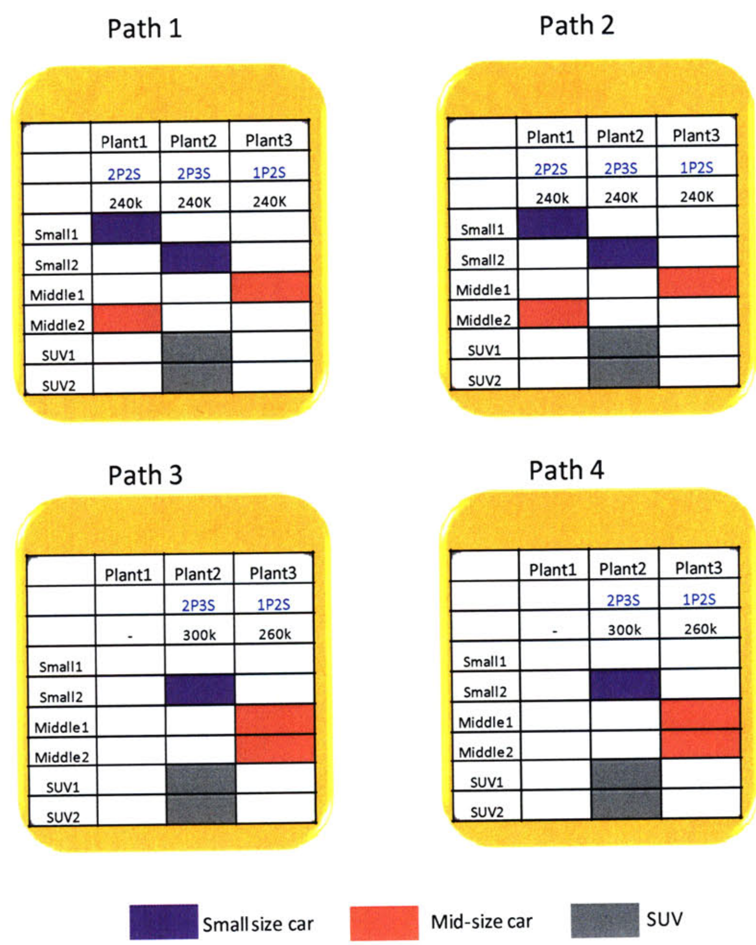

Figure 43 Decisions identified by the screening model through different search paths under DA4

As a result, under DA4, Path 1 and Path 2 led to the same decision candidate while Path 3 and Path 4 led to the same decision candidate. The decision identified through Path 1 and Path 2 is to build three plants: one plant is to produce two vehicles, one small size car and one mid-size car; the second plant is to produce three vehicles, one small size car, two SUVs; and the third plant is to produce one mid-size car. All three plants have capacities of 240,000. One can see that this decision is very different from the decision identified through Path 3 and Path 4, which is to build two plants, one of which is to produce three vehicles, one small size car and two SUVs while the other is to produce two mid-size vehicles.

The performances of these decisions are also very different. From Figure 44, one can see that the performances of the decision identified through Path 3 and Path 4, in general, performs better than the decision identified through Path 1 and Path 2 by having the whole curve shifting to the right with an improved ENPV and reduced downside risks.

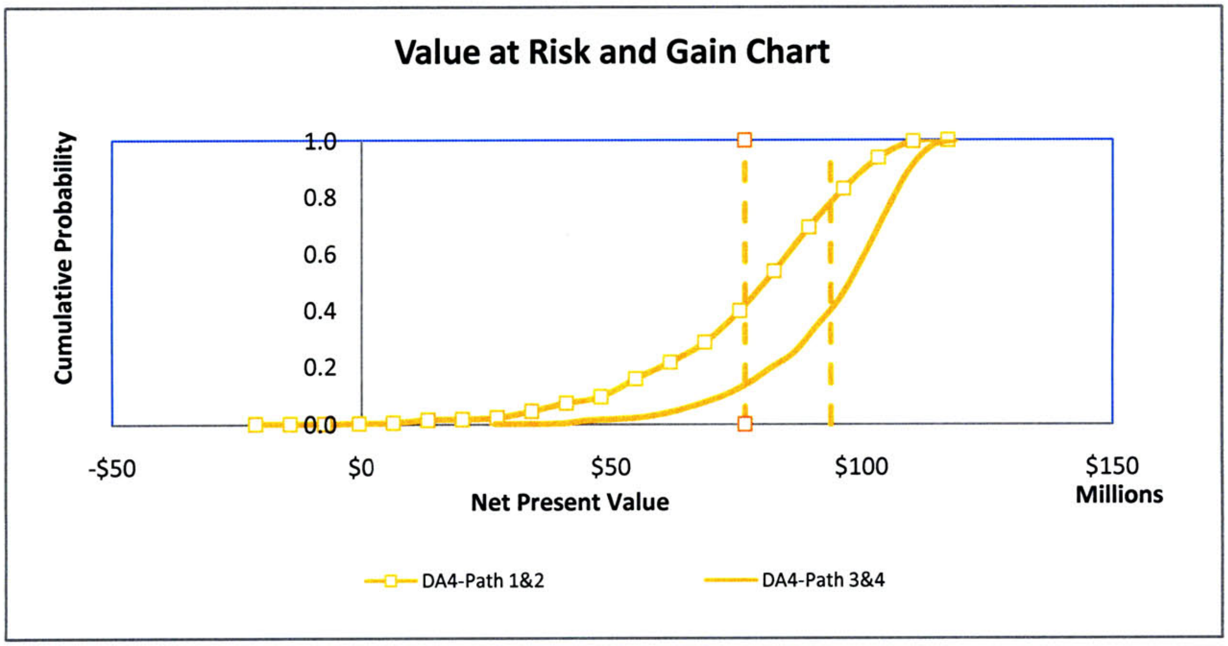

Figure 44 VaRG chart for decisions identified by the screening model through different paths

Table 35 Summary table for decisions identified through different exploration paths in the allocation decision space

Decision Approaches	Considers demand uncertainty?	Considers overtime flexibility?	INV (Million $)	NPV(million $)						Average Capacity Utilization	Expected Prod. (million units)
				ENPV	MIN	MAX	SD	VaR @5%	VaG @5%		
DA4-Path 1&2	Yes	Yes	476	76.7	(-21)	117	21	34	103	108%	38.92
DA4-Path 3&4	Yes	Yes	346	93.8	26	118	15	64	114	102%	28.52

Thus, the result indicates that although all of decisions identified by the screening model led to improvement of decision-making upon deterministic approaches, exploration of the allocation decision space through different paths leads to the identification of different decisions with different performances. On one hand, this suggests that when using the screening model, one should use different paths to explore the allocation decision space to improve the chance of identifying better decisions. Admittedly, this will increase the computational burden of the method. However, this is less of a concern with the multi-processors systems, which allows for parallel computing by different exploration paths. On the other hand, the result also indicates that future research should look into this issue to see how the convergence can be improved.

6.6 Summary

This chapter presents a case study in automotive industry with 6 different vehicles and 3 plants. Vehicle production to plant allocation decisions and plant capacities decisions are explored by using the screening model. To demonstrate the value of the proposed framework and the screening model, four decisions approaches to identifying decision alternatives are compared. These four decision approaches lead to four different strategic decisions. The result shows that using the screening model to identify decision candidate can lead to significant improvement of strategic decision making in improved ENPV, reduced downside risks and increased upside gain. In this case study, the application of screening model leads to about 40% of improvement for Expected NPV as compared to a deterministic optimization approaches. Finally, this chapter shows the convergence of the screening model from different exploration paths. It is found that although all these decisions improve upon decisions under the deterministic approaches, searching the allocation decision space through different paths leads to different decisions identified by the screening model. This result suggests that when using the screening model, exploring the allocation decision space through different paths will improve the chance of identifying good decision candidate. Also future research can explore how to improve the convergence of the solutions.

7 Computational evaluation

This chapter examines the computational efficiency and effectiveness of the screening model. In general, computational efficiency of a method can be measured by the computational time it takes a method to solve a formulated problem. Computational time is a function of the size of the problem to be solved. Normally, as the size of the problem gets larger, the computational time increases. On the other hand, computational times for different methods may scale at different rates. Thus, how quickly the computational time scales with the size of a problem is an important factor to evaluate computational performance of a method. In this chapter, the screening model is compared with two other methods: the exhaustive search method and the stochastic optimization method, in terms of the computational times it takes to solve a problem in the interest of this research.

Secondly, this chapter examines computational effectiveness of the screening model. Computational effectiveness means the quality of the solution provided by a method. Ideally, the method that provides better quality of solution will be preferred. However, this has to be balanced with the computational cost it takes the method to achieve the quality. If it takes too long time to get the best performance, the value of the method is reduced. As what will be shown in this chapter, although the exhaustive search method and the stochastic optimization method theoretically can lead to better performance than the screening model, the computational cost scales very rapidly with the size of the problem so that even for a moderate size of a problem, it is prohibitively high to get the optimal solution. Thus, it is not meaningful to compare the solution from the screening model with the solutions from the exhaustive search method and the stochastic optimization method. Instead, this thesis takes an alternative approach to evaluating the computational effectiveness of the screening model. It is done by measuring the improvement that the screening model can lead to upon the result from the optimization method that solves a deterministic and simplified problem which can be solved within a reasonable amount of time. Details are discussed in Section 7.2.

7.1 Evaluation of computational efficiency

The evaluation of computational efficiencies of different methods is made based on the computational times it takes different methods to solve a problem. The manufacturing planning problem studied in Chapter 6 is taken as an example problem for the computational efficiency evaluation while a simplified problem is taken as the example problem for the stochastic optimization. The simplification is that with the scenario-dependency of upcharge cost of flexible processes, it is hard to formulate the problem in the optimization framework, to the author's best knowledge. Thus, here in this chapter to compare the computational efficiency of the screening model to the stochastic optimization method, this is simplified by assuming the flexibility upcharge only depends on the number of styles added to a plant as shown in Formula (39). The resulted stochastic optimization formulation is provided in Appendix B.

For each method, the relationship between the computational time and the size of the problem is derived from either empirical tests or theoretical inference. The size of the problem is characterized by the number of input parameters. Based on the relationships, the scaling properties of the computational times for these three methods are then compared as to two inputs that are of the most interest in this research: the number of products and the number of plants in a system. All the computational time results are tested on a laptop with 2GHZ duo CPU and 2GB RAM.

7.1.1 Computational time for the exhaustive search method

The most direct way, which is also a "brute force" way, to solve the problem, is to exhaustively search the strategic decision space and get the decision that leads to the best performance by comparing all the decision alternatives. Because of the hierarchical structure of three levels of decisions, namely the product to plant allocation decision, the plant capacity decision and the operational production decision, the whole decision space can be exhaustively explored in a hierarchical manner. That is, at the highest level, to examine results for all the possible allocation scenarios; at the middle level, to examine all the possible capacity scenarios under an allocation scenario; at the low level, explore the operational decisions under a specific capacity plan and allocation scenario. Since operation decision space can be efficiently examined by linear optimization, only the allocation decision space and capacity decision space are examined exhaustively.

Assume $N_{allocation}$ is the total number allocation scenarios and N_{cap} is the total number of capacity decision scenarios under any allocation plan, and T_{opr} means the time needed to explore operational decision space by the SLP model under a specified allocation and capacity plan. Then total computational time can be represented by:

$$T = N_{allocation} \times N_{cap} \times T_{opr} \tag{40}$$

The following explains how these three numbers are derived for the exhaustive search method.

7.1.1.1 *The number of allocation alternatives: $N_{allocation}$*

Generally, for a problem with n products and m plants, every product can have m plants to be allocated. Then for every plant, there can be two options, 0 representing that a product is assigned to a plant or 1 otherwise. Thus, for every product, the number of allocation alternatives is

$$N_{product} = \underbrace{2 \times 2 \times \ldots \times 2}_{m} = 2^m \tag{41}$$

And there are n products, thus the total number of allocation alternatives is

$$N_{allocation} = \underbrace{2^m \times 2^m \times \ldots \times 2^m}_{n} = 2^{n \times m} \tag{42}$$

This shows that the total number of allocation plans grows exponentially with the product of the number products and the number of plants. As can be seen in Table 36, even when the size of the problem only grows slightly, the number of allocation scenarios grows substantially.

Table 36 Numerical example for the total numbers of allocation alternatives as a function of the number of products and the number of plants in a system

n	m	$N_{allocation}$
2	2	16
2	3	64
2	4	256
3	3	512
3	4	4096
3	5	32768

7.1.1.2 The number of capacity decision scenarios under an allocation plan: N_{cap}

To exhaustively explore the capacity decision space, it is discretized according to an interval δ. Assume the upper bound for a plant's capacity is represented by *UBC* and the lower bound for a plant capacity is *LBC*, then total number of capacity scenarios for a given plant *j* is

$$\left\lceil \frac{UBC_j - LBC_j}{\delta_j} \right\rceil$$

Assuming there are m plants in a system, the number of capacity scenarios under an allocation plan is:

$$N_{cap} = \left(\left\lceil \frac{UBC_j - LBC_j}{\delta_j} \right\rceil \right)^m \tag{43}$$

Some numerical example is helpful to show the scalability of this relationship. Assume the upper bound of a plant, *UBC,* is 300000 and lower bound, *LBC,* is 0, and the intervals between two levels next to each other is 2000, 150 levels of capacities for each plant needs to be examined. The number of capacities for a possible allocation plan is then:

Table 37 Number of capacities to be examined for a possible allocation plan

Number of plants (m)	N_{cap}
2	150^2=22,500
3	150^3=3,375,000
4	150^4=506,250,000
5	150^5=75,937,500,000

Combining with the number of allocation plans, the following table shows the total number strategic decisions to be examined:

$$N_{total} = N_{allocation} \times N_{cap} \tag{44}$$

Table 38 Total numbers of strategic decision alternatives under the exhaustive search method

Number of products	Number of plants	$N_{allocation}$	N_{cap}	N_{total}
2	2	16	22500	360000
2	3	64	3375000	216000000
2	4	256	506250000	1.296E+11
3	2	64	22500	1440000
3	3	512	3375000	1728000000
3	4	4096	506250000	2.0736E+12
4	2	256	22500	5760000
4	3	4096	3375000	1.3824E+10
4	4	65536	506250000	3.3178E+13
5	2	1024	22500	23040000
5	3	32768	3375000	1.1059E+11
5	4	1048576	506250000	5.3084E+14

Thus, the computational time for the exhaustive search method can be expressed as:

$$T_e = 2^{n\times m} \times \left(\left\lceil \frac{UBC_J - LBC_J}{\delta_J} \right\rceil \right)^m \times T_{opr} \tag{45}$$

This means that the linear optimization for operational decision space needs to be run $2^{n\times m} \times \left(\left\lceil \frac{UBC_J - LBC_J}{\delta_J} \right\rceil \right)^m$ times.

Thus if the time it takes to run one linear optimization, T_{opr}, is obtained, the total computational time is known. The following subsection studies how T_{opr} is obtained.

7.1.1.3 Computational time for operational decisions: T_{opr}

In the exhaustive search method and the screening model, the operational decision space is explored by solving the SLP model. The computational time to solve that model, denoted by T_{opr}, depends on the number of products, the number of plants, the number of periods and the number of scenarios simulated for uncertainty. Assume that the computational time of solving the SLP model is cast as a polynomial expression of the number of products and the number of plants such that

$$T_{opr} = \gamma_0 \times n^{\gamma_1} \times m^{\gamma_2} \times t^{\gamma_3} \times s^{\gamma_4} \tag{46}$$

Taking logrithm on both sides leads to the following relationshp:

$$\lg T_{opr} = \lg \gamma_0 + n \lg \gamma_1 + m \lg \gamma_2 + t \lg \gamma_3 + s \lg \gamma_4 \tag{47}$$

Then Full factorial design method is used to generate a set of experiments with the factors and levels shown in Table 39. Conducting all these experiments lead to the computatioal times for different sizes of the problem. The computational time results are shown in Appendix D.

Table 39 Factors and levels for full factorial design of experiments in operational decision space

Factors	levels
# of products (n)	2,3,4 ,5,6

# of plants (m)	2,3,4
# of periods(t)	1,3,5
# of scenarios(s)	250,500,1000

The computational times in is then regressed against the Equation (47) leads to the following result:

Table 40 Regression result for computational time of the SLP model

Regression Statistics	
Multiple R	0.934872
R Square	0.873985
Adjusted R Square	0.863698
Standard Error	0.172892
Observations	54

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
$lg\gamma_0$	-3.67831	0.278971	-13.1853	9.76E-18	-4.23892	-3.1177
$lg\gamma_1$	1.435307	0.227148	6.318829	7.53E-08	0.978837	1.891777
$lg\gamma_2$	0.446792	0.334156	1.337078	0.187372	-0.22472	1.118303
$lg\gamma_3$	0.844735	0.080677	10.4706	4.28E-14	0.682609	1.006861
$lg\gamma_4$	0.975415	0.095722	10.19003	1.07E-13	0.783053	1.167776

Converting the value of the coefficients in the regression results, the following relatinship is obtained:

$$T_{opr} = 0.00021 \times n^{1.54} \times m^{1.75} \times t^{0.84} \times s^{0.98} \tag{48}$$

Then the total computational time needed for the exhaustive search method is:

$$T_e = 2^{n \times m} \times \left(\left\lceil \frac{UBC_J - LBC_J}{\delta_J} \right\rceil \right)^m \times \left(0.00021 \times n^{1.54} \times m^{1.75} \times t^{0.84} \times s^{0.98} \right) \tag{49}$$

7.1.2 Computational time of the screening model

As described in Chapter 5, the screening model hierarchically explores the decision space: the allocation decision space, the capacity decision space and the operational decision space. So in this sense, the computational time can be expressed in the same way as the exhaustive search method:

$$T_p = N_{allocation} \times N_{cap} \times T_{opr} \tag{50}$$

However, different from the exhaustive search method, Design of Experiment methods are used to generate experiment plans to explore allocation decision space and capacity decision space, thus determining the number of experiments that need to be conducted at operational level. Although generating experiment plans by DoE methods takes time, but the time is very short (i.e. within seconds) and does not scale very much with the size of the problem, this time is illegible compared to the time it takes to conduct each experiment.

Firstly, for a problem with *n* number of products and *m* number of plants, the number of allocation scenarios required by the OFAT process is:

$$N_{allocation} = n \times m + 1 \tag{51}$$

Secondly, under a given allocation plan, the capacity decision space is searched by using Central Composite Design. The number of experiments that needs to be conducted only depends on the number of plants in the problem. The relationship is:

$$N_{cap} = 2^m + 2m + 1 \tag{52}$$

Where 2^m represents the number of full factorial designs, 2m represents the axis design, and 2m+1 represents the number of center runs.

$$T_p = (n \times m + 1) \times \left(2^m + 2m + 1\right) \times T_{opr} \tag{53}$$

Thus, the computational time for a problem with n products, m plants and t periods is derived as follows:

$$T_p = (n \times m + 1) \times \left(2^m + 2m + 1\right) \times \left(0.00021 \times n^{1\ 54} \times m^{1\ 75} \times t^{0.84} \times s^{0\ 98}\right) \tag{54}$$

7.1.3 Computational time for the stochastic optimization method

The stochastic optimization formulation of the example problem is presented in Appendix B.

Table 41 shows how the number of variables and the number of constraints of the stochastic optimization formulation scale with the number of parameters, including the number of products n and the number of plants m:

Table 41 Scaling issues of stochastic optimization formulation, assuming 5 periods and 5 demand scenarios for each product at each period

# of product	# of plant	# of integer variable (allocation decision)	# of nonlinear variable (capacity decision)	# of linear variable (operation decision)	Total variables	Total constraints
		O(mn)	O(m)	O(tns^n)	O(tns^n)	O(tns^n)
2	2	4	2	1,000	1,006	2,000
2	3	6	3	1,500	1,509	2,875
2	4	8	4	2,000	2,012	3,750
3	2	6	2	7,500	7,508	13,125
3	3	9	3	11,250	11,262	18,750
3	4	12	4	15,000	15,016	24,375
4	2	8	2	50,000	50,010	81,250
4	3	12	3	75,000	75,015	115,625
4	4	16	4	100,000	100,020	150,000
5	2	10	2	312,500	312,512	484,375
5	3	15	3	468,750	468,768	687,500
5	4	20	4	625,000	625,024	890,625
6	2	12	2	1,875,000	1,875,014	2,812,500
6	3	18	3	2,812,500	2,812,521	3,984,375
6	4	24	4	3,750,000	3,750,028	5,156,250

Table 41 is one way of characterizing the scaling property of a method with the size of the problem. But they do not necessarily lead to computational challenge. The computational time can be very short if the problem has good mathematical property, such as linearity or convexity. Thus, computational time is the ultimate measure for the computational effectiveness of a method.

An experiment is designed to obtain relationship between computational time it takes and the size of the problem, characterized by the number of products, the number of plants, the number of periods and the number of scenarios. The model is solved by using a commercially available software LINGO® 11.0 developed by the LINDO Systems, which has its own solvers for nonlinear and integer problems. The result is shown in Table 42. Note that the number of these parameters in the experiments in this table are relatively small, especially the number of products and the number of plants. This is because it takes too long to solve a problem with bigger size. For example, for a problem with 3 products, 3 plants, 5 periods and 5 scenarios for each demand, the problem didn't get solved after 20 hours.

Table 42 Computational times for experiments with stochastic optimization

No. of experiment	n(# of products)	m(# of plants)	t(# of periods)	s(# of scenarios)	CPU time (s)
1	2	2	3	5	128
2	2	2	5	3	50
3	2	2	5	5	444
4	2	3	3	3	171
5	2	3	3	5	842
6	2	3	5	3	405
7	2	3	5	5	1525
8	3	2	1	5	824
9	3	2	5	5	1980
10	3	3	1	5	32400
11	4	2	1	3	1002

Assume the relationship between computational time T_{so} and the parameters follows:

$$T_{so} = \zeta_0 \times n^{\zeta_1} \times m^{\zeta_2} \times t^{\zeta_3} \times s^{\zeta_4} \tag{55}$$

Taking logrithm on both sides leads to the following formula:

$$\lg T_{so} = \lg \zeta_0 + n \lg \zeta_1 + m \lg \zeta_2 + t \lg \zeta_3 + s \lg \zeta_4 \tag{56}$$

Then regressing the empirical results in Table 42 against Formula (56) leads to the following relationship:

Regression Statistics	
Multiple R	0.951384
R Square	0.905132
Adjusted R Square	0.841887
Standard Error	0.6764
Observations	11

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
$\lg \zeta_0$	-9.1729	2.689925	-3.41009	0.014317	-15.7549	-2.59089
$\lg \zeta_1$	6.195504	1.417461	4.370847	0.004715	2.727103	9.663906
$\lg \zeta_2$	5.51279	1.136731	4.849689	0.002853	2.731311	8.29427
$\lg \zeta_3$	0.446224	0.483679	0.922563	0.391823	-0.7373	1.629743
$\lg \zeta_4$	3.52675	0.837098	4.213068	0.005604	1.478445	5.575055

Then this result is converted to the relationship as expressed in Formula (55) so that the computational time for the stochastic optimization method is:

$$T_{so} = 0.000104 \times n^{6\,2} \times m^{5\,51} \times t^{0\,45} \times s^{3\,52} \tag{57}$$

7.1.4 Comparison of computational times for the methods

Now with Formula(49), (54), (57) representing the relationship between the computational times of different methods and the input parameters, computational efficiencies of methods can be compared. With these relationships, one can compare how different methods scale with the number of inputs in the problem. Two inputs are in the interest of this research: one is the number of products, the other is the number of plants. Therefore, the following is only going to show the scalability of different methods to these two parameters. The number of periods is assumed to be 5 and the number of simulated scenarios in SLP model is 500, and the number of scenarios for the stochastic optimization is assumed to be 5. Now the computational times for these three methods are shown in Formula (58), (59) and (60):

$$T_e = 2^{n\times m} \times \left(\left\lceil \frac{UBC_J - LBC_J}{\delta_J} \right\rceil \right)^m \times \left(0.36 \times n^{1.54} \times m^{1.75}\right) \tag{58}$$

$$T_p = (n \times m + 1) \times \left(2^m + 2m + 1\right) \times \left(0.36 \times n^{1.54} \times m^{1.75}\right) \tag{59}$$

$$T_{so} = 0.06 \times n^{6.2} \times m^{5.51} \tag{60}$$

Error! Reference source not found. shows computational times for three methods based on these relationships when m=3, meaning there are 3 plants in the manufacturing systems. It can be seen that computational time for the exhaustive search method scales in the most rapid way with the number of products. Because this scalability is in a different magnitude from stochastic optimization method and screening model, it makes the computational times of stochastic optimization and screening model almost indifferent. However, as **Error! Reference source not found.** shows, there is a big difference on the scalability between these two methods as well. Stochastic optimization takes much longer time than screening model method for larger size of problem. For the case studied in Chapter 6, it takes the screening model 2.5 hours to have one run. Even if the four paths are run successively instead of in parallel, it takes 10 hours to identify the solution. However, according to Figure 46, the estimated time is 500 hours to have the stochastic optimization problem solved. The same results are shown for a system with 4 plants in Appendix E.

Lastly, the computational time it takes for the screening model to solve a problem is shown in Figure 47 to give a sense of running time of the screening model for different sizes of a problem.

Different lines represent different numbers of plants in the manufacturing systems. Of course, it depends on the computer power that is used. With more computer powers, the time is going to be shorter.

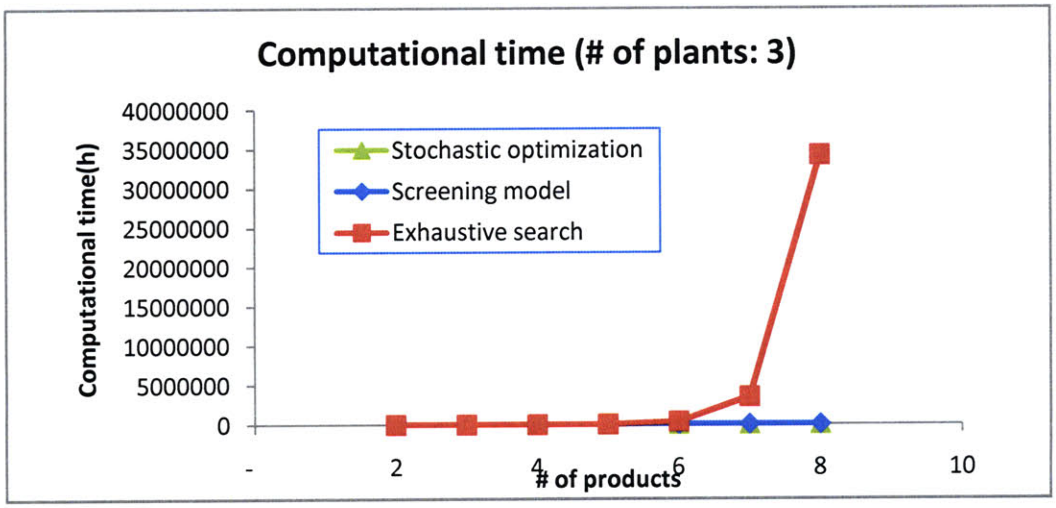

Figure 45 Increase of computational times for three methods as the number of products increases in a system with 3 plants.

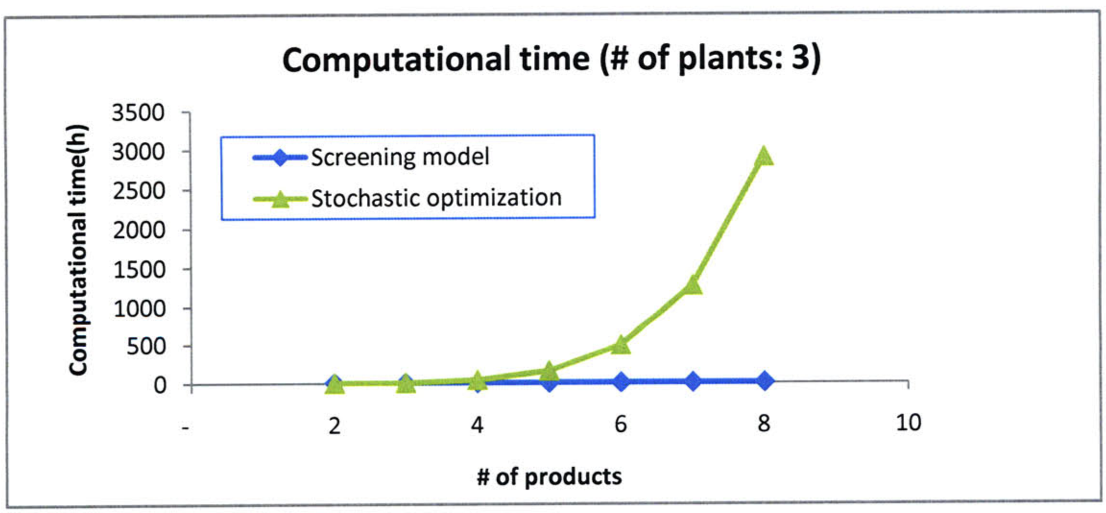

Figure 46 Increase of computational times for two methods as the number of products increases in a system with 3 plants.

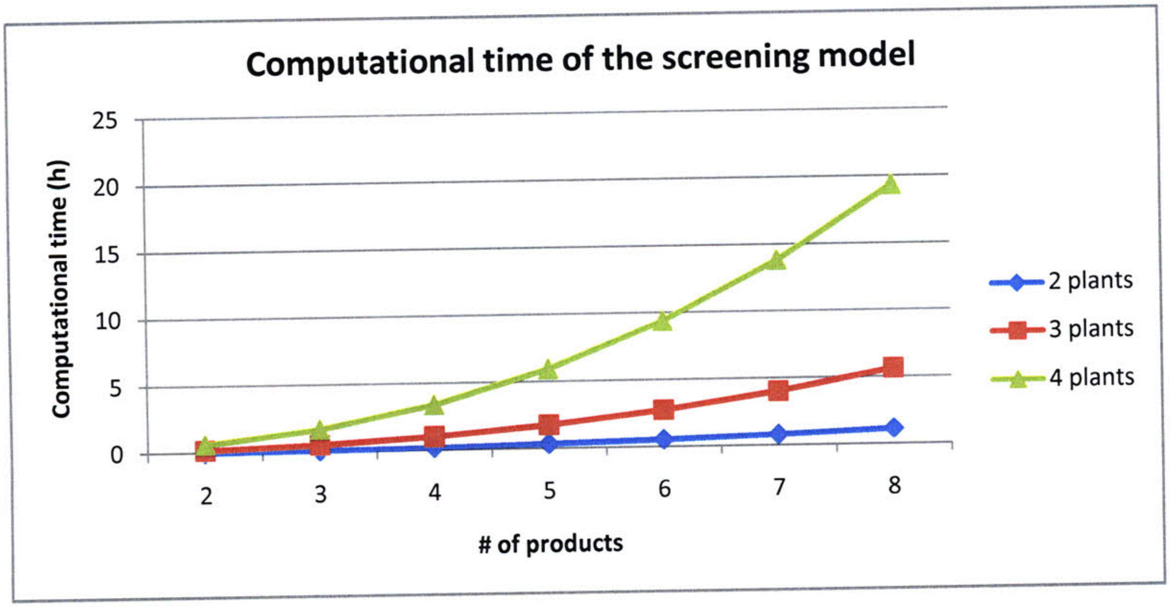

Figure 47 Computational time for the screening model

7.2 Evaluation of computational effectiveness

Computational effectiveness is to measure the quality of the results for a method. For the problem studied in this problem, the quality is here measured by the ENPV of the solution led to by a given method. Ideally, one would apply different methods on the same problem and compare the financial results of solutions from different methods. However, it is not feasible to compare the screening model to the exhaustive search method and the stochastic optimization method by applying them on the same problem for two reasons. One reason is that the exhaustive search method and stochastic optimization method scale too rapidly with the size of the problem so that it takes too long to get the result from these two methods even for a moderate size of the problem. The second reason is related only to stochastic optimization, which is that it is very hard to formulate the problem in the stochastic optimization framework, such as scenario-dependent process flexibility upcharge.

Alternatively, this research compares the solution of the screening model to the solution of the deterministic and simplified optimization approach, as was done in Case study 2 to specify the starting point. Then the computational effectiveness of the screening model is evaluated by the improvement of financial performance led by using the screening model as compared to the starting point.

Figure 48 shows this result for some cases based on the example problem studied in case study 2. 3 plants are considered in the system. Values of all parameters are the same as in case study 2. Then the products are added sequentially as the number of products increases. For example, the case with 3 products includes products A, B, and C; the case with 4 products includes products A, B, C and D. We can see that screening model consistently led to improvement of ENPV, at a range of 10 million to 40 million dollars as compared to the deterministic and simplified optimization method.

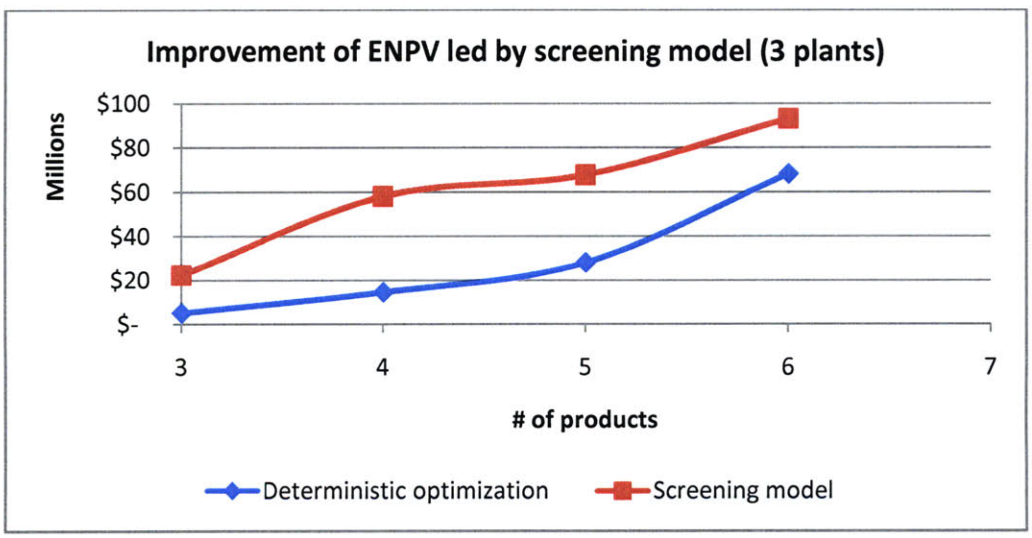

Figure 48 Improvement of ENPV by the screening model upon solutions of deterministic and simplified optimization approach for 3 plants.

7.3 Summary

This chapter evaluates the screening model in terms of its computational efficiencies and effectiveness. By examining the computational complexity of the screening model, exhaustive method and stochastic optimization method, this chapter compares how quickly each method scales with the size of the problem. It is shown that the screening model scales the least fast with the increase of the size of the problem, which makes it computationally appealing to explore large decision spaces. Then the computational effectiveness is examined based on sample problems in case study 2. The result shows that the screening model can lead to big improvement in terms of ENPV for the sample problem as compared to an optimization approach that assumes deterministic future demand and simplifies the complexity in the Body-In-White assembly systems.

8 Conclusions and future work

8.1 Summary and conclusions

This thesis describes research concerning methods to improve the planning and design of engineering systems that require large capital investment, involve many resources to be developed, are difficult to change once in place, and, yet, operate in an uncertain environment. The specific example of automotive manufacturing was selected as the case focus of this work. Economically effective decision making for such systems, including for automotive manufacturing systems, has been widely studied. Nevertheless, this thesis has identified three gaps in the literature and in current practice with regard to this area:

(1) For most firms today, strategic manufacturing planning decisions are often made based on deterministic demand forecasts. The implicit assumption is that decisions optimized for expected demand outcomes will lead to the best overall expected financial outcome. In most cases, this leads to implementation plans designed to just meet forecasted demand (possibly with an arbitrary factor of safety in one direction or the other) at lowest cost. However, because demands are uncertain and variable, the decision with the lowest cost may not be the optimal solution – foregoing revenue when demand is high and incurring undue cost when demand is low. In light of this mismatch between common practice and improved decision-making, this thesis has developed a computationally-tractable method to design and plan manufacturing flexibility.

(2) There is extensive research in the literature describing methods to identify appropriate forms and configurations of manufacturing flexibility during the early planning stage. In that body of work, although it is widely recognized that manufacturing flexibility can be improved through many mechanisms, few develop quantitative methods that value the interdependent value of multiple sources of

flexibility. More specifically, there has not been research that studies the following three decisions that determine three sources of flexibility: i) product to plant allocation, ii) capacity planning, and iii) overtime planning. To address this gap, this research examined the interactions of these three sources of flexibility and, in so doing, the impact of operational flexibility (overtime) on strategic decision-making (allocation and capacity).

(3) For real-world problems, the decision space associated with designing and planning manufacturing systems is immense. The consequential complexity poses a challenge for traditional optimization approaches when applied to uncertain, multi-period scenarios. Thus, this thesis presented a new method to efficiently explore a large decision space for large-scale manufacturing system planning.

In light of these three gaps, this has posed and answered four specific questions:

(1) What is the impact of considering demand uncertainty on strategic decision making for manufacturing systems?
(2) What is the impact of simultaneously considering operational flexibility on strategic decision making for manufacturing systems?
(3) How to evaluate the value of flexibility at the strategic planning stage?
(4) How can one identify good design candidates in a large design space?

To address these questions, this research developed a framework that contains two major components, as shown in Figure 49: the first is a screening model that adaptively explores a decision space to identify promising design candidates and the second is an evaluation model used to project the performance of candidates.

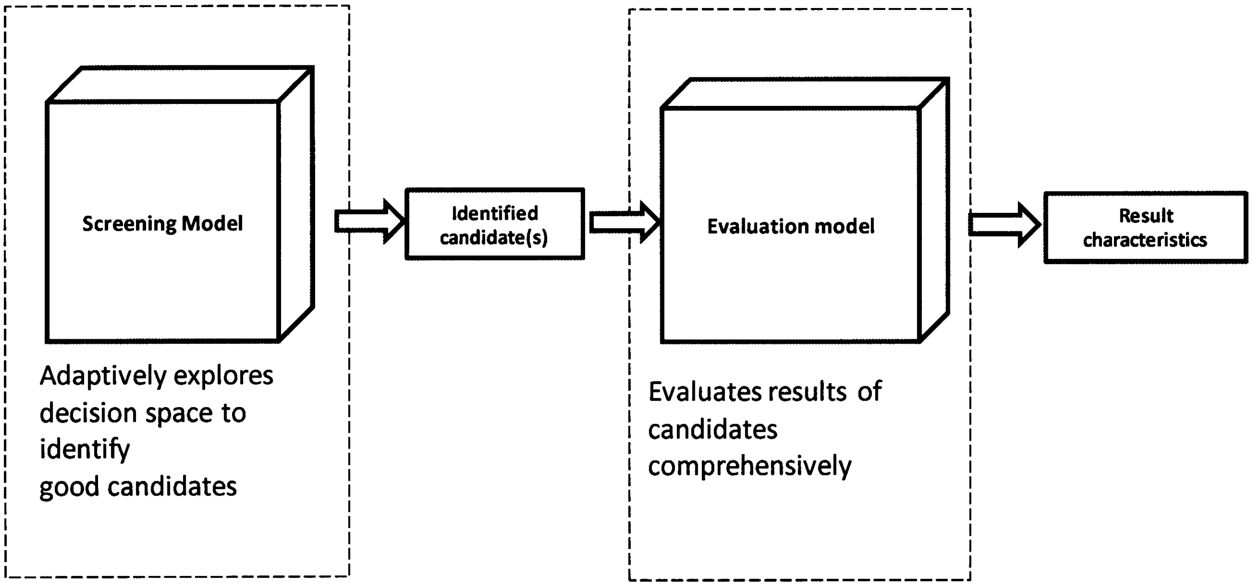

Figure 49 Graphic view of the framework developed in this research

The screening model provides a way to address the three pertinent decisions and demand uncertainty simultaneously. This model integrates an adaptive OFAT, the Response Surface Methodology, and a simulation-based linear optimization. Adaptive OFAT is used to explore the product to plant allocation decision space. Response Surface Methodology is used to explore the capacity decision space. Simulation based linear optimization is used to explore the operations decision space. Finally, this thesis employs the simulation approach to develop VaRG charts to characterize the performance of identified candidates.

Chapter 4 uses a simple case to demonstrate the value of considering uncertainty and operational flexibility – the first two questions raised in this research. The case considers a question about how to allocate two products to two plants and what capacity should each plant have. Overtime production decisions were considered - a source of operational flexibility.

In this simple case study, it was shown that consideration of demand uncertainty resolves the value of the flexible process design as compared to the deterministic approaches. Under the deterministic approaches, the optimal decision is to build 2 dedicated plants. But when demand uncertainty is considered, the optimal decision is to build 1 flexible plant. As a result, the flexible design leads to a much more stable cash flow than the dedicated design. Furthermore, these improvements do not require more upfront investment, but less investment. Notably, the flexible design consistently leads to lower expected production (or more expected lost sales), which means that firms must be prepared to accept strategies that sacrifice maximizing expected production and sales in exchange for a more stable cash flow.

In answering the second question as to the impact of considering operational flexibility, the simple case demonstrated that consideration of operational flexibility impacts the capacity planning decision and enhances the value of strategic process flexibility. When overtime flexibility is considered, the plant capacity becomes smaller, which reduces the upfront investment cost. Moreover, the expected net present value is improved, the downside risk is reduced, and the upside gain is increased! Furthermore, there is a synergy between overtime flexibility and process flexibility, even under positive demand correlation. This is embodied by that result that the benefit of overtime flexibility, which is characterized by an increased expected value, for a flexible process is more than the benefit for a dedicated process. Sensitivity analysis shows that the synergy is stronger under more negative correlation and higher standard deviation of demand uncertainty.

The third question is addressed by the evaluation model developed in this research. The identified decision candidate is evaluated using a simulation approach to simulate demand uncertainty. The results under the simulated scenarios are plotted in the VaRG chart complemented by the summary table. This chart shows all the possible outcomes of the simulated scenarios, and thus allowing one to evaluate the expected value, the downside risks, and the upside gains associated with the decision candidate. The summary table can also provide the key statistics of the VaRG chart, and other critical information that may affect decision making, such as required investment, expected production and capacity utilization. Hence, the VaRG chart and the complementary table provide a comprehensive way to evaluate the value of flexibility that some decision candidate may have, not only in terms of improving expected values, but also in terms of reducing downside risks and increasing upside gains.

The development of the screening model addresses the fourth question. Case study 2, presented in Chapter 6, demonstrates how the screening model can be used to explore problems with a large decision space that would be computational challenging for traditional optimization approaches. This case concerns the Body-In-White assembly system for the automotive industry. The planning question is to allocate 6 different vehicle bodies to 3 plants and to decide capacities for all plants. The six different vehicle bodies are distributed across three different platforms, two per platform. The size and complexity of the allocation decision space for this problem increases significantly so that it becomes computationally intractable for traditional stochastic optimization approaches. The screening model is able to search in this large decision space and identifies promising decision candidates with more flexible processing and fewer plants as compared to a deterministic optimization approach. These differences lead to about 40% improvement of expected net present value with reduced downside risks and increased upside gain.

In Chapter 7, the computational efficiency and effectiveness of the screening model are examined. To evaluate the computational efficiency, the screening model is compared with two other methods: the exhaustive search method and the stochastic optimization with recourse. Based on regressed computational time, it is shown that the screening model reduces the computational time significantly relative to these two methods. Then computational effectiveness is evaluated based on the improvement that the screening model can bring upon the solution provided by a deterministic and simplified optimization approach that can be solved computationally efficiently based on the assumptions of Case study 2. In this case, it is shown that the screening model leads to a sizable improvement overall as compared to the deterministic optimization approach.

8.2 Contributions

This research has made the following academic and industrial contributions:

(1) Proposed a systematic framework for planning and designing manufacturing systems with multiple products, multiple production facilities over multiple periods, which:

   a. Considers demand uncertainty, thus allowing one to recognize the value of flexibility in the manufacturing systems at the strategic planning stage;
   b. Considers multiple sources of flexibility existing in manufacturing systems, which allows one to study the interactions between these sources and improves the decisions making at the strategic planning stage; and
   c. Evaluates design alternatives by using VaRG charts complemented by a summary table so that decisions makers examine the probabilistic economic characteristics of design alternatives more comprehensively.

(2) Developed an integrated screening model approach to design and plan large-scale, complex manufacturing systems, which:

   a. Provides a computationally practical means to explore the large decision space associated with multi-product, multi-facility, multi-source flexibility decision-making;
   b. Comprises Design of Experiments methods – Adaptive one-factor-at-a-time (OFAT) to explore the product to plant allocation decision and Response Surface Methodology to explore plant capacity decision – and a simulation based linear optimization to explore operational decisions;
   c. Realizes a flexible decision-making approach in that it can work with complexity in manufacturing systems that may be challenging for traditional optimization approaches to formulate, but that can be integrated with traditional

optimization approaches.

(3) Applied the integrated screening model in a case study of the automotive industry, demonstrating that this method can lead to significant financial performance improvement as compared to a deterministic and simplified optimization approach.

8.3 Limitations and future work

There are several limitations associated with the method developed in this research and the industrial application of this method. The following discusses these limitations and suggests future work to address them:

(1) The cost model used in this work is at a mid-fidelity level. It is able to characterize the complexity of the manufacturing system while allowing quick calculation. In the evaluation model, the same cost model is used to evaluate identified candidates. It will be desirable to use a high-fidelity cost model at this stage to verify the consequence of decision candidates. Such a model has been developed separately by the author which is a Flexible Process-Based Cost Model. Thus, the immediate step continuing this work is to imbed the Flexible Process-Based Cost Model into the evaluation model with simulation, which should provide more accuracy to evaluate decision candidates.

(2) Although this research has incorporated the investment cost and production cost of manufacturing flexibility, it does not consider other aspects of the costs that are associated with the product to plant allocation decision. For example, the transportation costs for materials and for final products are not currently comprehended. Similarly, the different tax policies or rebates associated with specific regions are not comprehended. While the method provided in this research can be a valuable tool that helps decision making, it certainly needs to be combined with other

factors to make the decision.

(3) This research has considered product to plant allocation, capacity and overtime flexibility in addressing demand uncertainty. There are other sources of flexibility existing in practice. For example, shift selection is another operational flexibility often considered in practice to respond to demand uncertainty. Another example is that, if longer periods are considered, capacity expansions and plant reconfigurations are strategic options that are available to firms. The further examination of these factors on the impact of strategic planning decision making will help to improve a system's capability to respond to market uncertainty.

(4) This research assumes that firms make their production decisions based on make-to-order instead of make-to-stock. This is more common practice in the US while make-to-stock is more common in European manufacturing industries. It would be interesting to implement the other alternative in the framework developed in this research to see how that will affect decision making.

(5) This research assumes that not being able to meet a product's demand needed by the market only affects firms' revenue on that product while not considering the effect that this may have on long term profitability and consumer satisfaction. As Graves (2002) suggests, "a firm might incur a loss of customer goodwill that would manifest itself in terms of reduced future sales". However, this research also shows that strategies that have reduced lost sales may have high financial risks. So it would be an interesting research to look at how these tradeoffs should be considered in improving firms' strategic decision makings.

(6) Although the screening model developed in this research can lead to improvement of systems' performance, it has the following limitations: (1) It does not guarantee

global optimality. OFAT method only explores a fraction of the allocation decision space; RSM also introduces regression error to the model. For both reasons, the solution from the screening model may not be the global optimal solution. (2) It does not guarantee convergence of solutions. Starting from different initial solutions can lead to different solutions; exploring the allocation decision space through different paths can also lead to different solutions. (3)Its computational efficiency may be further improved. The current exploration of product to plant the allocation decision space by the OFAT method does not consider some special property that may exist in the system. For example, there may be symmetry in the system if plants under consideration are indifferent before products are assigned and capacities are decided. In this case, the actual decision space that OFAT method needs to explore can be reduced. Future work can look to addressing these limitations.

(7) Running the screening model on a multiple-processor system can help to further improve its computational efficiency so as to allow access to larger problems, e.g. 20 products with 20 plants, which is a more realistic size for many companies. On the other hand, multiple-processor system enables the screening model to explore a decision space through different paths simultaneously, so it can also help to improve the computational effectiveness or optimality of the solutions without significantly increasing computational time.

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Appendix A Optimization problem to specify a starting point for the screening model in case study 2

As discussed in Chapter 6.3.1, the optimization problem that is formulated and solved to specify a starting point for the screening model has three simplifications:

(1) No demand uncertainty
(2) Simplification of the tool flexibility upcharge
(3) No economies of scale

The meanings of the symbols are the same as described in the thesis, and thus not repeated here.

$$\underset{x,y,w,z}{Max} \quad \underbrace{-\sum_{j}\left(\frac{y_j}{200,000}\right)\times\left(F_e + F_t\times\left(1+\beta_0\times\left(\sum_{i} x_{ij}-1\right)\right)+F_b\right)}_{first\ stage\ decision} + \underbrace{\sum_{t}\frac{1}{(1+r)^t}\times\left(\sum_{ij}\left(p_i\left(w_{ijt}+z_{ijt}\right)-\left(vc_{ni}w_{ijt}+vc_{oi}z_{ijt}\right)\right)\right)}_{second\ stage\ decision}$$

(61)

$$where \quad x\in(0,1), y, w, z\geq 0$$

s.t.

$$y_j \leq H\times x_{ij} \qquad \forall i,j \qquad (62)$$

$$w_{ijt} \leq H\times x_{ij} \qquad \forall i,j,t \qquad (63)$$

$$z_{ijt} \leq H\times x_{ij} \qquad \forall i,j,t \qquad (64)$$

$$\sum_{i} w_{ijt} \leq y_j \qquad \forall i,j,t \qquad (65)$$

$$\sum_{i} z_{ijt} \leq \theta y_j \qquad \forall i,j,t \qquad (66)$$

$$\sum_{j}\left(w_{ijt}+z_{ijt}\right)\leq \bar{d}_{it} \qquad \forall i,t \qquad (67)$$

$$\sum_{i}\left(w_{ijt}+z_{ijt}\right)\leq CAP_j \qquad \forall j,t \qquad (68)$$

Appendix B Stochastic optimization formulation of the simplified problem

The following stochastic optimization formulation is used in the evaluation of computational efficiency. The computational time it takes this formulation to solve a problem is compared to the computational times with the screening model and with the exhaustive search method. This formulation simplifies the original problem in that the tool flexibility upcharge is assumed to only depend on the number of product styles allocated to a plant.

$$\underset{x,y,w,z}{Max} \quad \underbrace{-\sum_{j}\left(\frac{y_j}{200000}\right)^{\alpha}\times\left(F_e+F_t\times\left(1+\beta_0\times\left(\sum_{i}x_{ij}-1\right)+F_b\right)\right)}_{\textit{first stage decision}}$$
$$+\underbrace{\sum_{s,t}\frac{1}{(1+r)^t}\times\varphi_s\times\left(\sum_{ij}\left(p_i\left(w_{ijst}+z_{ijst}\right)-\left(vc_{ni}w_{ijst}+vc_{oi}z_{ijst}\right)\right)\right)}_{\textit{second stage decision}} \tag{69}$$

$$where \quad x\in(0,1),y,w,z\geq 0$$

s.t.

$$y_j\leq H\times x_{ij} \qquad \forall i,j \tag{70}$$

$$w_{ijst}\leq H\times x_{ij} \qquad \forall i,j,s,t \tag{71}$$

$$z_{ijst}\leq H\times x_{ij} \qquad \forall i,j,s,t \tag{72}$$

$$\sum_i w_{ijst}\leq y_j \qquad \forall i,j,s,t \tag{73}$$

$$\sum_i z_{ijst}\leq \theta y_j \qquad \forall i,j,s,t \tag{74}$$

$$\sum_j\left(w_{ijst}+z_{ijst}\right)\leq d_{ist} \qquad \forall i,s,t \tag{75}$$

$$\sum_i\left(w_{ijst}+z_{ijst}\right)\leq CAP_j \qquad \forall j,s,t \tag{76}$$

Appendix C Intermediate results for applying the screening model on the case study 2

The following table shows the intermediate results for applying the screening model in the case study 2. It shows the allocation plan that is explored during each step of the OFAT process ($X_{(k)}$), the response that is obtained through the RSM model and the SLP model ($\Gamma_{(k)}$), and the corresponding capacity decision ($y_{(k)}$).

It also shows the values of the regression coefficients in the RSM regression model. The values are, in order, for the regression coefficients λ_0, λ_1, λ_2, λ_3, λ_{11}, λ_{22}, λ_{33}, λ_{12}, λ_{13}, and λ_{23}, with which the regression model is extended as:

$$\Gamma = \lambda_0 + \lambda_1 y_1 + \lambda_2 y_2 + \lambda_3 y_3 + \lambda_{11} y_1^2 + \lambda_{22} y_2^2 + \lambda_{33} y_3^2 + \lambda_{12} y_1 y_2 + \lambda_{13} y_1 y_3 + \lambda_{23} y_2 y_3 + \varepsilon \tag{77}$$

The r-squares of the regression analyses are shown in the next column.

Finally, it shows whether the change of allocation plan is retained or not depending on whether it leads to an improvement of the response as compared to the previous allocation plan.

Table 43 Intermediate results for applying the screening model in the case study 2

Experiment No.	Allocation Plan $X_{(k)}$	Response $\Gamma_{(k)}$	Capacity $y_{(k)}$	Regression coefficients λ (*10^7)	R^2	Change retained or not
0	$X_{(0)} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{bmatrix}$	\$68,430,666	[175,643 237,118 131,732]	7.3515 4.3316 5.6995 4.3913 0.0000 0.0000 0.0000 1.4060 1.0606	0.7800	N/A

				1.8039		
1	$X_{(1)} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix}$	$55,278,695	[154,146 181,450 154,763]	9.8734 4.2244 7.4237 6.7915 0.0000 0.0000 1.9547 1.3703 1.2121 1.0483	0.6702	No
2	$X_{(2)} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	$26,090,289	[153,536 124,278 124,550]	7.2973 4.9337 5.3264 4.9933 0.0000 0.0000 0.0000 1.6067 2.1429 2.0045	0.6203	No
3	$X_{(3)} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 1 & 1 & 0 \end{bmatrix}$	$59,683,438	[259,031 139,958 121,396]	8.1037 4.9237 6.4080 4.3301 1.2593 0.0000 0.0000 0.6102 1.1239 1.7835	0.7653	No
4	$X_{(4)} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 1 & 0 \end{bmatrix}$	$55,455,782	[154,184 176,684 161,261]	1.0330 0.4187 0.7838 0.6896 0.0000 0.0000 0.2047 0.1358 0.1284 0.1017	0.6976	No

5	$X_{(5)} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}$	$26,841,170	[153,625 118,143 124,041]	6.8675 4.8156 4.9742 4.8753 0.0000 0.0000 0.0000 1.5673 2.1051 1.9652	0.6657	No
6	$X_{(6)} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \\ 1 & 1 & 0 \\ 0 & 1 & 0 \end{bmatrix}$	$59,034,642	[271,198 133,990 121,344]	8.5245 5.0198 6.7813 4.3204 1.3195 0.0000 0.0000 0.5995 1.1952 1.7802	0.7777	No
7	$X_{(7)} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{bmatrix}$	$87,618,393	[0 294,451 257,719]	8.7591 4.5867 5.1321 5.9310 0.0000 1.7957 0.0000 0.9942 0.8715 1.1507	0.8309	Yes
8	$X_{(8)} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \\ 1 & 1 & 1 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{bmatrix}$	$79,036,370	[0 300,000 228,418]	9.3062 4.6806 4.2976 5.9050 0.4040 1.6280 0.1819 0.9914 0.4401 1.1731	0.8062	No
9	$X_{(9)} =$	$84,244,851	[0 300,000	5.6478 6.5827 4.6003 2.2364 0.0000	0.9475	No

	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{bmatrix}$		300,000]	0.0000 0.0000 0.7212 0.6942 0.0163		
10	$X_{(10)} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{bmatrix}$	$44,795,984	[0 300,000 0]	1.2804 1.6014 4.8582 1.6014 0.0000 1.3221 0.0000 0.0710 0.7802 0.0710	0.9411	No
11	$X_{(11)} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 1 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{bmatrix}$	$78,068,602	[0 300,000 220141]	9.6426 4.6049 4.3455 6.2289 0.1837 1.8530 0.4988 0.9226 0.3446 1.0749	0.8292	No
12	$X_{(12)} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 1 & 0 & 1 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{bmatrix}$	$84,244,851	[300000 300000 0]	8.3553 4.8656 4.6231 4.8656 0.0000 2.7039 0.0000 0.6227 0.7018 0.6227	0.8897	No
13	$X_{(13)} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{bmatrix}$	$58,775,086.23	[239,191 239,191 239,191]	7.1875 3.7231 5.0041 1.6186 0.0000 0.2739 0.0000 1.1275 0.8288	0.7914	No

				0.0062		
14	$X_{(14)} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{bmatrix}$	$93,818,969	[0 300,000 260,118]	8.6204 4.5115 2.5874 5.8558 0.0000 1.7957 0.0000 0.9692 0.0590 1.1256	0.8566	Yes
15	$X_{(15)} = \begin{bmatrix} 0 & 0 & 0 \\ 1 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{bmatrix}$	$59,458,191	[239,191 239,191 239,191]	7.9934 2.0185 2.8839 3.5571 0.2182 0.9342 0.1290 0.1478 0.0671 0.1755	0.8625	No
16	$X_{(16)} = \begin{bmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{bmatrix}$	$61,455,386	[118,276 300,000 300,000]	7.1154 3.7111 2.5002 1.5492 0.0000 0.3700 0.0000 1.0995 0.0880 0.0331	0.8193	No
17	$X_{(17)} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{bmatrix}$	$78,292,773	[0 300000 258,756]	8.7777 4.5537 1.7073 5.8980 0.0000 1.7957 0.0000 0.9833 0.1983 1.1397	0.8212	No
18	$X_{(18)} =$	$71,292,302	[239,191 239,191 239,191]	6.8753 1.2159 2.2050 3.0486	0.8626	No

	$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{bmatrix}$			0.0000 0.6864 0.0000 0.2181 0.1865 0.1666		

Appendix D Computational times of the SLP model

Table 44 shows the computational time to solve the SLP model with different sizes, which are characterized by the number of products, plants, periods and scenarios that simulates demand uncertainty. The experiments are the result of Full Factorial Design. This result is used in Section 7.1.1.3 to derive the relationship between the computational time of the exhaustive search method and the screening model and the number of input parameters in order to evaluate the computational efficiency of different methods.

Table 44 Computational times of the SLP model for the operational decision space

n(# of products)	m(# of plants)	t(# of periods)	s(# of Scenarios)	CPU time (s)
2	2	1	500	0.88
2	2	3	500	1.42
2	2	5	500	1.81
3	2	1	500	0.71
3	2	3	500	1.18
3	2	5	500	2.07
3	3	1	500	0.94
3	3	3	500	1.49
3	3	5	500	3.41
4	3	1	500	0.95
4	3	3	500	2.10
4	3	5	500	3.61
5	4	1	500	1.54
5	4	3	500	3.94
5	4	5	500	7.84
6	3	1	500	1.48
6	3	3	500	5.56
6	3	5	500	13.83
2	2	1	250	0.38
2	2	3	250	0.49
2	2	5	250	0.63
3	2	1	250	0.41
3	2	3	250	0.63

3	2	5	250	0.92
3	3	1	250	0.44
3	3	3	250	0.84
3	3	5	250	1.16
4	3	1	250	0.50
4	3	3	250	0.94
4	3	5	250	1.37
5	4	1	250	0.82
5	4	3	250	1.63
5	4	5	250	3.22
6	3	1	250	0.66
6	3	3	250	2.09
6	3	5	250	4.84
2	2	1	1000	0.61
2	2	3	1000	1.33
2	2	5	1000	1.99
3	2	1	1000	0.79
3	2	3	1000	1.90
3	2	5	1000	2.90
3	3	1	1000	1.09
3	3	3	1000	2.94
3	3	5	1000	4.23
4	3	1	1000	1.30
4	3	3	1000	3.47
4	3	5	1000	5.56
5	4	1	1000	3.50
5	4	3	1000	11.27
5	4	5	1000	30.33
6	3	1	1000	3.40
6	3	3	1000	18.08
6	3	5	1000	45.78

Appendix E Comparison of computational times for 4 plants

The following charts show how the computational time of different methods scales with the number of products for a system with 4 plants.

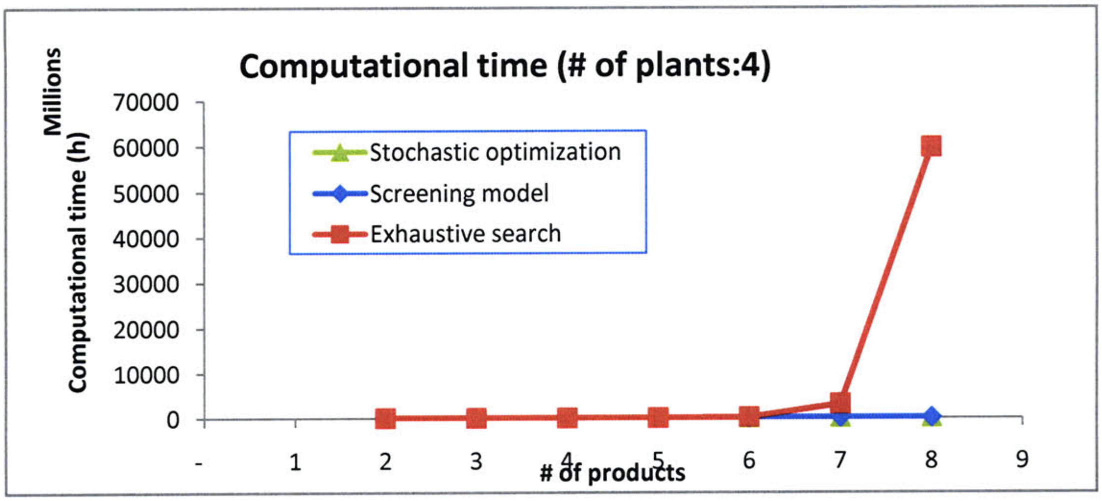

Figure 50 Increase of computational times for three methods as the number of products increases in a system with 4 plants

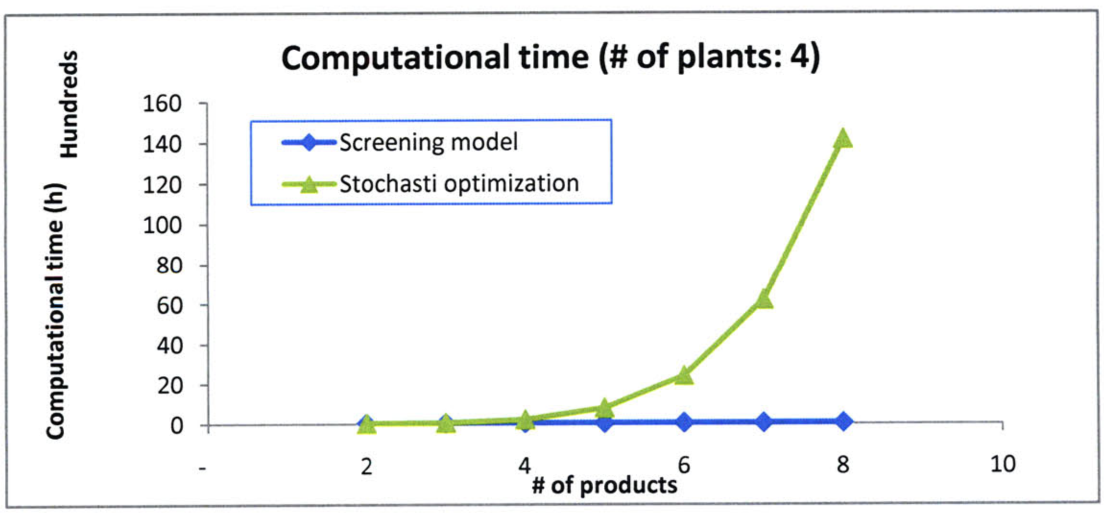

Figure 51 Increase of computational times for two methods as the number of products increases in a system with 4 plants

Appendix F VBA code for the screening model

```
Sub DOEsolve()
Sheets("results").Range("c25:h25").ClearContents
Sheets("results").Range("c26:c33").ClearContents


Sheets("Input").Range("b27:i27").Copy

Sheets("results").Select
Range("allocationproduct").Select
Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
:=False, Transpose:=True

Sheets("results").Range("d14:i14").Copy

Sheets("results").Select
Range("allocationplant").Select
Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
:=False, Transpose:=False

Dim a As Variant
Dim b As Variant
Dim c As Variant
Dim d As Variant
Dim e As Variant


a = Timer()

Dim nproduct As Integer
Dim nplant As Integer
Dim minlevel As Double
Dim medlevel As Double
Dim highlevel As Double
Dim M As Double
Dim ralpha As Double

minlevel = Range("min_level").Value
medlevel = Range("med_level").Value
highlevel = Range("high_level").Value
```

```
nproduct = Range("nfproduct").Value
nplant = Range("nfplant").Value
M = Range("bigM").Value
ralpha = Range("ralpha").Value

''''''get the value for nplant and nproduct and generate allocation scenario. The current code
just picks up one scenario, which needs to
'be modified in a loop format.

MLEvalstring "clear all"
MLShowMatlabErrors "yes"

MLputvar "nprod", nproduct
MLputvar "nplant", nplant
MLputvar "min", minlevel
MLputvar "med", medlevel
MLputvar "high", highlevel
MLputvar "M", M
MLputvar "ralpha", ralpha


MLEvalstring "[X,design,capacitymat] = DOEtry(nplant,min,med,high)"
MLgetmatrix "capacitymat", Sheets("results").Range("Target2").Address
MatlabRequest

MLEvalstring "num_cap_expm = size(capacitymat,1)"
MLgetmatrix "num_cap_expm", Sheets("results").Range("numcapexpm").Address
MatlabRequest

Dim profit As Variant
Dim optim_profit As Variant
optim_profit = -1000000000
Dim optim_optim_profit As Variant

Dim optim_x As Variant
Dim optim_allo As Variant

Dim x As Variant
Dim k As Integer

Dim i As Integer
Dim j As Integer
```

```
Dim q As Integer

i = 1

Dim expm As Double
expm = Range("numcapexpm").Value

     MLputmatrix "allo", Sheets("results").Range("allocation")

''''''''''The following line of code insures that, if this is what one wants, then start the point of
the optimal point for deterministic approach.
     'Range("track_optallo").Value = Range("allocation").Value

     Call startingpointDoE
     optim_profit = Range("optim_profit").Value

     '''Alter allocation values

     Do While (i <= nproduct)

        'MsgBox "goi" & i
        j = 1
          Do While (j <= nplant)
          q = 1

          'MsgBox "goj" & j
          Sheets("results").Range("allocation").Value = Range("track_optallo").Value

          If j > 0 Then

          If Sheets("results").Range("Target1").Offset(rowoffset:=i - 1, columnoffset:=j - 1).Value
= 0 Then
          Sheets("results").Range("Target1").Offset(rowoffset:=i - 1, columnoffset:=j - 1).Value =
1
          Else
          Sheets("results").Range("Target1").Offset(rowoffset:=i - 1, columnoffset:=j - 1).Value =
0
          End If
          End If

          MLputmatrix "allo", Range("allocation")
```

```
''''''''''''''''Simulate response surface
    'MsgBox "go" & expm
     Do While (q <= expm)

            Sheets("results").Range("capacity").Value =
Sheets("results").Range("capplant").Offset(rowoffset:=q - 1, columnoffset:=0).Value


            Range("finish").Value = 0
            Application.DisplayAlerts = False
            Call LINGOSolve
            Application.DisplayAlerts = True
            Do Until x = 1
              If Range("finish").Value = Range("bigM").Value Then x = 1
              DoEvents
            Loop

            Range("profitexpm").Offset(rowoffset:=q - 1, columnoffset:=0).Value =
Range("profit").Value

            q = q + 1
      Loop
    MLputmatrix "Y", Range("profitall")
    MLputmatrix "data", Range("capacitydata")
    MLEvalstring "maxsampleind=find(Y == max(Y))"
    MLEvalstring "maxsampleprofit=Y(maxsampleind(1))"
    MLEvalstring "maxsamplecap=data(maxsampleind(1),:)"

    MLgetmatrix "maxsampleprofit", Range("maxsampleprofit").Address
    MatlabRequest

    MLgetmatrix "maxsamplecap", Range("maxsamplecap").Address
    MatlabRequest

    MLgetmatrix "beta", Range("Target3").Address
    MatlabRequest

''''''''''''''''''''''''''''''''regression for response surface and optimize
    MLEvalstring "stats=regstats(Y,data,'quadratic')"
    MLEvalstring "beta=stats.beta"

    MLgetmatrix "beta", Range("Target3").Address
```

```
    MatlabRequest


    MLEvalstring "[x,fval]=optimrst(nprod,nplant,allo,beta,high,M)"
    MLEvalStringWithErrBox ("[x,fval]=optimrst(nprod,nplant,allo,beta,high,M)")
    MLgetmatrix "x", Range("Target4").Address
    MatlabRequest
    MLEvalstring "regprofit=beta(1)-fval"
    MLgetmatrix "regprofit", Range("regprofit").Address
    MatlabRequest

    Range("optcapacity").Copy
    Range("capacity").Select
    Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
    :=False, Transpose:=True

    Range("finish").Value = 0

    Application.DisplayAlerts = False
    Call LINGOSolve
    Application.DisplayAlerts = True

    Do Until x = 1
      If Range("finish").Value = Range("bigM").Value Then x = 1
      DoEvents
    Loop

'''''''' get optimal setting

    If Range("profit").Value >= Range("maxsampleprofit").Value Then


      If (optim_profit - Range("profit").Value) < 0.001 Then
        optim_profit = Range("profit").Value
        Range("optim_profit").Value = Range("profit").Value

        Range("track_optcapacity").Value = Range("optcapacity").Value

        Range("track_optallo").Value = Range("allocation").Value

        MLEvalstring "optim_beta = beta"
        MLputmatrix "optim_allo", Sheets("results").Range("track_optallo")
```

```
      End If

    Else

      If (optim_profit - Range("maxsampleprofit").Value) < 0.001 Then
        optim_profit = Range("maxsampleprofit").Value
        Range("optim_profit").Value = Range("maxsampleprofit").Value
        Range("maxsamplecap").Copy
        Range("track_optcapacity").Select
        Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
        :=False, Transpose:=True

        MLEvalstring "optim_beta = 0"
        Range("track_optallo").Value = Range("allocation").Value
        MLputmatrix "optim_allo", Sheets("results").Range("track_optallo")
      End If

    End If

    'MsgBox "optim for this run is" & optim_profit
'd = Timer()
'e = d - a
'Sheets("results").Range("time").Value = e

    j = j + 1

  Loop

    i = i + 1
Loop

Range("track_optcapacity").Copy
Range("capacity").Select
Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
:=False, Transpose:=True

MLgetmatrix "optim_beta", Range("Target3").Address
MatlabRequest

MLgetmatrix "optim_allo", Range("allocation").Address
MatlabRequest
```

```
    MLputmatrix "allo", Sheets("results").Range("allocation")

    Range("finish").Value = 0
    Application.DisplayAlerts = False
    Call LINGOSolve
    Application.DisplayAlerts = True
    Do Until x = 1
      If Range("finish").Value = Range("bigM").Value Then x = 1
      DoEvents
    Loop

b = Timer()
c = b - a

Sheets("results").Range("time").Value = c
```