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Sustainable Infrastructure System Modeling under Uncertainties and Dynamics

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Sustainable Infrastructure System Modeling under Uncertainties and Dynamics

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Dedication

To Jingjing Zhang, Tao Huang, and Furong Yang

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A five-year endeavor of dissertation research is coming to the end. Though only my name appears on the cover of this dissertation, a great many people have contributed to its production. I am grateful to all of them who made the dissertation possible and because of whom my graduate experience has been one that I will cherish forever.

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Abstract

Infrastructure systems support human activities in transportation, communication, water use, and energy supply. The dissertation research focuses on critical transportation infrastructure and renewable energy infrastructure systems. The goal of the research efforts is to improve the sustainability of the infrastructure systems, with an emphasis on economic viability, system reliability and robustness, and environmental impacts.

The research efforts in critical transportation infrastructure concern the development of strategic robust resource allocation strategies in an uncertain decision-making environment, considering both uncertain service availability and accessibility. The study explores the performances of different modeling approaches (i.e., deterministic, stochastic programming, and robust optimization) to reflect various risk preferences. The models are evaluated in a case study of Singapore and results demonstrate that stochastic modeling methods in general offers more robust allocation strategies compared to deterministic approaches in achieving high coverage to critical infrastructures under risks. This general modeling framework can be applied to other emergency service applications, such as, locating medical emergency services.

The development of renewable energy infrastructure system development aims to answer the following key research questions: (1) is the renewable energy an economically viable solution? (2) what are the energy distribution and infrastructure system requirements to support such energy supply systems in hedging against potential risks? (3) how does the

energy system adapt the dynamics from evolving technology and societal needs in the transition into a renewable energy based society?

The study of *Renewable Energy System Planning with Risk Management* incorporates risk management into its strategic planning of the supply chains. The physical design and operational management are integrated as a whole in seeking mitigations against the potential risks caused by feedstock seasonality and demand uncertainty. Facility spatiality, time variation of feedstock yields, and demand uncertainty are integrated into a two-stage stochastic programming (SP) framework.

In the study of *Transitional Energy System Modeling under Uncertainty,* a multistage stochastic dynamic programming is established to optimize the process of building and operating fuel production facilities during the transition. Dynamics due to the evolving technologies and societal changes and uncertainty due to demand fluctuations are the major issues to be addressed.

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1.1. Research Background and Motivations for Sustainable Infrastructure Systems

Civil infrastructure systems support human activities in transportation, communication, water use, and energy supply. For instance, road networks support vehicle movements; wireless base stations transmit wireless signals; dams control floods and generate hydro-power; energy infrastructure systems support energy production and delivery. In general, these infrastructures are: (1) capital cost and time intensive, (2) difficult to change once implemented, and (3) vulnerable to risks.

Among all these types of infrastructure systems, the dissertation research focuses on the critical transportation infrastructure and renewable energy infrastructure systems. The goal of the research efforts is to improve the sustainability of the infrastructure systems, with an emphasis on economic viability, system reliability and robustness, and environmental impacts.

1.1.1 Critical Transportation Infrastructure (CTI) Systems

The critical transportation infrastructures (CTI) include bus terminals and interchanges, mass rapid transit (MRT) stations, tunnels, airports, and seaports, which as a whole is vital for maintaining normal societal functionality, especially viable for metropolitan areas. On the other hand, these facilities also feature high maintenance and repairing cost, considering the high labor cost in metropolitan areas and significant societal impacts. It is therefore crucial to improve the efficiency and reliability of protection to the infrastructures from potential disasters and attacks through providing robust emergency service resource allocation strategy under stringent budget limits.

1.1.2 Renewable Energy Infrastructure Systems

Renewable energy is promoted for supplementing traditional energy sources to sustain future energy use. As the two most important types of renewable energy to fuel the future transportation, biofuel and hydrogen carry significant environmental and energy-security benefits (European Parliament and Council, 2003; U.S. Congress, 2007). Extensive research work (De La Torre et al., 2000; National Research Council, 2004) has been conducted to understand their advantages in terms of greenhouse gas emissions, energy security, etc.

There is a vast collection of feedstock resources available for fuel production. Depending on the types of feedstock, their life-cycle environmental impacts will be different. Taking ethanol (a type of biofuel) as an example, the ethanol produced from the lignocellulosic biomass (e.g., agricultural residue, forestry residue, and municipal solid wastes) has significant benefits over the current corn grain based ethanol in land use, life-cycle emissions, source diversity, etc (Farrell et al., 2006; Hill et al., 2006; Jenkins et al., 2007; Perlack et al., 2005). Therefore, the lignocellulosic biomass based biofuel, namely, cellulosic biofuel, is an ideal alternative to the conventional biofuel and considered in the study.

To improve the efficiency and reliability of the energy systems, the entire energy supply chain should be considered as a whole due to the interdependency between different components in the system. For instance, having a large-size centralized refinery facility can decrease the production costs through increased economies of scale but imposes higher cost on feedstock procurement and fuel distribution. In addition, the system reliability is going to be incorporated into the modeling framework against potential risks caused by demand fluctuations, operational failures and disasters.

1.1.3 Challenges in Sustainable Infrastructure System Planning

Although the critical infrastructure systems protection and renewable energy infrastructure systems planning seem distinct in context, they share commonalities in three ways: (1) they both seek optimal strategies in allocating limited resources to achieve system-wide effectiveness and efficiency; (2) they both require a system modeling method for incorporating spatiality and temporality; and (3) both problems face a challenge of handling high level of uncertainties. In general, existing studies are concerned with achieving system-wide economic efficiency through system optimization approaches, most of which addressed spatial dimensions in the systems but yet considered inherent uncertainties.

In particular, to improve the protection strategies for CTI systems, potential unavailability of service has been explicitly addressed in the existing research efforts by use of chance-constraint programs. However, external uncertainties in service accessibility due to traffic congestion, as an example, can have heavy impacts on developing robust resource allocation strategies and will be addressed integrally with uncertain service availability in a single modeling framework.

Renewable energy system planning as an emerging field of application of operations research presents rich research opportunities. Current research efforts in this field are interested in enhancing the cost competitiveness of renewable energy through improving the economic efficiency of part of the systems, such as, feedstock procurement, fuel production and delivery, etc. This dissertation research is extended to take the entire system into consideration in recognition of the interdependency between different system components. Simultaneously, system reliability against risks caused by demand fluctuations and natural and human-made disasters is improved through stochastic modeling methods. System adaptability is also considered to hedge against seasonality and dynamics caused by evolving technology and societal needs. The intellectual contributions of this dissertation will be discussed in more detail in Section 1.4.

1.2. Research Scope

1.2.1 CTI Protection

One way to protect the CTIs is to improve emergency response readiness. This requires sufficient amount of emergency service resources to be able to serve CTIs within acceptable time. This research effort focuses on optimal allocation of emergency service resources to protect CTIs. Ideally one wants to deploy as much resource as possible to protect the CTIs. However, service resources are often limited in reality. The question therefore becomes how to allocate limited resources to a set of possible service units in order to serve as many CTIs as possible, i.e., to maximize the service coverage to the CTIs.

From an operations research viewpoint, the problem addressed in this study belongs to the general category of facility location problems (see Chapter 2 for details of existing literatures in facility location problems). In particular, a covering model is adopted to locate emergency service resources for two reasons: (1) in reality, acceptable service standards in terms of travel time are usually predetermined by emergency management agencies and naturally become the constraints in our model; (2) this study aims at maximizing service coverage to CTI nodes with limited emergency resources.

Allocating emergency service resource is a planning problem, which heavily involves prediction of model parameters such as the incident rate at demand sites and the transportation network performance. In reality, these parameters are often random. How to tackle uncertainty in disaster mitigation problems has become a timely subject recently and motivated this study.

Various stochastic modeling approaches have been used in the study to measure different risk-averse preferences. In particular, stochastic programming and robust optimization methods are used to minimize the regrets across all possible scenarios or in the worst-case scenario. All models are evaluated in the case study considering Singapore's CTIs and emergency service resources.

1.2.2 Renewable Energy Infrastructure System Planning and Management

In optimizing the sustainable renewable energy infrastructure systems, its economic viability is one of the critical measurements, which relies on its production cost and more importantly the costs associated with logistics including transport and storage. Renewable energy sources are intermittent in nature and must be stored to provide energy on demand. Excessive feedstock procurement will raise the storage cost while fuel production deficiency will cause penalty cost (imports from outside). Therefore, the problem will be investigated in the context of considering the entire energy supply chain system, including feedstock procurement and delivery, energy production and storage, and energy distribution to end users.

Strategic supply chain management aims to find the best supply chain configuration, including location and size setup, delivery, production, storage, and distribution, to support efficient operations of the whole supply chain (Cordeau et al., 2006). The optimization of renewable energy supply system is within the general category of multi-location-layer supply chain management problems. Research contributions in supply chain management have substantially increased in recent years, which will be thoroughly discussed in next chapter Section 2.2.

The dissertation research efforts are especially concerned with improvement of system reliability in an uncertain decision-making environment in addition to economic viability. In particular, a stochastic programming model with multiple time periods is proposed to develop a reliable biofuel pathway, considering feedstock seasonality. In addition, system dynamics due to the evolving technology and societal demands are addressed in a multistage stochastic dynamic model for strategic planning of transitional hydrogen systems. Both models are evaluated in California case studies, for the wide range of policies encouraging low-carbon fuels (such as, AB32, AB1493, Low Carbon Fuel Standard, etc).

1.3. Dissertation Structure

The dissertation is consisted of six chapters. The first chapter is a general introduction. Conclusions and future work are outlined in the Chapter 6. The remaining chapters are organized as follows:

Chapter 2 reviews existing literature in facility location and supply chain design and management problems, with emphases on their applications in infrastructure systems. The chapter provides background for the various mathematical modeling techniques that are used in the dissertation. In particular, a set of advanced optimization approaches are reviewed in section 2.3 and their own features are highlighted. Due to the complexity of the model structure and the large scale of the study region, solving the models to optimality is computationally challenging, which motivates more research efforts in developing efficient decomposition methods. The basics of these solution algorithms are briefly discussed in section 2.4.

Chapter 3 studies the problem of allocating multiple emergency service resources to protect critical transportation infrastructures. Different modeling approaches, including deterministic, stochastic programming, and robust optimization, are used to model various risk preferences in decision making under uncertain service availability and accessibility. Singapore is used as a case study for numerical experiments. The performances of different models are compared in terms of allocation strategies and the reliability and robustness of the system.

Chapter 4 presents research effort in improving the reliability of the biofuel system against potential disruptions caused by supply seasonal variations, demand fluctuations, and facility damages. Storage facilities for both feedstock and fuel are included in the biofuel supply chain to provide self-healing functions (via smoothing and redistribution) against unexpected system risk. A stochastic mixed-integer programming model that integrates feedstock seasonality, geographic variation, and demand fluctuation is developed, with the goal of minimizing the total expected cost of the entire supply chain of biofuel from biowastes to end users. The model is evaluated using a case study considering California corn stover feedstock resource.

Chapter 5 proposes a stochastic dynamic programming model that integrates the spatial and temporal dimensions for sequentially building a renewable energy production and distribution system under dynamics and uncertainties. The decision variables are the sequence and locations of the production sites and the corresponding distribution systems from supply to demand sites in hedging against uncertainty. A case study based on the hydrogen system in Northern California is included.

1.4. Contributions

The dissertation research intellectually contributes to the improvement of the sustainability of infrastructure systems in economic viability, system robustness, and environmental acceptability.

- *CTI protection*

This study for the first time evaluates the performances of various modeling approaches in response to different risk preferences based on a real-world case study. The results are informative for policy makers to deploy limited service resources to achieve effective system performances. The research effort enriches the literature of developing robust resource allocation strategies in disaster mitigation and emergency service problems. In particular, the explicit consideration of external uncertainties (e.g., traffic congestion) integrated with uncertain service accessibility fills the void in the existing emergency service siting problems. In addition, this general modeling framework is applicable for other emergency service contexts, such as, locating emergency medical service.

- *Renewable energy infrastructure system planning and management*

This research study develops a decision support system to help design renewable energy systems that is profitable, reliable, and environmentally acceptable. This research integrates expertise in stochastic and dynamic system modeling, alternative fuel technologies, life-cycle analysis, resource allocation, and supply chain and logistics.

The following key features distinguish this study from previous studies in literature:

1. *Stochastic optimization approaches* are used to explicitly incorporate uncertainties in feedstock supplies and fuel demand.
2. A *multistage* optimization framework is established produce time-dependent resource allocation and infrastructure expansion strategies in order to support long-term strategic planning of future energy system that evolves over time.
3. Supply *seasonality* is investigated. The roles of storage facilities in enhancing the robustness of the system against supply disruptions are investigated for the first time in literature.

This research path will lead to sustainable energy infrastructure systems that are cost-effective, secure, and adaptive to changing and unpredictable environment. The research has a potential of providing a scientific basis for renewable energy policy formulation and decision-making.

Chapter 2 Literature Review

Summary

The dissertation research of sustainable infrastructure system modeling is built upon the literature in f*acility location problems* and *supply chain design and management problems*. In short, the facility location problem is to answer the questions of where and how to locate facilities within a given space. Supply chain design and management problem is developed from facility location problem by adding decisions on deliveries between facilities. To improve the sustainability measured in economic viability, reliability and security, and impacts on environment and natural resources, advanced mathematical modeling techniques are used, in particular, stochastic programming, robust optimization, and dynamic programming. Moreover, due to the complex modeling structures, even solving a model with moderate size to optimality is computationally challenging so that the development of efficient algorithms becomes important.

In this chapter, facility location and supply chain design problems are first reviewed in section 2.1 and 2.2, respectively. Mathematical programming techniques that can handle risk and dynamics are summarized in section 2.3. Decomposition methods used to improve the solution efficiency are introduced in section 2.4.

2.1. Facility Location with Applications in Emergency Service Problems

2.1.1 Summary of Facility Location Problems

Facility location problem was first studied by Alfred Weber in 1929 to locate a single warehouse (Weber, 1929). Since then, it has been applied to broad applications, such as healthcare facilities, plants and warehouses, post offices, landfills, etc (Daskin, 1995; Eiselt, 2007; Owen and Daskin, 1998). The facility location problem is designed to make decisions on optimal or at least good facility locations in a quantifiable way and mathematical models were designed to address a number of questions including (Daskin, 1995):

(1) How many facilities should be sited?

(2) Where should each facility be located?

(3) How large should each facility be to accommodate how many service units?

(4) How should demand for be allocated to the facilities?

Based on the objectives, facility location problems can be categorized into three general types, which are covering problems, median problems, and center problems (Daskin, 1995). A thorough review on strategic facility location problems is provided by (Owen and Daskin, 1998; Schilling et al., 1979b; Snyder, 2006).

Covering problems locate facilities according to some pre-specified performance standards. A demand node is deemed as served only if it is within a pre-specified distance of a facility. The Location Set Covering Problem (LSCP) (Toregas and ReVelle, 1973; Toregas et al., 1971) is perhaps the simplest covering model. However, one shortcoming associated with the set covering model is that the number of facilities that are needed to cover all demand nodes is likely to exceed the number that can actually be built. Furthermore, the set covering model treats all demand nodes equally. The Maximum Covering Location Problem (MCLP) was then introduced by (Church and ReVelle, 1974) to possibly distinguish the importance of different demand nodes. An extension of MCLP was made to account for the possibility of severe congestion or being busy, which led to the Maximum Expected Covering Location Problem (MEXCLP) (Daskin, 1983) and TIMEXCLP-MEXCLP with time variation (Repede and Bernardo, 1995).

Center problems locate facilities so as to minimize the maximum travel cost between any demand node and a facility. This problem has the same objective as the LSCP, which requires all demand nodes covered. However, instead of using an exogenously specified coverage distance and asking the model to minimize the number of facilities needed to cover all the demand nodes, the *P*-center problem minimizes the maximum coverage distance such that each demand node is covered by one of the facilities. A number of authors have considered extensions to the centre problems , including (Martinich, 1988; Minieka, 1977).

Median problems attempt to locate facilities to minimize the total weighted travel cost between demand locations and a facility. All variants of covering and center problems assume that a demand node receives full service from a facility if it is within the coverage distance and no service if the distance between the demand node and the nearest facility exceeds the coverage distance. In many cases, however, the level of service associated with a demand node-facility pair decreases gradually with the distance. Median problems are to account for the relationship between the distance and associated cost between a demand node and a facility, which was first introduced by (Hakimi, 1964).

All facility location problems are NP-hard or complete problems (Daskin, 1995). Effective algorithms are required if one wants to solve problems in a realistic size with a reasonable amount of time, which will be explicitly discussed in Section 2.4.

2.1.2 Applications of Facility Location Problems in Disaster Mitigation and Emergency Service

Typical examples of facility location problems applied in the context of emergency management include: (1) allocating Emergency Medical Services (EMS) for recurrent emergency cases such as house fires, and (2) planning the location and inventory strategies for local staging centers to receive and redistribute medical supplies from the strategic national stockpiles (SNS) for non-recurrent emergency cases such as large-scale natural and human-caused disasters.

TABLE 2.1 Examples of Facility Location Problems Using Different Modeling Methods

Type	Objective	Constraints	Examples
Covering problem	Maximize Coverage of demands (Church and ReVelle, 1974; Schilling et al., 1979a; White and Case, 1974)	• Required service standards; • Limited resource	• Locate EMS vehicles(Eaton, 1979, 1980; Eaton et al., 1985); • Locate rural health care workers (Bennett et al., 1982); • Place a fixed number of engine and truck companies (Marianov and ReVelle, 1991, 1992)
	Set covering: minimize the cost of facility location (Toregas et al., 1971)	• Specified level of coverage obtained; • Required service standards	Identify EMS vehicles locations (Berlin and Liebman, 1971; Jarvis et al., 1975)
P-Median problem	Minimize the total travel distance/ time between demands and facilities (Hakimi, 1964)	• Full coverage obtained • Limited resource	• Ambulance position for campus emergency service (Carson and Batta, 1990); • Locate fire stations for emergency services in Barcelona (Serra and Marianov, 1998)
P-Center problem	Minimize the maximum distance between any demand and its nearest facility	• Full coverage obtained ; • Limited resource	Locate EMS vehicles with reliability requirement (ReVelle and Hogan, 1989)

The effectiveness of a decision on locating and allocating emergency service resources could be evaluated by total capital and operating *costs*, incident demand *coverage*, and incident *response timeliness*. Depending on how these three considerations are modeled, either as an objective or a constraint, mathematical models can be categorized into three types: covering models, *P*-median models, and *P*-center models, which have been briefly introduced in Section 2.1.1. Comprehensive reviews on mathematical formulations and numerical implementations of the three types of problems in the context of emergency service location-allocation problems have been conducted in (Jia et al., 2007). Typical objective functions, constraints, and sample applications of the three types of facility location models in emergency management are listed in TABLE 2.1.

The two important performance measures in emergency service allocation problems, service *availability* and *accessibility*, can be highly uncertain particularly following a large-scale disaster.

Unavailability of emergency services, caused by system congestion, appears frequently in non-recurring emergency cases when demand for emergency service spikes (Jia et al., 2007). Existing methods for addressing system congestion issues include providing redundant or multi-layer coverage, e.g., (Hogan and ReVelle, 1986), using chance constraints to ensure certain level of reliability of having available service, e.g., (Daskin, 1983; Daskin et al., 1988; Marianov and ReVelle, 1995; ReVelle and Hogan, 1989; ReVelle and Marianov, 1991), and explicit incorporation of queuing theory, e.g. (Larson, 1974; Marianov and ReVelle, 1996). Berman and Krass (2002) have provided a thorough discussion on facility location problems addressing service congestion issues.

Uncertainty in service accessibility could be caused by daily traffic fluctuation or sudden disruption to transportation systems, which has been less discussed in the existing literature. Several papers have addressed the issue of uncertainty in travel times (Daskin, 1982; Daskin, 1987; Daskin and Haghani, 1984; Mirchandani and Odoni, 1979). Serra and Marianov (1998) provided a case study to demonstrate the value of using stochastic approaches to address uncertain access time.

A comprehensive review on facility location problems under uncertainty (costs, demands, travel times, and other possible inputs) is referred to (Snyder, 2005).

2.2. Supply Chain Design and Management with Applications in Renewable Energy Infrastructure System Modeling

2.2.1 Introduction to General Supply Chain Management

A supply chain involves a process of moving goods from raw material sites to processing facilities (e.g. production plants), and finished goods will be delivered to distribution centers then to retailers or customers. Supply chain management is to answer following questions: (1) where to locate plants for producing goods, and how much needs to be produced at each plant, (2) what amount of goods need to be held in inventory at each time stage and where to hold the goods, and (3) how to distribute the goods to retailers or customers. Strategic supply chain management aims at finding the best supply chain configuration. In addition to facility location decision makings, it also includes decisions on procurement, production, storage, and distribution, in order to support efficient operations of the whole supply chain (Cordeau et al., 2006). Advanced mathematical models, e.g., (Chardaire et al., 1996; Daskin et al., 2002; Dias et al., 2007; Geoffrion and Powers, 1995; Lieckens and Vandaele, 2007; Revelle and Laporte, 1996; Van Roy and Erlenkotter, 1982) have been proposed.

A typical supply chain system consists of facilities on hierarchical layers (Klose and Drexl, 2005). The models for supply chain management are often based on multistage location problems, in which facility locations are often determined in the first stage of the model and other decisions are made in subsequent stages. As emphasized in (Daskin et al., 2005), location decisions are crucial and difficult to make, due to its intensive capital cost. For example, once a plant is implemented, it is unrealistic to relocate it as a result of changes of customer demands. Comprehensive reviews on facility location in supply chain design are referred to (Daskin et al., 2005; Klose and Drexl, 2005; Melo et al., 2007).

Conventionally, routing and inventory decisions are made secondary to facility locations in the sense that the routing and inventory decisions are more flexible and can be modified periodically in response to the demand changes (Daskin et al., 2005). Although empirical location decisions are isolated from routing and inventory's decisions, an integrated decision making on location, routing and inventory in a systematic manner can potentially improve the system performance, which invoked research on location-routing and location-inventory problems.

Location-Routing Problems (LRPs) are often described as a combination of three distinct components, including facility location, allocation of users to facilities, and vehicle routing (Geoffrion and Graves, 1974; Laporte, 1988; Perl and Daskin, 1985). The objective of LRPs is to minimize a linear combination of routing costs, vehicle fixed costs, and depot operating costs (Laporte, 1988). From problem modeling perspective, LRPs can be further classified into single-stage or two-stage problems. The single-stage LRP is primarily concerned with the locations of facilities serving customers and the establishment of outbound delivery routes around those facilities, and the two-stage LRP extends the problem to additionally consider both outbound (Fuel Delivery Temperature Study) and inbound (pickup) distribution processes (Min et al., 1998)**Error! Reference source not found.**.

The location-inventory problem is developed in recognition of inventory impacts on facility location decisions, which was first highlighted in (Baumol and Wolfe, 1958). Traditional location problems trade off the number of facilities and travel costs, but ignore the inventory influence. A non-linear model, namely, Location Model with Risk Pooling

(LMRP) was first introduced in (Shen et al., 2003; Shen, 2000) to solve the problem quantitatively. Prior to that, there had been several joint location-inventory models, such as, (Barahona and Jensen, 1998; Erlebacher and Meller, 2000; Nozick and Turnquist, 2001a, b; Teo et al., 2001). Although merging inventory management with facility location decisions suffers the same conceptual and computational difficulty, it is still worthwhile continuing in the area of integrated inventory-location modeling as suggested by (Daskin et al., 2005).

2.2.2 Supply Chain Management under Risk

The concept of supply chain, through better integration and coordination of various components of a supply system (such as procurement, production, storage, and marketing), can greatly improve the system efficiency. On the other hand, reduced redundancy and buffer, which improves the system efficiency under normal conditions, may present higher vulnerability under unexpected events such as supply shortage, demand spike, technological failure, or attacks and disasters. Supply chain risk management is receiving increasing attention in recent research efforts. Empirical examples have demonstrated the vulnerability of supply chains under disturbances and disruptions. Recent examples include 2004 flu vaccine shortage in the US because of the contamination of products by one of the only two suppliers (Pearson, 2004) and Ericsson's production shutdown in March 2000 due to the fire of its only supplier of chips (Latour, 2001). Following the definition by (Tang, 2006), the supply chain risks are categorized into operational risks and disruption risks. An operational risk refers to those recurrent risks such as supply and demand fluctuations that are inherent in supply chains. A disruption risk usually refers to external disruptions caused by natural and man-made disasters.

The recurrent risks caused by fluctuated demands (e.g., (Aghezzaf, 2005; Chan et al., 2001; Daskin et al., 2002; Goh et al., 2007)), uncertain travel times (Hwang, 2002), or both (Sabri and Beamon, 2000; Santoso et al., 2005; Snyder et al., 2007) are usually inherent in the supply chain. These recurrent risks are normally incorporated into the supply chain management as uncertainty (Sabri and Beamon, 2000). Stochastic modeling techniques are often considered (Melo et al., 2007) to take these uncertainties as a discrete set of scenarios or assume a continuous distribution function associated with uncertain parameters. Nevertheless, in the existing literature, integration of stochasticity with location decisions in supply chain management context is still scarce, which motivates the recent research efforts in enriching the literature.

On the other hand, a number of scholarly studies focused on supply chain management in the context of disruptions and risks caused by natural disasters, human attacks, unexpected accidents, operational difficulties, etc (Yu et al., 2009). Those threats are rare but have more severe impacts on the system. Over decades, disruption management has been given limited attention in comparison with the research efforts on supply chain management under uncertainty (Qi et al., 2004). More recently, Sheffi (2001) conceptually discussed the tradeoffs between redundancy and efficiency, centralization and dispersion, low cost and reliability, and collaboration and secrecy, and identified shipment visibility, improved collaboration and public-private partnership as means of improving the vulnerability of supply chains against major attacks. A few other conceptual papers listed in (Chopra and Sodhi, 2004; Cranfield Management School, 2002) and categorized (Tang, 2006) the major supply chains risks by different natures. Quantitative studies on supply chain disruption management have been conducted from various aspects of supply chains, such as personnel scheduling (Bard et al., 2001; Clausen et al., 2010; Kohl et al., 2007), machine scheduling (Abumaizar and Svestka, 1997; Aytug et al., 2005; Bean et al., 1991; Qi et al., 2006), supply sourcing (Chopra and Sodhi, 2004; Xiao and Qi, 2008; Yu et al., 2009), inventory (Vlachos and Tagaras, 2001), and marketing strategies (Chopra and Sodhi, 2004; Tang, 2006; Vlachos and Tagaras, 2001; Xiao and Qi, 2008; Xiao and Yu, 2006; Yu et al., 2009). These studies, though focus on different components of supply chains, are all from the perspective of operational management rather than planning of supply chains. This is not surprising because the problems studied in those papers are for existing and mature production systems, which may not present a need or an opportunity for completely redesigning the configuration of the whole supply chain.

2.2.3 Applications in Renewable Energy Systems Modeling

The supply chain design and management models have been applied in renewable energy systems to answer some key questions in transition to a renewable energy based society:

- Is renewable energy (e.g., biofuel and hydrogen) an economically viable solution?
- What are the infrastructure requirements to support such energy supply systems?

The problem spans both spatial and temporal dimensions. The *spatial dimension* mainly lies in the geographic distributions of the feedstock resources, the fuel demands, and the production and transportation infrastructures. The costs of feedstock, fuel production, and transport are interdependent. For instance, having a large-size centralized refinery facility can decrease the production costs through increased economies of scale but imposes higher cost on feedstock procurement and fuel distribution. Hence, considering the entire fuel supply chain as a whole is important (Delucchi M., 2006; Farrell and Sperling, 2007; Kim and Dale, 2005; Turner and Plevin, 2007; Unnasch and Pont, 2007; Zah et al., 2007). However, such a systems approach has not been widely adopted in renewable energy planning literature. Most of the studies only consider part of the energy pathway (Graham et al., 2000; Gunnarsson et al., 2004; Kaylen et al., 2000; Kumar et al., 2003; Tembo et al., 2003; Zhan et al., 2005). Only limited studies considered an entire energy pathway, including an optimization model for forest biomass allocation (Freppaz et al., 2004) and a study of optimizing the process of converting agricultural residues to hydrogen in California (Parker, 2007b). The *temporal dimension* arises in long-term system planning especially when system transition issue is considered. The production and distribution infrastructure system will have to be expanded over time in response to the growing demand. To achieve an overall effectiveness of the system expansion, the dynamics of such an evolving process needs to be taken into consideration in the system planning. Hence, the conventional time-independent snapshot method, as used in previous studies, is inadequate (Fiksel, 2006). For example, in a recent study (Lin et al., 2008), a dynamic programming model is proposed to identify the least-cost sequence of building up a hydrogen infrastructure system for Southern California.

Risks arise in the supply chain system due to the unpredictable weather conditions, fluctuated demands, varied supplies, etc. Incorporating those considerations can potentially strengthen the performance of the entire energy system in hedging against the unexpected occurrences. However, those studies are rare in the existing literature. One of the pilot studies (Cundiff et al., 1997) formulated the uncertain production levels due to weather into a two-stage stochastic model with recourse. Most of the studies are however deterministic, in which all parameters are assumed to be known. The simplification of modeling structure compromises computational difficulty. The research efforts presented in this dissertation are meant to fill the void.

Another feature of renewable energy supply chain design and management is to possibly integrate engineering-economic modeling of decisions on facility locations and sizes into the optimization framework, with a goal of achieving a better and more realistic solution. This is motivated by the fact that many system parameters are tangible with the changes of system configurations. Use feedstock procurement decision making as an example. The amount of feedstock procured depends on the price level of that feedstock so that it may loose some accuracy when the procurement cost is modeled as a linear function of procurement amount; instead a piece-wise linear function can do better but introduce additional computational difficulty as the same time. Some existing studies have already explicitly included engineering-economic models, e.g., (Johnson, 2007; Lin et al., 2008; Parker, 2007a) in which engineering-economic models are implemented to optimize a coal-based hydrogen infrastructure system in California. In other energy supply systems, techno-economic models were integrated into linear programming models to take various factors into consideration, including economics, techniques, regulatory, and social impacts (Freppaz et al., 2004; Rentizelas et al., 2009).

2.3. Mathematical Programming Methods for Handling Risk and Dynamics

2.3.1 System Optimization under Risk

In handling possibilities of a random event, a common engineering approach is to examine each scenario separately and then to aggregate scenario-specific solutions based on engineering judgment. Another simple approach is to aggregate all scenarios to a single scenario (such as, expected value) and then solve the corresponding deterministic problem. These deterministic approaches which are not capable of handling uncertainty involving in random data are conceptually and computationally simple, but may be unreliable. Thereby, stochastic approaches that hedge better against a wide range of possible scenarios is necessary.

Stochastic programming (SP) and *robust optimization* (RO) are two major stochastic modeling approaches that have been widely used. In general, SP emphasizes on the expectation of a performance measure (Birge and Louveaux, 1997), while RO tends to focus more on the worst case scenario (Kouvelis and Yu, 1997). Criticisms against SP are its dependence on knowledge of complete probability distribution of random parameters and its lack of consideration on risk. On the other hand, RO may be too conservative and may never lead to profitable results in reality.

A SP model seeks a strategy that is feasible in all possible scenarios and provides the best system performance in an expectation sense. The majority of SP models feature a two-stage structure with recourse. The basic idea is to make one decision now and minimize the expected costs (or utilities) of the consequences of that decision after uncertainty is disclosed. The two-stage structure can be described in this way. A number of decisions are made before uncertainty is revealed and these decisions are called first-stage decisions. The period when the decisions are taken is called first stage. After the uncertainty becomes known, a number of decisions will be taken and these decisions are called second-stage decisions. The corresponding period is called second stage. In the contexts of facility location and supply chain management, the first-stage decisions are planning decisions including the location and the size of facilities and the second-stage decisions are operational decisions, such as, the flow, production, resource allocation decisions, etc. The two-stage SP model can be extended to include more stages. With a multistage problem, one makes one decision now, waits for some uncertainty to be realized, and then makes another decision based on what has happened. The objective is to minimize the expected costs of all decisions taken.

Probabilistic programming (or chance constrained) is another stochastic modeling approach, which is considered when the cost and benefits of second-stage decisions are difficult to assess (Birge and Louveaux, 1997). In this case, some of the constraints or the objective is expressed in probabilistic statements about the first-stage decisions and second-stage description is thus avoided. Some typical examples in the context of emergency service include (Daskin, 1983; ReVelle and Hogan, 1989; ReVelle and Marianov, 1991; Toregas et al., 1971).

RO method on the other hand emphasizes on the worst case scenario. It is usually considered for a given problem under uncertainty with no probability information and modelers tend to avoid extremely bad consequence naturally. If the model parameters such as travel time over the traffic network were known in advance, one could input their values to the base model and achieve the best possible coverage. The difference between the best possible objective value and the realized objective value from a chosen strategy is called "regret" of the strategy in that realization (Daskin et al., 2005). Some robust optimization approaches deal directly with the objective values across all possible realizations. In this case, the criterion is to find a strategy that maximizes the worst benefit across all possible realizations, also called absolute robustness criterion – for example, the location of fire stations (Serra and Marianov, 1998). Some robust approaches use robust deviation criterion, which is to minimize the largest regret (Kouvelis and Yu, 1997).

2.3.2 System Optimization under System Dynamics

Problems of transitioning a current state to meet the growth of demand, technology improvement or other possible societal changes for the future fall within the general category of dynamic location problem. It is one of the major research trends in location and logistics science. Several past studies were based on *multistage deterministic* or *stochastic programming* approaches (Chardaire et al., 1996; Kelly and Marucheck, 1984; Melo et al., 2006; Sheppard, 1974; Wesolowsky and Truscott, 1975). Solution efficiency is an inherent issue with all the models that the models may become computational challenging with the increase of system planning horizon, uncertainty, and change of model structure.

Dynamic programming (DP) is often used to solve sequential decision problems. DP method was introduced by (Bellman and Kalaba, 1965) and thoroughly discussed in (Bertsekas and Tsitsiklis, 1996; Dreyfus and Law, 1977). DP has been applied in a wide range of problems, including budgeting problems, assessment acquisition problems, resource allocation problems, shortest path problems, dynamic assignment, etc (Powell, 2007). A good application of DP in location problems was presented in (Wesolowsky and Truscott, 1975), in which a dynamic multi-period location-allocation model was proposed to specify the plan for facility location and relocation as well as allocation of demands to facilities. It has also been applied in agricultural chains problems (Gigler et al., 2002), in which a DP based model takes the appearance and quality as the two types of states of a product and describes quality development of a product as a function of process conditions. In a recent review by Melo et al., (2006), more research efforts were called upon to develop realistic models that consider stochasticity and dynamics. The study presented in Chapter 5 has made original contribution to this research effort, in which a stochastic dynamic programming model is developed to sequentially expand a hydrogen supply chain system in Northern California.

2.4. Solution Algorithms

Most problems in facility location and supply chain management are NP-hard/complete (Daskin, 1995) and hence extremely difficult to solve to optimality for a realistic size.

Although there has been an impressive growth of powerful general-purpose mathematical programming software such as, CPLEX, large-scale mixed integer problems are still computational challenging, which motivates continuous development of new solution methods in both exact solution and heuristic solution.

Facility location problems are suitable for applying decomposition methods (Mirchandani and Francis, 1990), due to the two inherent types of decisions – location decisions and operational decisions. The rationale is that once the facility location decisions have been determined, the resulting problem only contains continuous variables, which is simpler to solve. Dantzig-Wolfe decomposition (Dantzig and Wolfe, 1960) and Benders decomposition (Benders, 1962) are the two decomposition methods, which are mainly used for decomposing linear deterministic mixed-integer problems in the early stage.

The Benders decomposition method was then extended to stochastic programming problems to handle feasibility questions and is known as *L-shaped method* (Van Slyke and Wets, 1969). The basic idea of L-shaped method is to approximate the nonlinear term (the recourse function) in the objective of the problems by building a master problem only in first-stage decisions, and evaluate the recourse function exactly as a subproblem. Its procedures and proof have been elaborated in (Birge and Louveaux, 1997).

However, the performance of L-shaped method in solving large-scale or mixed integer problems strongly relies on tuning of certain parameters, which makes the implementation of the method sometimes extremely difficult and unsuccessful. Based on previous research experience and numerical experiments, the *Progressive Hedging* (PH), method is also well suitable for the problems in the research. PH algorithm is a scenario-based decomposition technique originally proposed by (Rockafellar and Wets, 1991b), and has been successfully implemented and further popularized in subsequent works including (Mulvey and Vladimirou, 1991; Watson et al., 2008). The PH method decomposes a problem across scenarios to form manageable subproblems (Fan and Liu, 2007), which is distinctive from the cutting-plane based L-shaped method. The details of solving procedures of PH method can be found in (Watson et al., 2008). The PH has been implemented in solving the storage problem in Chapter 4 Section 4.4. Significant reduction in solution time has been observed and high solution quality remains.

Chapter 3 Strategic Resource Allocation for Critical Transportation Infrastructure Protection

Summary

Optimal deployment of limited emergency resources in a large-scale area to sustain the protection to critical infrastructures is the focus of this study and of interests to public agencies at all levels. In this chapter, the problem of allocating multiple emergency service resources to protect critical transportation infrastructures is studied. Different modeling approaches, including deterministic, stochastic programming, and robust optimization, are used to model various risk preferences in decision making under uncertain service availability and accessibility. Singapore is used as a case study for numerical experiments. The performances of different models are compared in terms of allocation strategies and the reliability and robustness of the system.

3.1. Introduction

Emergency preparedness is essential for maintaining a safe and sustainable society. One important element for emergency preparedness is the ability of sending emergency services and relief goods to incident locations in a timely manner. Both *availability* and *accessibility* of emergency services play important roles in emergency response. Availability depends on the relationship between supplies of emergency resources and incident demands; while accessibility is measured by the transportation costs between service locations and incident sites. Therefore, an essential question in emergency service planning is: *how many* emergency resources are needed and *where* should these resources be located? This question falls within the general category of facility location problems which have been comprehensively reviewed in Chapter 2.

The two important performance measures in emergency service allocation problems, service availability and accessibility, can be highly uncertain particularly following a large-scale disaster. Most existing studies address availability and accessibility issues separately. In this research, the uncertainties of both measures are captured, through a stochastic modeling framework that explicitly models random scenarios of accessibility costs, with built-in reliability constraints on service availability.

Stochastic programming (SP) and Robust Optimization (RO) methods are the two major stochastic modeling methods (see literature review on SP and RO methods in Chapter 2).

Considering the advantages and limitations of the two methods, this chapter investigates, in a real-world application, on how different modeling techniques may impact the effectiveness of emergency service resources allocation. In addition, uncertainties inherent in service availability and accessibility will be addressed in an integrated modeling framework, which has not been studied in the exiting literature. To avoid abstractness, discussions will be cast in a specific context, where multiple types of emergency services (e.g., fire trucks, fire engines, and ambulances) are required to maximize the protection coverage for critical transportation infrastructure (e.g., transit stations, ports, airports, etc).

The rest of the chapter is organized as follows. In Section 3.2, formulations will be provided for different risk preferences in emergency service location problems. A case study based on geographical settings of Singapore is included in Section 3.3, demonstrating the effects of different risk preferences and data qualities on system performance. Conclusions are made and future research is outlined in Section 3.4.

3.2 Mathematical Formulations

Given demands for emergency services at critical transportation infrastructure (CTI) nodes, our goal is to find an optimal strategy to allocate limited number of fire engines, fire trucks, and ambulances to a set of pre-defined candidate fire stations so as to maximize the coverage of the CTIs. A CTI node is considered "covered" when it is served by at least one fire engine, one fire truck, and one ambulance simultaneously within their respective service time standards. Service availability is considered through incorporation of chance constraints, requiring that the probability of at least one vehicle of each type being available at any time be no less than a given service reliability level α (Marianov and ReVelle, 1995).

Additional modeling assumptions are:

(1) Each fire station has a capacity restriction of having no more than four vehicles of each type.

(2) Incident occurrence rates at CTI nodes are estimated based on historic data.

(3) Service availability and travel times of emergency service vehicles are uncertain.

TABLE 3.1 Notation Table

Constant Parameters
I: index *i*, set of demand nodes (CTI nodes); *J*: index *j*, set of candidate fire stations; *H*: index *h*, set of vehicle types, i.e., fire engine, fire truck, and ambulance; t_{ji} : the travel time between station *j* and demand node *i*; S^h : the service standard in terms of travel time for vehicle type $h \in H$; $N_i^h = \{j \mid t_{ji} \leq S^h, h \in H\}$, the set of fire stations located within S^h of demand node *i;* r_i^h : the minimum number of vehicles of type *h* that must be located within S^h of node *i*, to ensure that node *i* is covered with the predefined reliability level α , which needs to be determined before it is used as model input; P^h: the total number of available vehicles of type *h*; B_j^h : the maximum number of vehicles of each type *h* that can be accommodated by each station, which equals four in this study.
Decision Variables
y_i = 1 if demand node *i* is covered by r_i^h vehicles of type *h* (all three types of vehicles); otherwise, y_i =0; x_j^h : integer variable, number of vehicles of type *h* located at fire station *j*;

First, let us formulate the maximum covering problem without considering random access time. This model is similar in spirit to the proFLEET model in (ReVelle and

Marianov, 1991). Notations used in this model are defined in TABLE 3.1 below. Later this model will be extended to incorporate stochastic travel times.

The minimum number of vehicles of type h required at demand node i (r_i^h) is obtained through two steps: estimating the local busy fraction (q_i^h) and solving the chance constraint that the probability of having at least one vehicle of each type available within its service standard of node i when node i is requesting service is no less than a given reliability level α. The local busy fraction was first introduced in (Marianov and ReVelle, 1995) and quantitatively defined in (ReVelle and Hogan, 1989) as the fraction of required service time in the service region around demand node i out of the total available service time in that region. The chance constraint is then mathematically expressed as,

$$1-\left[q_i^h\right]^{r_i^h} \geq \alpha \text{ for each node } i \text{ and for each type } h \in H,$$

assuming that the probability of one or more servers being busy follows binomial distribution. The detailed procedure of obtaining r_i^h is described in details in (Huang et al., 2008).

A complete formulation is given in (3.1)-(3.4).

Maximize $$\sum_{i \in I} y_i \quad (3.1)$$

Subject to

$$\sum_{j \in N_i^h} x_j^h \geq r_i^h y_i \qquad \forall i \in I, h \in H \tag{3.2}$$

$$\sum_{j \in J} x_j^h \leq P^h \qquad \forall h \in H \tag{3.3}$$

$$0 \leq x_j^h \leq B_j^h \qquad \forall j \in J, \forall h \in H \tag{3.4}$$

$$y_i = 0,1 \qquad \forall i \in I$$

$$x_j^h = \text{nonnegative integer} \ \forall i \in I, h \in H$$

The objective maximizes the total number of covered CTIs. Note that other variants of this objective function may be considered, such as a weighted sum of the coverage of the CTIs based on their importance levels. Adoption of a weighted sum of the coverage would not change the structure of the problem. Constraint (3.2) states that for each demand node *i*, the number of emergency service vehicles of type *h* located at fire stations within S^h of node *i* cannot be less than the minimum number of vehicles needed at node *i* in order to meet the reliability requirement. Inequality (3.3) constrains the maximum number of vehicles for each type. The capacity constraint at each fire station is imposed in inequality (3.4).

3.2.1 A Stochastic Programming Model for the Maximum Coverage Problem

In addition to the service availability chance constraints, which are usually required by emergency planning agencies to account for service congestion, the random accessibility (transportation costs) is now incorporated into a stochastic programming framework. The objective is to find an optimal solution that *maximizes the expected coverage* of CTI nodes. It is noted that the minimum number of vehicles of each type of emergency service fleet is scenario dependent. For a fixed required response time window, different travel times translate to different service areas, leading to different estimations of the local busy fraction (q_i^h) and service availability (r_i^h). Additional notations used in the model are defined in TABLE 3.2.

TABLE 3.2. Additional Notations Used in Stochastic Programming Model

Ω: index ω, set of possible scenarios;
$p(\omega)$: the probability of scenario ω occurred;
$t_{ji}(\omega)$: the travel time between *i* and *j* in scenario ω;
$N_i^h(\omega)=\{j \mid t_{ji}(\omega) \le S^h, h \in H\}$: the sets of stations located within S^h of demand node *i* in scenario ω;
$r_i^h(\omega)$: r_i^h in scenario ω;
$y_i(\omega)$: binary variable, the coverage of node *i*, y_i, in scenario ω.

A stochastic programming formulation is given below.

Maximize
$$\sum_{i \in I} \sum_{\omega \in \Omega} p(\omega) y_i(\omega) \tag{3.5}$$

Subject to

$$\sum_{j \in N_i^h(\omega)} x_j^h \ge r_i^h(\omega) y_i(\omega) \quad \forall i \in I, h \in H, \omega \in \Omega \tag{3.6}$$

$$y_i(\omega) = 0,1 \qquad \forall i \in I, \omega \in \Omega$$

including constraints (3.3)-(3.4).

The objective function (3.5) is to maximize the expected coverage over all possible scenarios. Inequality (3.6) is similar to constraint (3.2), but requires that the reliability constraint be satisfied for all scenarios.

3.2.2 A Robust Optimization Model for the Maximum Coverage Problem

Robust optimization emphasizes on the worst situation (Kouvelis and Yu, 1997), thus suits the preference of more risk-averse decision makers. Note that a planning decision is usually made before the realization of a random event, while the results of the decision are often judged *ex post* of an incident when random data are already realized. If one knows perfectly which scenario will actually happen, one could make an optimal plan to achieve the best coverage accordingly, which is also called "wait-sand-see" solution. Any other solutions would result in a worse coverage in this particular scenario. The gap between the actual coverage and the best possible coverage is called "*regret*" in this scenario. Let Z_s be the actual coverage in scenario *s*. Let Z_s^* be the best possible coverage as a result of the "wait-and-see" solution of scenario *s*, which can be obtained separately by solving the deterministic model for scenario s. The regret r_s in scenario *s* can be mathematically defined as $r_s = Z_s^* - Z_s$. For decision makers who have a strong desire of avoiding extremely bad public blame, a robust optimization approach that *minimizes the worst possible regret* across all scenarios, also called deviation robust criterion, may be preferable. Additional notations used in this formulation are defined in TABLE 3.3.

TABLE 3.3. Additional Notations Used in Robust Optimization Model

$z(\omega)$: parameter, the optimal objective value in scenario ω, which is obtained externally by solving the scenario-specific deterministic model for scenario ω;
R: integer variable, the worst regret between the realized coverage and the optimal coverage across over all scenarios.

A robust optimization model focusing on deviation robust criterion is given below:

Minimize $\quad R$

Subject to

$$\sum_{j \in N_i^h(\omega)} x_j^h \geq r_i^h(\omega) y_i(\omega) \quad \forall i \in I, h \in H, \omega \in \Omega$$

$$z(\omega) - \sum_{i \in I} y_i(\omega) \leq R \quad \forall \omega \in \Omega \tag{3.7}$$

$$y_i(\omega) = 0,1 \quad \forall i \in I, \omega \in \Omega$$

R= nonnegative integer, plus constraints (3)-(4)

The objective is to minimize the worst regret across all scenarios. The worst regret *R* is defined in constraint (3.7) as the largest regret across all scenarios.

3.3 Case Study of Singapore

3.3.1 Background

Singapore is chosen for the case study, considering its representation of high population density and also the availability of data.

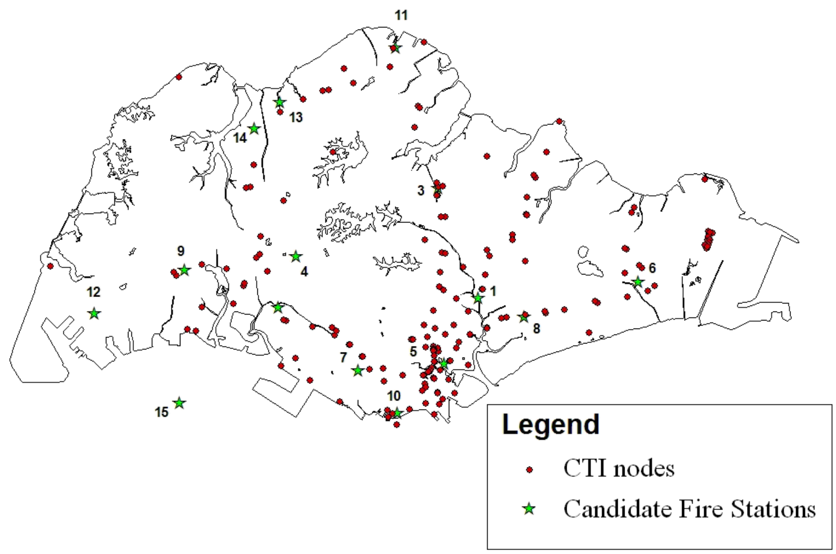


FIGURE 3.1. Map of Singapore with Candidate Fire Stations and CTI Nodes

The map in **FIGURE 3.1** shows the locations of 15 candidate fire stations and 151 CTIs in Singapore Island. The CTIs include mass rapid transit stations, transit and/or bus interchanges, bus terminals, expressway tunnels and interchanges, seaport and airport terminals.

Singapore Civil Defense Force (SCDF) is the government agency responsible for providing emergency response services. SCDF operated a total of 15 fire engines and 15 fire trucks as well as a fleet of 30 ambulances. The three types of vehicles are all based at fire stations, which are responsible for all fire and medical emergency response. Recent published service standard of SCDF was 8 minutes for fire engines and fire trucks, and 11 minutes for ambulances to reach an incident site (SCDF, 2003). The average service times for fire engines, fire trucks and ambulances were set to be 2, 2, and 1.5 hours respectively, which were adopted from ReVelle and Marianov (1991). A total of 3912 fire cases during year 2003 reported by SCDF were used as historic data to estimate the local busy fraction q and the minimum number of vehicles r at each fire station. As a result, the two vectors, q and r, are model inputs, each having 151 elements. The service reliability required by SCDF was 90% (i.e., α =90%).

Emergency vehicles have right of way and can travel at free flow speed if situation allows. However, traffic congestion or physical damage to road segments may cause uncertain travel times for emergency vehicles. In this case study, random travel time was set to be $t(1+n)$ (i.e., t multiplies $(1+n)$), where t is the free flow travel time on each segment, and n is a random noise between 0 and 1 following a discrete probability distribution given in TABLE 3.4. The four discrete values of n were chosen to reflect different levels of congestion, measured by Level of Service (LOS) in traffic engineering (Khisty and Lall, 2003). A low value of n is associated with a less congested condition. For example, the scenario with n=0 represents a traffic condition of LOS A (free flow condition), n =0.2 represents a traffic condition between LOS B and C (lighted reduced speed but still within the range of stable flow), n=0.5 represents a traffic condition between LOS D and E (approaching unstable flow), and n=1 represents a traffic condition between LOS E and F (unstable flow). Please note that varying travel time based on varying levels of congestion will result in different demand node covering set N_i^h .

TABLE 3.4. Probabilities Associated with Four Congestion Levels as Model Inputs

	$n = 0$	$n = 0.2$	$n = 0.5$	$n = 1$
Discrete probability	30%	50%	15%	5%

3.3.2 Results and Findings

3.3.2.1 Model solutions

Three different models (deterministic, stochastic programming, and robust optimization) are solved using AMPL-CPLEX software package (Fourer et al., 2003). In the deterministic model, the travel times are set to be $t(1+\overline{n})$ (i.e., t multiplies $(1+\overline{n})$), where $\overline{n}$ is the expected value of n (i.e., $\overline{n}$ equals 0.225). The expected-value solution is the solution to the deterministic model (i.e. formulation (1)-(4)). For stochastic programming (SP) and robust optimization (RO) methods, there are four discrete scenarios as summarized in TABLE 3.4.

TABLE 3.5. Vehicle Allocation Strategies by Different Models (Solution Set 1)

	Methods	Fire Engine	Fire Truck	Ambulance	Cost (US$ million)
Solutions	Expected-value solution	1, 2^{2*}, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14	1, 2^2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14	1^2, 2^2, 3^2, 4, 5^2, 6^2, 7^2, 8^2, 9, 10^2, 11, 12, 13, 15	19.8
	Stochastic programming solution	1^2, 2, 3, 4, 5^2, 6, 7, 8, 9, 10, 11, 13, 14	1^2, 2, 3, 4, 5^2, 6, 7, 8, 9, 10, 11, 13, 14	1^2, 2^2, 3^2, 4^2, 5^2, 6^2, 7^2, 8^2, 9^2, 10^2, 11, 12, 13, 14, 15	20.4
	Robust optimization solution	1^2, 2, 3, 4, 5^2, 6^2, 7, 8, 9, 10, 11, 13	1^2, 2, 3, 4, 5^2, 6^2, 7, 8, 9, 10, 11, 13	1^2, 2^2, 3^2, 4^2, 5^2, 6^2, 7^2, 8^2, 9^2, 10^2, 11, 13, 14, 15	20.4

*Note: i^j denotes that j fire engines are allocated to fire station #i.

Solutions to the three models are summarized in TABLE 3.5. Columns 3 to 5 contain resource allocation strategies in terms of where and how many vehicles to be allocated. The last column shows the total monetary cost of the allocated resources, given unit prices of fire engine, fire truck, and ambulance reported by SCDF as 325, 700 and 200 (in thousand US dollars), respectively.

3.3.2.2 Performance of model solutions in simulated conditions

In this section, the reliability and robustness of different model solutions are evaluated in simulated traffic conditions. Using Monte Carlo simulation, 500 scenarios are randomly generated to simulate the varied traffic conditions by randomizing the travel times of service vehicles, following the two steps: (1) randomly select one of the three noise ranges based on the associated probability distributions in TABLE 3.6; (2) within each noise range generate random scenarios (i.e., travel times) with a uniform distribution. Note that the two conditions used for model evaluation are intentionally set to be different from the original model inputs, reflecting possible imperfect prediction of random parameter distribution. Apparently, condition B deviates more from the original model inputs, and it represents a more congested situation than condition A.

TABLE 3.6. Probabilities Associated with Noise Ranges in Monte Carlo Simulation for Model Evaluation

Simulations	n		
	[0, 0.2]	[0.2, 0.5]	[0.5, 1]
Traffic condition A	50%	30%	20%
Traffic condition B	20%	30%	50%

The performances (average, minimum, and maximum coverage and regret) of the expected-value, SP, and RO solutions across the 500 simulated scenarios in both traffic conditions are summarized in TABLE 3.7. Columns 2-4 report coverage information. For example, the second column contains the coverage results following the expected-value solution. Use traffic condition A as an example, the average coverage is 107, and the highest and lowest coverage are 58 and 122, respectively. Performances of different model solutions in terms of regret are reported in columns 5-7. Readers are referred to the section of mathematical models for the definition of regret.

TABLE 3.7. Evaluation Results of Model Solution Set 1

	Coverage			*Regret*		
	Expected-value	Stochastic	Robust	Expected-value	Stochastic	Robust
	Traffic Condition A					
Average	107	113.5	112.3	7.51	1.02	2.23
Min	58	81	81	0	0	0
Max	122	123	123	24	3	4
	Traffic Condition B					
Average	93.1	105.1	104.4	12.88	0.84	1.58
Min	58	81	81	0	0	0
Max	122	123	123	24	3	4

In general, as the congestion level increases from condition A to B, the coverage decreases because it becomes more difficult for emergency services to reach incidents within their required service time windows. The stochastic models including both SP and RO models have substantially smaller gaps between the minimum and maximum coverage and regret than the counterparts by the expected-value solution. For example, the coverage gap is 64 (=122-58) following the expected-value solution while it is 42 (=123-81) following the stochastic models. Similar observations can be made for regret gaps. It is also observed that overall SP solution has a better performance compared to the other two solutions. As shown in TABLE 3.7, SP solution achieves the highest average coverage (113.5 in condition A and 105.1 in condition B) and the lowest average regret (1 in both conditions A and B). Moreover, SP solution also performances well in the worst-case scenario (min coverage is 81, and max regret is 3). Note that the RO solution is supposed to give the lowest regret in the worst-case scenario, if the results are evaluated in exactly the same condition as the model inputs. In this case study, the RO solution does not provide the best regret in the presence of prediction error of random parameter distribution.

3.3.2.3 Sensitivity of solutions to model input

In this section, the sensitivity of different model solutions to changes of uncertain parameter settings is evaluated. The knowledge of uncertain parameters at the time of model construction may not be accurate. If a small change in parameters results in a significant change in optimal strategies, then the model is considered to be sensitive to data input. A sensitive model heavily relies on the accuracy of model input in order to produce meaningful results, thus is less preferable in an uncertain decision environment.

The three models (expected-value, SP, and RO) are solved with the same set of four noise levels but associated with a different probability distribution as shown in TABLE 3.8. This new dataset presents a more congested traffic situation for modeling, which would result in a more "conservative" solution set.

TABLE 3.8. Second Set of Probabilities Associated with the Four Congestion Levels as Model Inputs (Dataset 2)

	$n = 0$	$n = 0.2$	$n = 0.5$	$n = 1$
Discrete probability	5%	15%	30%	50%

TABLE 3.9. Vehicle Allocation Strategies by Different Methods (Solution to Dataset 2)

	Methods	Fire Engine	Fire Truck	Ambulance	Cost (US$ million)
Solution set 2	Expected-value solution	1, 2, 3, 4, 5^2, 6, 7, 8, 9, 10, 11, 13	1, 2, 3, 4, 5^2, 6, 7, 8, 9, 10, 11, 13	1^2, 2^2, 3, 4, 5^2, 6, 7, 8^2, 9, 10^2, 11, 13	16.7
	Stochastic programming solution	1^2, 2, 3, 4, 5^2, 6, 7, 8, 9, 10^2, 11, 13	1^2, 2, 3, 4, 5^2, 6, 7, 8, 9, 10^2, 11, 13	1^2, 2^2, 3^2, 4^2, 5^2, 6^2, 7^2, 8^2, 9^2, 10^2, 11, 12, 13, 14, 15	20.4
	Robust optimization solution	1^2, 2, 3, 4, 5^2, 6^2, 7, 8, 9, 10, 11, 13	1^2, 2, 3, 4, 5^2, 6^2, 7, 8, 9, 10, 11, 13	1^2, 2^2, 3^2, 4^2, 5^2, 6^2, 7^2, 8^2, 9^2, 10^2, 11, 12, 13, 14, 15	20.4

The location-allocation strategies from this sensitivity analysis are summarized in TABLE 3.9. Compared to solution from dataset 1 (see TABLE 3.7), one may notice that the expected-value solution is most sensitive to model input (total cost changes from \$19.8M to \$16.7M), while the stochastic solutions are less sensitive (total cost remains at \$20.4M). The reduction of the total cost (from \$19.8M to \$16.7M) is due to the change of the location strategy - three fire stations at locations 12, 14, and 15 that are included in solution set 1 are eliminated in the optimal solution for dataset 2. This is because when traffic becomes more congested, service vehicles face more difficulty in reaching the CTI nodes within the required service time widows, leading to less CTI nodes being covered and less total mitigation resources needed.

In contrast, stochastic solutions yield more stable strategies in response to external model inputs. For instance, the SP solution in dataset 2 allocates the same total number of vehicles of each type as in dataset 1, with a slight modification of the allocation strategy –

location 14 is eliminated from solution set 2 and the emergency vehicles are moved from location 14 to location 10. The RO solution remains unchanged. This is because changing probability distribution of the set of scenarios does not affect the RO model, as long as the set of scenarios is the same.

TABLE 3.10 Evaluation Results of Model Solution Set 2

	Coverage Expected-value	Stochastic	Robust	Regret Expected-value	Stochastic	Robust
	Traffic Condition A					
Average	108.6	112.8	112.3	5.90	1.73	2.23
Min	81	82	81	0	0	0
Max	119	122	123	12	4	4
	Traffic Condition B					
Average	102.2	105.2	104.4	3.75	0.78	1.58
Min	81	82	81	0	0	0
Max	119	122	123	12	4	4

The solution to dataset 2 was evaluated in the same way as solution set 1. The simulated results summarized in TABLE 3.10 support the following observations:

- Stochastic solutions (both SP and RO) perform better than expected-value solution in terms of the average and maximum coverage and regret;
- SP solution performs better than RO solution in terms of the average coverage and regret in both traffic conditions A and B;
- Smaller discrepancy between model inputs and the simulated condition leads to less regret. This can be observed by comparing the average regret in traffic conditions B and A. Note that traffic condition B matches data set 2 better than condition A does.

- The simulated coverage results are worse in traffic condition B than that in traffic condition A. This is due to the heavier congestion level in condition B that affects the overall accessibility of the emergency service, despite of the choice of modeling approaches.

The above observations are consistent with those from solution set 1. Overall, the stochastic models are less sensitive to imperfect information about uncertain parameters. This is an important virtue for planning under uncertainties. A planning decision usually needs to be made before the exact values of the uncertain parameters are known. This feature of planning decisions is known as non-anticipativity (Rockafellar and Wets, 1991a). Once a planning decision is in place, it may not be easily or instantly adjustable thus involving a penalty in modifying the decision. A modeling approach that requires significant modification of planning decisions (such as, relocating fire stations and emergency resources) depending on the actual realization of uncertain parameters is impractical. In addition, a solution that is sensitive to the knowledge of uncertain parameters (including the set of scenarios and their associated probabilities) is considered less robust, because perfect information about the range and distribution of uncertain parameters is almost impossible in reality.

3.4 Conclusions and Discussions

In this chapter, modeling approaches have been discussed for addressing emergency service allocation problems when service availability and transportation costs are uncertain. The discussion is cast in a specific context of locating emergency vehicles to fire stations, but the methods can be extended to other resource allocation applications such as location of emergency medical services and relief goods distribution centers.

In terms of modeling emergency resource location problems, the contribution is on combining chance constraints and stochastic programming or robust optimization to address uncertainties in both service availability and transportation accessibility. In terms of decision making under uncertainties, the study has explored how different risk preferences and stochastic modeling approaches perform in uncertain environments using a real-world case study. Even though stochastic modeling approaches are more computational challenging, the case study clearly demonstrates the value of stochastic models through an improved reliability and robustness of system performance. Sensitivity analyses show that stochastic solutions are less sensitive to errors in prediction of random parameters.

The above conclusions are drawn based on our limited numerical experiments. Future research includes comparison between stochastic models of different risk measures and conducting more case studies in regions of different spatial characteristics. In the case study here, only existing fire stations as candidate locations are considered. This may limit the efficiency of the solution compared to the alternative of allowing new locations. On the other hand, since Singapore has a well developed emergency response system and many fire stations are already in place, completely reconfiguring the whole system may not be reasonable. One may take an incremental step by allowing a few new locations added to the pool of existing stations to form a candidate set. An extended pool of candidate locations will not change the structure of the problem, but will increase the computational complexity. Each modeling method has its own emphasis of objective and different data and computational needs. Therefore, how to compare and evaluate solutions from different models is arguable. Till now, there is no definite answer to this question. Considering a broad range of performance measures and possible data errors could be a fair way to go in evaluating alternative solutions.

Chapter 4 Renewable Energy System Planning with Risk Management

Summary

A biofuel supply chain consists of various components that are interdependent on each other. In the process of seeking the least-cost infrastructure system, a crucial question is how to improve the reliability of the biofuel system against potential disruptions caused by supply seasonal variations, demand fluctuations, and facility damages. In this chapter, storage facilities for both feedstock and fuel are included in the biofuel supply chain to provide self-healing functions (via smoothing and redistribution) against unexpected system risk. A stochastic mixed-integer programming model that integrates feedstock seasonality, geographic variation, and demand fluctuation is developed, with the goal of minimizing the total expected cost of the entire supply chain of biofuel from biowastes to end users. The model is evaluated using a case study considering California corn stover feedstock resource. It was found that corn stover alone can support ethanol production up to 45 million gallons per year in California, with a cost of delivered fuel ranging from \$2.03 to \$2.75 per gallon depending on the demand. The case study also demonstrates

the role of storage facilities in smoothing the negative impact of supply seasonality and demand fluctuation on the biofuel supply chain system.

4.1 Introduction

The goal of this study is to establish a reliable and efficient biofuel supply chain system against potential supply and demand fluctuations, by integrating the design of storage facilities into the planning of the entire supply chain. The concept of supply chain, through better integration and coordination of various components of a supply system (such as procurement, production, storage, and marketing), can greatly improve the system efficiency. On the other hand, reduced redundancy and buffer, which improves the system efficiency under normal conditions, may present higher vulnerability under unexpected events such as supply shortage, demand spike, technological failure, or attacks and disasters. Following the definition by Tang (2006), the supply chain risks are categorized into operational risks and disruption risks. An operational risk refers to those recurrent risks such as supply and demand fluctuations that are inherent in supply chains. A disruption risk usually refers to external disruptions caused by natural and man-made disasters. By this definition, the types of risks we are addressing, supply seasonality and demand fluctuation, belong to the category of recurrent operational risks.

In this study, the potential disruptions caused by feedstock seasonality and demand uncertainty of biofuel supply chains will be addressed from a strategic supply chain planning viewpoint. Biofuel supply chain planning is of importance for the following reasons:

1. Cellulosic biofuel has a great potential of reducing greenhouse gas emission and diversifying transportation fuel.
2. Studies have shown the interdependence of various components of biofuel supply chains and the importance of planning the system as a whole. However, system approaches have not been widely adopted in biofuel supply chain planning.
3. Most production and delivery infrastructures of this emerging system are not in place yet, which presents an opportunity for incorporating risk management directly into its strategic planning of the supply chains.

The key feature distinguishing this study from most existing work is the integration of physical design and operational management as a whole in seeking mitigations against the above mentioned recurrent risks. Additional physical layers of feedstock and fuel storage are introduced into the supply chain for two reasons: (1) the *storage* function provides "buffer" for the system to adjust to the feedstock seasonal variation and demand fluctuation; and (2) the *redistribution* function of storage facilities over time and space increases the self-reorganization of the system hedging against potential disruptions. Facility spatiality, time variation of feedstock yields, and demand uncertainty are integrated into a two-stage stochastic programming framework where the first-stage is devoted to planning decisions while the second-stage addresses the recourse of operational decisions. Optimal strategies on biofuel production, feedstock and fuel storage, and delivery are sought simultaneously to achieve the least expected total system cost. The proposed model is used to evaluate the economic potential and system effectiveness of converting corn stover to ethanol in California. In addition to the conceptual design of the supply chain under operational risks, the real-world case study provides a realistic model incorporating both system dynamics and uncertainties, identified as lacking in the literature by (Melo et al., 2007).

This chapter is organized as follows. In section 4.2, the model formulation will be presented. The input data for the case study will be first reviewed in section 4.3, following by the results and analysis. Decomposition methods are discussed and numerical results are summarized in section 4.4. Conclusion and discussions are presented in section 4.5.

4.2. Model Formulation

FIGURE 4.1 represents a biofuel supply chain system from waste resources to end users, including feedstock storage, fuel production, and fuel storage in between. The arrows in FIGURE 4.1 denote flow (feedstock or fuel) directions. Note that the supply chain ends at city gates and that further fuel dispensing to individual refueling stations is omitted in this study. The strategic planning of this supply chain includes designing of the physical configuration of the supply chain system such as the locations and the sizes of the production and storage facilities, as well as making corresponding operational decisions such as the procurement strategy of the feedstock, the production and storage amount, and the flow transported between different layers of the supply chain.

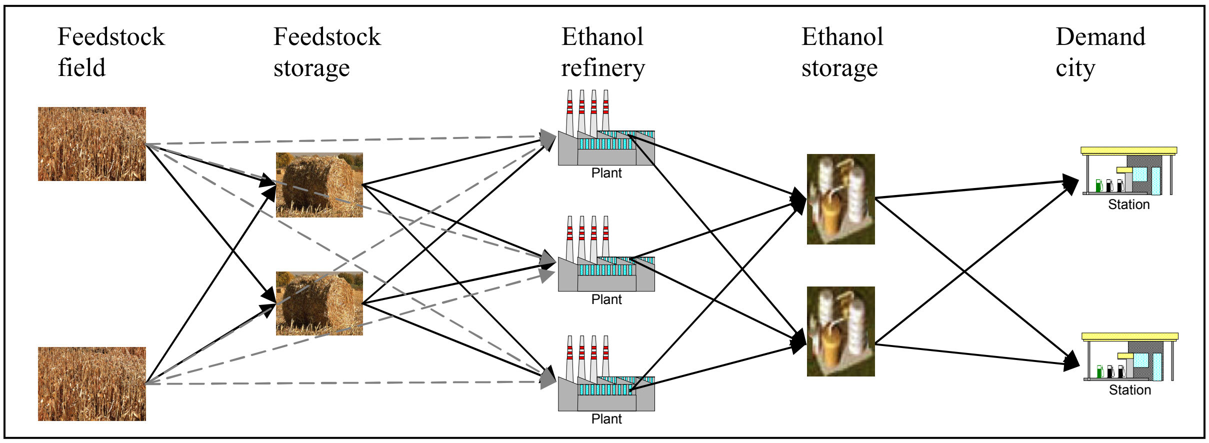


FIGURE 4.1 A Complete Biofuel Pathway

This problem spans over both spatial and temporal dimensions. The spatial dimension comes from the geographical distribution of the feedstock supply, facility locations, and demand sites. The temporal dimension is mainly caused by the seasonality of the feedstock supply. Design for such a complex system is not trivial due to the existence of several tradeoffs in the system. For example, a centralized facility takes the advantage of economy of scale, but may result in higher transport cost. Storage of feedstock and fuel may impose an extra cost to the system, but may lower the risk of future supply shortage. With the integration of the physical design of infrastructure systems and the system operation management, this study aims to balance the tradeoffs in both temporal and spatial dimensions.

In addition to the seasonality of feedstock supply, handling demand uncertainty imposes another modeling challenge. Planning decisions such as the locations and sizes of facilities (i.e., feedstock storages, refineries, and fuel storages) are usually made before the uncertain demand is known. Once these decisions are implemented, they cannot be easily modified. Operational decisions such as the production and storage quantities can be adjusted based on the actual realization of the uncertain demand. These decisions are also called recourse decisions. This feature fits well in a two-stage stochastic programming (SP) framework (Birge and Louveaux, 1997; Louveaux, 1986), which distinguishes planning and operating decisions. In this study, fuel demand is assumed to take a discrete set of possible scenarios with associated probabilities. A mixed integer SP model is developed with a goal of minimizing the expected total system cost across all possible scenarios. To reflect the temporal dimension of the problem, all recourse decision variables are time (season) dependent. The decision variables to be determined by the model include:

- locations and sizes of refineries and the storages of feedstock and fuel,
- feedstock procurements,
- feedstock storages and deliveries, and
- ethanol productions, storages and distributions.

Notations used for decision variables and model parameters are defined in TABLE 4.1.

TABLE 4.1 Notation Table

Model Parameters
T: index t, set of four seasons;
I: index i, set of feedstock fields; index i', set of feedstock storages, $i' \in I$;
J: index j, set of ethanol refineries;
K: index k, set of ethanol storages (terminals);
M: index m, set of demand cities;
Ω: index ω, set of uncertain scenarios;
p: procurement cost (\$/dry ton);
c: ethanol production cost (\$/gallon);
p^f: unit feedstock storage cost (\$/dry ton);
f_j^F : refinery fixed capital cost (\$) at location j, e.g., land price;
f_j^V : refinery variable capital cost (\$) at location j, linear function of refinery size, e.g., fixed O&M cost;
F_k^S : capital cost (\$) of ethanol storage at location k, which is fixed at a given size;
v: the average truck traveling speed (mile/hr);
d_{ij}: distance (mile) between node i and j;
t_b^d :distance dependent transportation cost (\$/mile/truckload) of bulk solids, i.e., the cost of traveling one mile per truckload, including truck fuel, insurance, maintenance, and permitting expenses;
t_b^t : travel time dependent transportation cost (\$/hr/truckload) of bulk solids, i.e., the cost of traveling one hour per truckload, including labor and capital costs;
cap_b : truck capacity (wet ton) of bulk solids;
lu_b: truck loading and unloading cost of bulk solids (\$/wet ton);
t_{lq}^d :distance dependent transportation cost (\$/mile/truckload) of liquids;
t_{lq}^t : travel time dependent transportation cost (\$/hr/truckload) of liquids;
cap_{lq} : truck capacity (gallon) of liquids;
lu_{lq}: truck loading and unloading cost of liquids (\$/gallon);
η : conversion rate (gallon/dry ton), i.e., amount of ethanol converted from one dry ton of feedstock;
cap_j^M : the maximum allowable refinery capacity (gallon) at location j;
$yield_i^t$: the maximum amount (dry ton) of feedstock available for harvesting at field i in season t;
d^t : degradation factor, accounting for the loss of feedstock in storage over season t;
$D_m^t(\omega)$: ethanol demand (gallon) at city m in season t under scenario ω;
pl : the unit penalty cost (\$/gallon) of demand shortage (i.e., imports from other states);
Decision Variables
z_j := 1 if an ethanol refinery is built at location j; =0 otherwise;
$z_{i'}^f$:= 1 if a feedstock storage facility is built at location i'; =0 otherwise;

z_k^S := 1 if an ethanol storage facility is placed at location *k*; =0 otherwise;
cap$_j$: the size of refinery (gallon) at location *j*;
Y_i^t : the amount of feedstock procured from location *i* during season *t*;
$x_{ij}^t(\omega)$: generic notation for quantity of goods (i.e. feedstock or fuel) transported from node *i* to node *j* in season *t* under scenario ω;
$FSQ_{i'}^t(\omega)$: the amount of feedstock available at in the feedstock storage i' at the beginning of season *t* under scenario ω;
$FQ_k^t(\omega)$: the quantity of ethanol available in the fuel storage *k* at the beginning of season *t* under scenario ω;
$yin_j^t(\omega)$: the total amount of feedstock delivered to refinery *j* in season *t* under scenario ω;
$pr_j^t(\omega)$: the amount of ethanol produced at refinery *j* in season *t* under scenario ω;
$q_m^t(\omega)$: unsatisfied demand (shortage) of city *m* in season *t* under scenario ω.

The complete model formulation is presented by (4.1)-(4.26):

Minimize:

$$\sum_{j\in J}(f_j^F z_j + f_j^V cap_j) + \sum_{i'\in I} z_{i'}^f + \sum_{k\in K} F_k^S z_k^S + \sum_{i\in I} pY_i^0 +$$
$$E_\omega\left(\sum_{t\in T}(T_{feedstock}(\omega,t) + T_{fuel}(\omega,t) + \sum_{i'\in I} p^f FSQ_{i'}^t(\omega) + \sum_{j\in J} c\times pr_j^t(\omega) + \sum_{m\in M} pl\times q_m^t(\omega)) + \sum_{t=1}^{3}\sum_{i\in I} pY_i^t(\omega)\right) \tag{4.1}$$

where,

$T_{feedstock}(\omega,t) =$

$$\sum_{i\in I}\sum_{j\in J}\left(\frac{(t_b^d + \frac{t_b^t}{v})\times d_{ij}}{cap_b} + lu_b\right)x_{ij}^t(\omega) + \sum_{i\in I}\sum_{i'\in I}\left(\frac{(t_b^d + \frac{t_b^t}{v})\times d_{ii'}}{cap_b} + lu_b\right)x_{ii'}^t(\omega) + \sum_{i'\in I}\sum_{j\in J}\left(\frac{(t_b^d + \frac{t_b^t}{v})\times d_{i'j}}{cap_b} + lu_b\right)x_{i'j}^t(\omega) \tag{4.1a}$$

$T_{fuel}(\omega,t) =$

$$\sum_{j\in J}\sum_{k\in K}\left(\frac{(t_{lq}^d + \frac{t_{lq}^t}{v})\times d_{jk}}{cap_{lq}} + lu_{lq}\right)x_{jk}^t(\omega) + \sum_{k\in K}\sum_{m\in M}\left(\frac{(t_{lq}^d + \frac{t_{lq}^t}{v})\times d_{km}}{cap_{lq}} + lu_{lq}\right)x_{km}^t(\omega) \tag{4.1b}$$

The objective function (4.1) minimizes the expected total system cost, a sum of the planning costs and the expectation of the recourse costs. The planning costs, including the facility (feedstock storage, refinery, and fuel storage) capital costs and the initial feedstock procurement cost, do not depend on the scenarios. The recourse costs are scenario dependent, which include feedstock delivery ($T_{feedstock}$), ethanol distribution (T_{fuel}), feedstock storage, ethanol production, penalty, and the feedstock procurement cost for the remaining seasons. Note that the feedstock procurement is considered as a planning decision (made at one season ahead of time) – the procurement decision for the first season is made at the end of the 0^{th} stage when the actual random demand of the first season is not known yet. This is why in the recourse cost term, the feedstock procurement cost only occurs in the first three seasons. The feedstock delivery and fuel distribution costs are defined in (4.1a) and (4.1b), respectively. Use feedstock delivery cost ($T_{feedstock}$) as an example to illustrate the cost structure. The supply chain involves three types of delivery: from field to refinery (denoted as *ij*), from field to feedstock storage (denoted as *ii'*), and from feedstock storage to refinery (denoted as *i'j*). In all the deliver trips, the transport cost is estimated by distance (t^d)- and time (t^t)- dependent costs, and loading/unloading cost. Delivery quantity is divided by truck capacity to be converted to number of truckloads, based on which the distance- and time-dependent costs are calculated. The loading/unloading cost is linear to the delivery quantity.

Constraints on ethanol refineries:

$$\sum_{i \in I} x_{ij}^t(\omega) + \sum_{i' \in I} x_{i'j}^t(\omega) = yin_j^t(\omega) \quad \forall j \in J, t \in T, \omega \in \Omega \tag{4.2}$$

$$\sum_{k \in K} x_{jk}^t(\omega) = pr_j^t(\omega) \quad \forall j \in J, t \in T, \omega \in \Omega \tag{4.3}$$

$$cap_j = \max_{\omega}\{\sum_{t \in T} pr_j^t(\omega)\} \quad \forall j \in J \tag{4.4}$$

$$cap_j \le cap_j^M \quad \forall j \in J \tag{4.5}$$

$$yin_j^t(\omega) \times \eta = pr_j^t(\omega) \quad \forall j \in J, t \in T, \omega \in \Omega \tag{4.6}$$

$$pr_j^t(\omega) \le \overline{M} z_j \quad \forall j \in J, t \in T, \omega \in \Omega \tag{4.7}$$

Equation (4.2) states that the feedstock used for fuel production can be from fields and/or storages. Equation (4.3) is a flow conservation constraint, meaning that the amount of produced ethanol equals the total outflow to fuel storage. The refinery size (cap_j) is defined in Equation (4.4), which equals the maximum total production among all possible scenarios. Inequality (4.5) restricts the refinery size within the maximum allowable capacity. Equation (4.6) computes the energy conversion from feedstock to ethanol. Constraint (4.7) is a logic constraint, where $\overline{M}$ is a large positive number, enforcing that no ethanol is produced at location j unless a refinery operates at that location.

Constraints on feedstock sites:

$$Y_i^t \le yield_i^t \quad \forall i \in I, t \in T \tag{4.8}$$

$$Y_i^t = \sum_{j \in J} x_{ij}^t(\omega) + \sum_{i' \in I} x_{ii'}^t(\omega) \quad \forall i \in I, t \in T, \omega \in \Omega \tag{4.9}$$

As constrained by inequality (4.8), the feedstock procurement cannot exceed the total available yields at field *i*. Equation (4.9) ensures that procured feedstock is delivered to feedstock storages for inventory and/or directly to refineries for production.

Constraints on feedstock storages:

$$FSQ_{i'}^{t+1}(\omega) = d^t FSQ_{i'}^t(\omega) + \sum_{i' \in I} x_{ii'}^t(\omega) - \sum_{j \in J} x_{i'j}^t(\omega) \quad \forall i' \in I, t \in T, \omega \in \Omega \tag{4.10}$$

$$FSQ_{i'}^t(\omega) \le \overline{M} z_{i'}^f \quad \forall i' \in I, t \in T, \omega \in \Omega \tag{4.11}$$

$$x_{ii'}^t(\omega) \le \overline{M} z_{i'}^f \quad \forall i' \in I, i \in I, t \in T, \omega \in \Omega \tag{4.12}$$

Equation (4.10) is a flow conservation constraint at feedstock storage in both spatial and temporal dimensions. The feedstock inventory at the beginning of season t+1 (denoted as $FSQ_{i'}^{t+1}$) equals the discounted feedstock inventory of season t (i.e., $FSQ_{i'}^t$ multiplies the degradation factor d^t), plus the amount of feedstock delivered to feedstock storage ($\sum_{i' \in I} x_{ii'}^t$), and subtracted by the amount of feedstock outflow to refineries ($\sum_{j \in J} x_{i'j}^t$). Inequality (4.11) and (4.12) are two logic constraints on feedstock storages, which can be similarly explained as for constraint (4.7).

Constraints on ethanol storages:

$$FQ_k^{t+1}(\omega) = FQ_k^t(\omega) + \sum_{j \in J} x_{jk}^t(\omega) - \sum_{m \in M} x_{km}^t(\omega) \quad \forall k \in K, t \in T, \omega \in \Omega \tag{4.13}$$

$$FQ_k^t(\omega) \le cap^S \quad \forall k \in K, t \in T, \omega \in \Omega \tag{4.14}$$

$$FQ_k^t(\omega) \le \overline{M} z_k^S \quad \forall k \in K, t \in T, \omega \in \Omega \tag{4.15}$$

$$x_{jk}^t(\omega) \le \overline{M} z_k^S \quad \forall j \in J, k \in K, t \in T, \omega \in \Omega \tag{4.16}$$

Constraint (4.13) is the flow conservation constraint at ethanol storage, which can be similarly explained as for constraint (4.10) except that there is no need to discount the fuel inventory over time. Inequality (4.14) imposes a fuel storage capacity. Inequalities (4.15) and (4.16) are logic constraints at fuel storages.

Constraints on demand centers:

$$\sum_{k \in K} x_{km}^t(\omega) + \sum_{m \in M} q_m^t(\omega) = D_m^t(\omega) \quad \forall m \in M, t \in T, \omega \in \Omega \tag{4.17}$$

Equation (4.17) computes the recourse for the amount of demand unsatisfied by in-state production. The recourse may be considered as imported fuel from other states.

Integer and nonnegativity constraints:

$$z_j \in \{0,1\} \quad \forall j \in J \tag{4.18}$$

$$z_{i'}^f \in \{0,1\} \quad \forall i' \in I \tag{4.19}$$

$$z_k^S \in \{0,1\} \quad \forall k \in K \tag{4.20}$$

$$cap_j \ge 0 \quad \forall j \in J \tag{4.21}$$

$$x_{ij}^t(\omega) \ge 0 \ \forall i \in I, j \in J, t \in T, \omega \in \Omega \tag{4.22}$$

$$FSQ_{i'}^{t}(\omega) \geq 0 \quad \forall i' \in I, t \in T, \omega \in \Omega \tag{4.23}$$

$$FQ_{k}^{t}(\omega) \geq 0 \quad \forall k \in K, t \in T, \omega \in \Omega \tag{4.24}$$

$$yin_{j}^{t}(\omega) \geq 0 \quad \forall j \in J, t \in T, \omega \in \Omega \tag{4.25}$$

$$pr_{j}^{t}(\omega) \geq 0 \quad \forall j \in J, t \in T, \omega \in \Omega \tag{4.26}$$

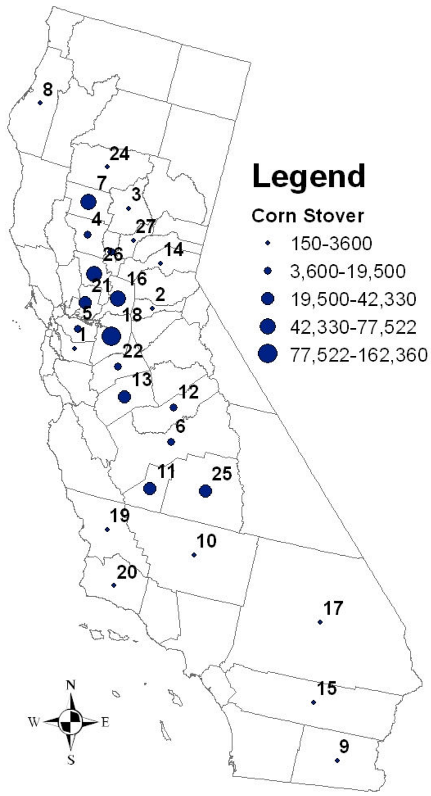
$\overline{M}$ is a big positive number

4.3. Case Study

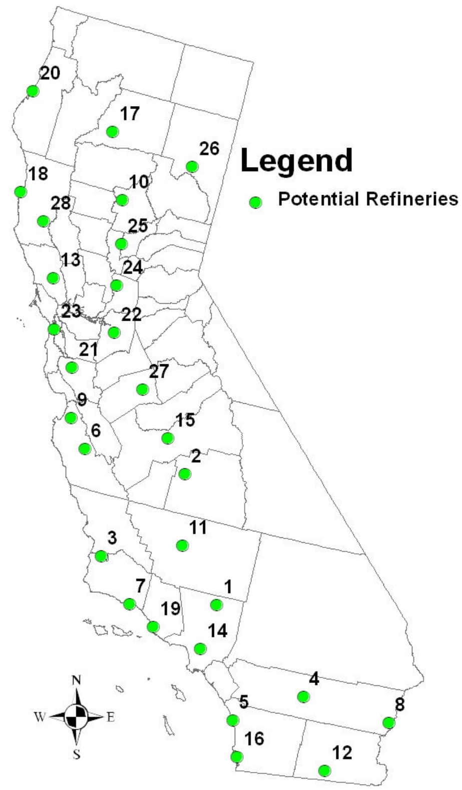
4.3.1 Input data

Geographical Data

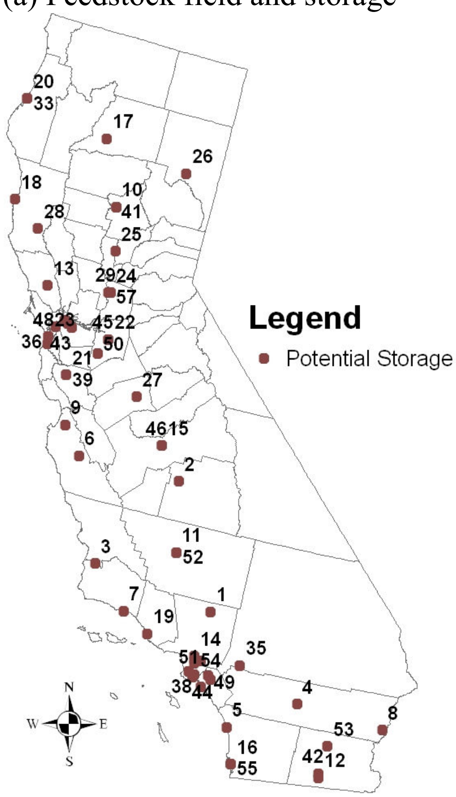
Different types of feedstock have different specific harvesting time period. Corn stover being a typical agriculture residue for ethanol production is considered in this study as a proof of concept. As shown in FIGURE 4.2, corn stover is unevenly distributed in California, mainly clustered in the central valley areas. The locations and the annual yields of corn stover are aggregated at centroids of counties or cities in Geographic Information System (GIS), in order to integrate the feedstock resources with transportation network.



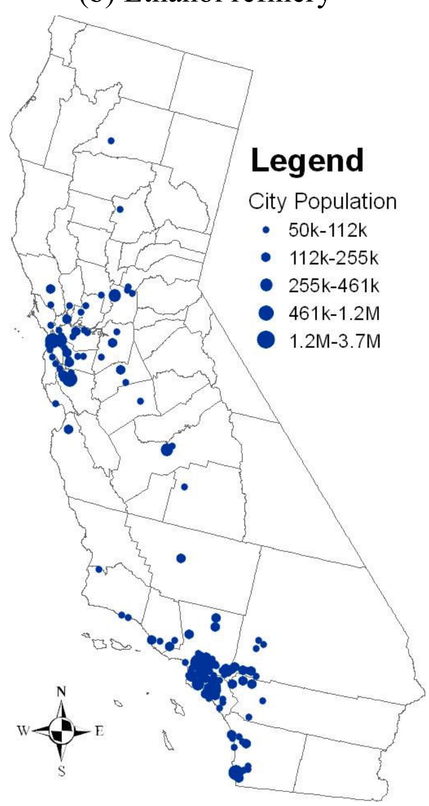
(a) Feedstock field and storage



(b) Ethanol refinery



(c) Ethanol storage



(d) Demand city

FIGURE 4.2 Facility Geographical Distribution

.Totally there are 27 corn stover sites, 28 potential refinery sites, 57 ethanol storage sites, and 143 demand clusters. Candidate refinery and storage sites include existing facilities and potential sites within a close proximity to water, labor, and major freeways. Demand clusters include cities with population larger than 50,000. The details of facility location criteria are available in the Western Government Association report (Parker et al., 2007).

Feedstock Data

The total corn stover yield is 562,667 dry ton per year and its harvesting period is between September 1st and December 1st (National Agricultural Statistics Service, 1997). Theoretically, the total amount of available corn stover can produce 45.3 million gallon per year (MGY) of ethanol, given a conversion rate of 80.6 gallon/dry ton[1](Parker et al., 2007). The moisture content is about 15% (Parker et al., 2007), which will affect the delivery cost.

Corn stover harvesting needs to go through a sequence of procedures: shredding, baling, and stacking. Its procurement cost is $13.1/dry ton (Sokhansanj et al., 2002).

The storage operating cost is $8/dry ton. The facility capital cost is negligible when the uncovered or tarped storage types are adopted (Sokhansanj et al., 2002).

[1] One dry ton of corn stover can produce 80.6 gallons of ethanol.

Conversion Technology, Refinery, and Ethanol Storage Data

The LignoCellulosics Ethanol (LCE) via hydrolysis and fermentation conversion technology with specific Dilute Acid pretreatment process was used (Parker et al., 2007) for its low cellulose enzyme cost and reasonably high conversion rate. According to the recent report (Office of the Biomass Program, 2009), producing ethanol involves pretreatment, production, and recovery processes, and approximately costs $0.92 per gallon.

The refinery cost includes fixed capital cost (facility setup cost) and variable capital cost (facility size-dependent cost), The fixed capital cost was annualized assuming a real discount rate of 10% and lifetime of 20 years, based on the 2015-year technology performance. The fixed capital cost is $6.157m and the variable capital cost is $0.314 per gallon for the whole study area. The size of the refinery is determined by the model subject to the constraint of maximum refinery capacity as 100MGY.

For fuel storage, single-size tank with a capacity of 100 thousand barrels (equivalent, 4.2 million gallons) was considered. The total capital cost is $1.57m, which consists of the tank cost of $1.26m, the blending system cost of $0.3m, and the cost of $10,000 for product receipt by truck (Downstream Alternatives Inc., 2000).

Transportation Cost

For in-state production, trucking is considered as the only transportation mode. The maximum load is set to be 25 wet tons for bulk solids and 8,000 gallons for liquid. Considering the combined effects of local and highway traffics, the average travel speed is assumed to be 40 mile/hr. In a California road network (containing local, rural, urban roads, and major highways), shortest paths (paths with minimum cost) are calculated and assumed to be the shipping routes. The transportation cost has three parts: loading/unloading cost, time dependent travel cost, and distance dependent travel cost (see TABLE 4.2) (Parker et al., 2007). Time dependent cost includes labor and capital cost of trucks, while distance dependent cost includes fuel, insurance, maintenance, and permitting cost. The truck is fueled by diesel with a cost of $2.50 per gallon.

TABLE 4.2 Trucking Cost

	Liquids	***Bulk solids***
Loading/unloading	$0.02/gallon	$5/wet ton
Time dependent	$32/hr/truckload	$29/hr/truckload
Distance dependent	$1.30/mile/truckload	$1.20/mile/truckload
Truck Capacity	8,000 gallons	25 wet tons

<u>Demand Scenarios</u>

Three possible demand scenarios (for in-state corn stover based ethanol) are considered with equal probability: median, high, and low (see TABLE 4.3). The average demand is set to 6.75 million gallon per year reported in (Downstream Alternatives Inc., 2000). The seasonal demand distribution is 24.4%, 25.5%, 25.3%, and 24.8% (over four seasons), estimated based on the Energy Information Administration's historical ethanol consumption data. The state-wide fuel consumption is distributed to demand clusters proportionally to their populations.

TABLE 4.3 Three Demand Levels

	Median	*High*	*Low*
% difference from median	0	+2%	-2%
Probability	1/3	1/3	1/3

4.3.2 Results and Analysis

Results of Baseline Case Study

The penalty cost of fuel shortage is set high at $5 per gallon to encourage in-state production. The optimal solution suggests a centralized system pattern - one feedstock storage, one refinery, and one fuel storage in the central valley area, as shown in FIGURE 4.3. The system configuration is summarized in TABLE 4.4.

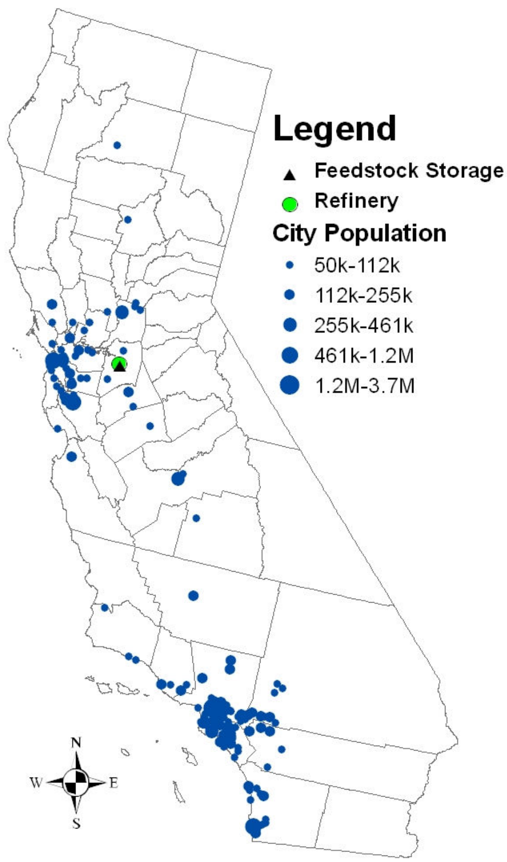


FIGURE 4.3 An Optimal System Layout in the Baseline Case Study

TABLE 4.4 The Optimal System Configuration of Baseline Scenario

	Quantity	Location[1]	Size
Feedstock storage	1	#18	14,709 (dry ton)
Ethanol refinery	1	#22	6,885,000 (gallons)
Ethanol storage	1	#22	4,200,000 (gallons)[2]

1: Location ID number are from GIS map.
2: The size of ethanol storage is predefined.

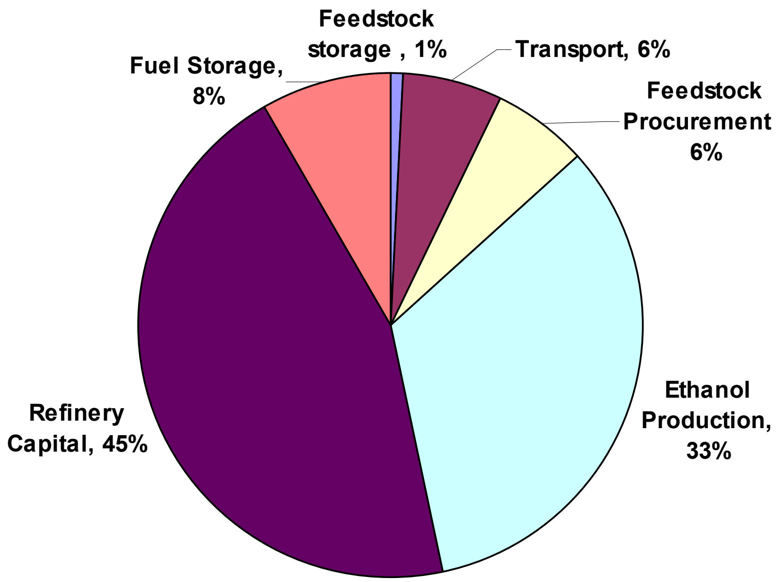


FIGURE 4.4 Breakdown of Total System Cost

The expected cost of delivered ethanol is $2.75 per gallon. The cost breakdown of the six cost components - feedstock procurement cost, refinery capital cost, production cost, transport cost, and feedstock and fuel storage costs, is given in FIGURE 4.4. The refinery capital cost is identified as the major cost driver, taking almost half of the total system cost. This high percentage is largely because of the low economy of scale as a result of low demand. The feedstock storage contributes least to the total cost (only 1%). However, together with fuel storage, it smoothens out the supply-demand discrepancy over seasons, as illustrated in FIGURE 4.5 by using the low-demand scenario as an example.

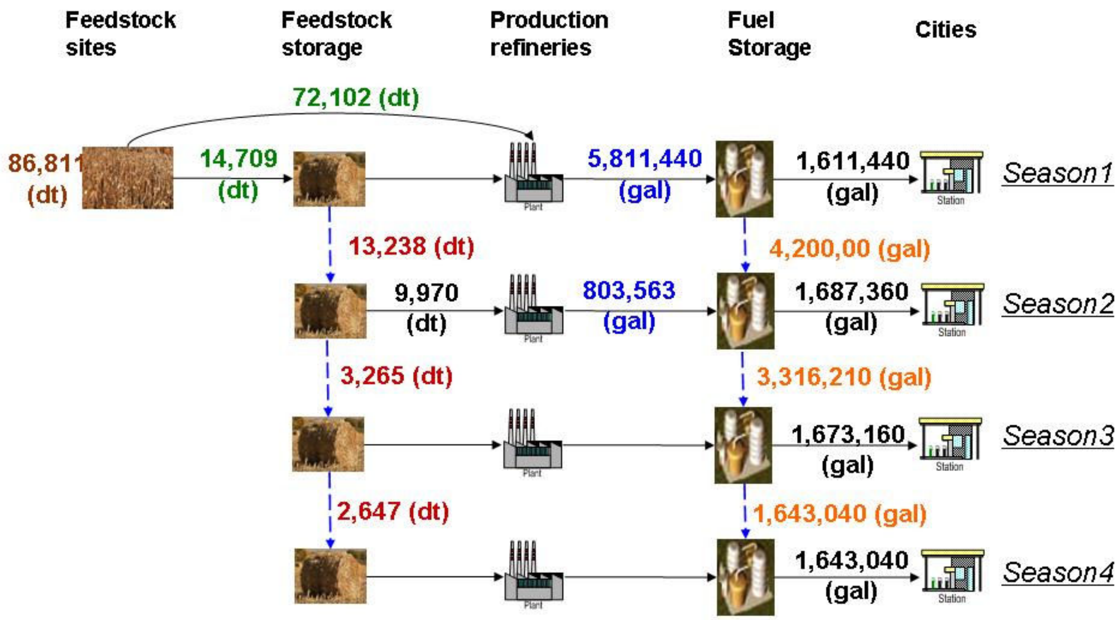


FIGURE 4.5 System Operations in Low-Demand Scenario

Sensitivity Analysis

1. Critical role of feedstock storage

Feedstock storage, different from fuel storage, is optional to the system. However, it was chosen as part of the optimal solution. A sensitivity analysis is carried out to test the impact of feedstock storage on the total system cost. FIGURE 4.6 shows the benefit of having feedstock storage (saving total system cost by about 3% to 7%) under a range of penalty cost between \$2.5 and \$5 per gallon. The penalty cost may be considered as the price of imported biofuel. The light-color bars in the figure represent the expected total system cost of having both types of storages; the dark-color bars represent the total system cost when feedstock storage is excluded. It is clear that inclusion of feedstock storage is more cost-effective. Moreover, feedstock storage also reduces the sensitivity of the system toward the change of penalty cost, indicated by the flatly distributed light-color bars. By contrast, the total system cost could fluctuate up to 5% in the case without feedstock storage. These observations clearly indicate the critical roles of feedstock storage in reducing the risk caused by supply/demand fluctuation.

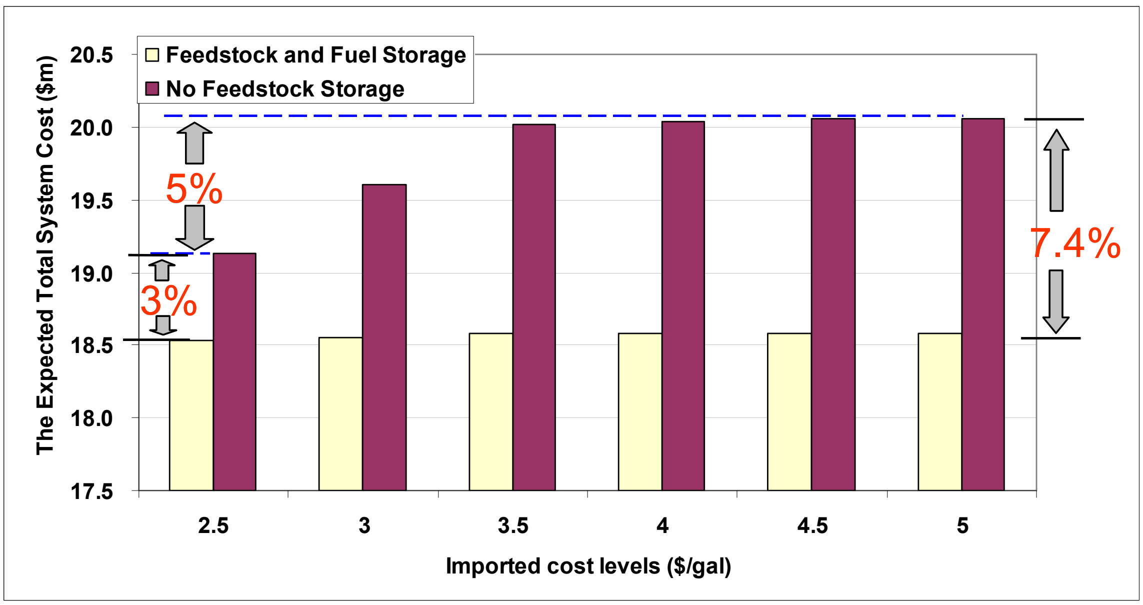


FIGURE 4.6 Feedstock Storage Functionality in Improving System Reliability

2. Variations of Uncertain Parameter Settings

In this section, we test the sensitivity of the model against different settings of uncertain parameters. In general, a solution that is sensitive to the knowledge of uncertain parameters (including the set of scenarios and their associated probabilities) is considered less robust, because perfect information about the distribution of uncertain parameters is almost impossible in reality. Two parameter settings are separately tested:

- *unevenly distributed demand scenarios*: a different distribution of uncertain demand scenarios (1/6, 2/3, and 1/6 for low, median, and high demand levels, respectively) is tested, rather than the even distribution assumed in the baseline case;
- *Higher demand variation*: we increase the demand fluctuation (i.e., relative difference in comparison with median-level demand) from 2% to 10% to understand how demand variation might influence the system decisions.

The results of all the sensitivity analyses are summarized in TABLE 4.5. The following observations are made:

- *The planning decisions (facility locations and sizes) are not sensitive to the changes of uncertain parameter setting*. This is an important virtue for planning under uncertainties. A planning decision usually needs to be made before the exact values of the uncertain parameters are known. This feature of planning decisions is known as non-anticipativity (Rockafellar and Wets, 1991a). Once a planning decision is in place, it may not be easily or instantly adjustable thus involving a penalty in modifying the decision. Therefore, a model that requires significant modification of planning decisions depending on the actual realization of uncertain parameters is impractical.
- Higher risk/uncertainty level directly results in a higher total system cost. For example, the total system cost resulted from the uneven distribution, which is less

uncertain (entropy = 0.377), is smaller than the total system cost resulted from the even distribution (entropy = 0.477) assumed in the baseline scenario.

TABLE 4.5 Sensitivity Analyses for Some Model Parameters

Cost components	**Baseline scenario**	Uneven demand distribution		Higher demand fluctuation	
		absolute value	rate of change compared to baseline	absolute value	rate of change compared to baseline
Feedstock Procurement	**$1,137,226**	$1,113,440	-2.09%	$1,232,369	8.37%
Feedstock storage	**$149,835**	$105,786	-29.40%	$349,650	133.36%
Ethanol Production	**$6,210,000**	$6,189,804	-0.33%	$6,210,000	0.00%
Refinery Capital	**$8,319,590**	$8,278,233	-0.50%	$8,489,150	2.04%
Fuel storage	**$1,570,000**	$1,570,000	0.00%	$1,570,000	0.00%
Penalty cost	**$0**	$109,762		$0	
Transportation*	**$1,198,347**	$1,185,800	-1.05%	$1,229,214	2.58%
Feedstock field to feedstock storage	**$60,779**	$53,062	-12.70%	$91,646	50.79%
Feedstock field to refinery	**$333,195**	$333,195	0.00%	$333,195	0.00%
Feedstock storage to refinery	**$51,634**	$50,383	-2.42%	$51,634	0.00%
Refinery to fuel storage	**$135,000**	$134,561	-0.33%	$135,000	0.00%
Fuel storage to city	**$617,740**	$614,600	-0.51%	$617,740	0.00%
Total system cost	**$18,584,999**	$18,552,825	-0.17%	$19,080,383	2.67%
Delivered cost ($/gallon)	**$2.75**	2.75		$2.83	
Refinery location	**#22**	#22		#22	
Feedstock storage location	**#18**	#18		#18	
Fuel storage location	**#22**	#22		#22	
Refinery size (million gallon)	**6.885**	6.885		6.885	

*note: the total transportation cost is further broken down to five segments.

3. Demand increase

The total available corn stover in the state can theoretically produce up to 45MGY of ethanol. A set of sensitivity analyses (see FIGURE 4.7) were conducted to identify the impacts of demand changes on delivered ethanol cost and costs of system components.

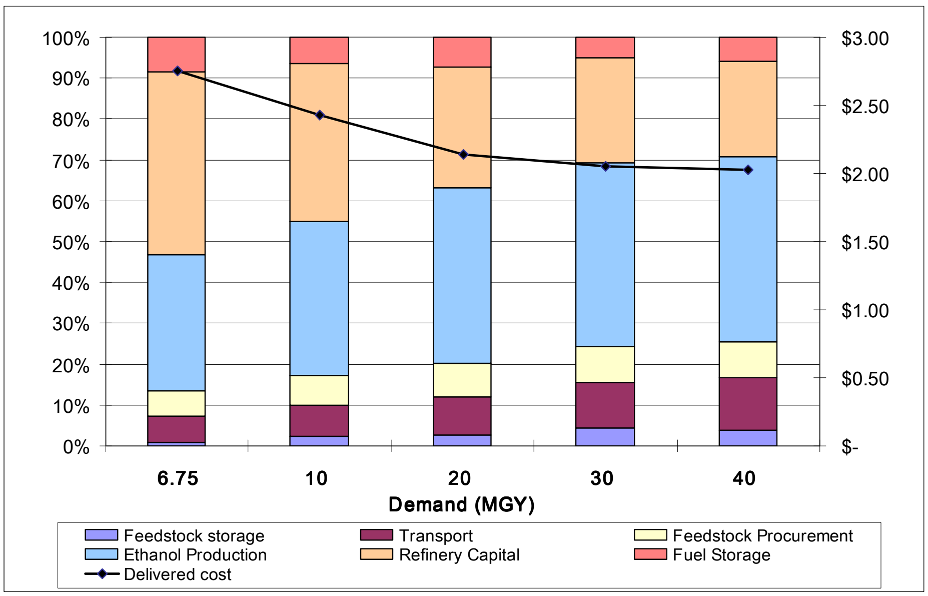


FIGURE 4.7 Cost Components and Average Delivered ethanol Cost under Different Demands

The results clearly indicate that higher demand leads to a reduced delivered cost from \$2.75 to \$2.03 per gallon due to the improved economy of scale. The capital cost percentage decreases from 45% to 33%. However, the fuel production cost weights more, which in turn raises the costs in transporting and procuring more feedstock from remote areas.

4.4. Computational Challenges: Decomposition Method

Solving SP model plainly by AMPL-CPLEX is computationally challenging, especially for large-scale problems with complex modeling structure, which motivates additional research endeavor in developing an efficient decomposition method. The Progressive Hedging (PH) method is considered to partition the SP model across scenarios as a means of reducing computing difficulty (Watson et al., 2008), which was invented by Rockafellar and Wets (1991a).

The basic scheme of PH method is described blow by using a generic mathematical model in an Extensive Form (4.27) and (4.28):

$$\text{Minimize: } (c \cdot x) + \sum_{s \in S} P_s (t_s \cdot y_s) \tag{4.27}$$

$$\text{Subject to: } (x, y_s) \in F_s \qquad \forall s \in S \tag{4.28}$$

where S is the set of possible scenarios, and s ($s \in S$) denotes an individual scenario for future demand, x denotes the first-stage decisions (non-distinguishable across scenarios) with a cost coefficient vectors c, and y_s represents the second-stage decisions with associated cost coefficient vectors t_s. For each scenario $s \in S$, the probability of the occurrence is denoted as P_s. The objective is to minimize the total expected cost as described in (4.27). The decisions are subject to the constraints defined by the feasibility set F_s for each scenario s as described in constraint (4.28). In this study, the decisions (x) are refinery locations and sizes, feedstock and fuel storage locations, and feedstock procurement decisions, and the decisions (Sheehan et al.)are operational decisions on the second stage.

The model defined by Eqs (4.27) and (4.28) can be partitioned to scenario dependent sub-problems. Solving the scenario sub-problems for all s ($s \in S$) will result in different *s*-dependent first-stage solutions, denoted as x_s for each $s \in S$. However, these solutions cannot be directly implemented, because at the time when the location decision solutions are implemented, one does not know yet which scenario is going to happen. In order to consolidate the *s*-dependent solutions to an *implementable* solution, one must impose a *non-anticipativity* constraint defined in (Rockafellar and Wets, 1991a):

$$x_s - z = 0 \qquad \forall s \in S \tag{4.29}$$

where z is a vector of free variables. This condition states that a reasonable policy should not require different actions relative to different scenarios if the scenarios are not distinguishable at the time when the actions are taken. The SP model can be reformulated as:

$$\text{Minimize } (c \cdot x_s) + \sum_{s \in S} P_s (t_s \cdot y_s) \tag{4.30}$$

$$\text{Subject to: } (x_s, y_s) \in F_s \qquad \forall s \in S \tag{4.31}$$

$$x_s - z = 0 \qquad \forall s \in S \tag{4.29}$$

The PH method decomposes a stochastic problem across scenarios and partitions the problem into manageable sub-problems. Define

$$L_r(X,Y,z,W) = \sum_{s\in S} P_s Q_s(x_s, y_s) + (w_s)' \cdot (x_s - z) + \frac{1}{2}\gamma \left\| x_s - z \right\|^2 \qquad (4.32)$$

as the augmented Lagrangian, where W is the vector of dual variables for the constraints in (4.29), and $\gamma > 0$ is a penalty parameter associated with violation of the *non-anticipativity* constraints. Function $Q_s(x_s, y_s)$ is the total first- and second- stage cost in a given scenario s, which depends on the decisions x_s and y_s. Therefore, the augmented Lagrangian integrates the non-anticipativity constraint with the original objective function. The stochastic problem becomes

Minimize $L_r(X,Y,z,W)$ for all $(x_s, y_s) \in F_s$. (4.33)

PH algorithm procedure is described as follows:

Step 1

Set the iteration index $k = 0$.

Solve for each scenario sub-problem and then obtain $(x_s^{(0)}, y_s^{(0)}), \forall s \in S$.

Initialize $z^{(0)} := \sum_{s\in S} P_s x_s^{(0)}$ and $w_s^{(0)} := \gamma(x_s^{(0)} - z^{(0)})$

If $x_s^{(0)} = z^{(0)}, \forall s \in S$ then the optimal solution is found; otherwise continue with *step 2*.

Step 2

$k = k+1$

Solve for each scenario $\forall s \in S$

$$x_s^{(k)} := \arg\min_x (cx_s + t_s \cdot y_s + w_s^{k-1} x_s + \frac{\gamma}{2} \left\| x_s - z^{k-1} \right\|^2) : (x_s, y_s) \in F_s$$

Update $z^{(k)} := \sum_{s \in S} P_s x_s^{(k)}$ and $w_s^{(k)} := w_s^{(k-1)} + \gamma(x_s^{(k)} - z^{(k)}), \forall s \in S$

Step 3

Stop, if $\varepsilon = [\left\| z^{(k)} - z^{(k-1)} \right\|^2 + \sum_{s \in S} P_s \left\| x^{(k)} - z^{(k)} \right\|^2]^{1/2} \approx 0$ is reached; otherwise, go to *step 2*.

The performances of the PH method are evaluated on three cases derived from the study and descriptions are given in TABLE 4.6, in which the number of potential facility locations is set to be different. All numerical experiments were executed on 3.06GHz dual Intel Xeon running Windows XP, with 4GB of RAM.

TABLE 4.6 Descriptions of Three Cases

	# of candidate feedstock storage locations	# of candidate refinery locations	# of candidate fuel storage locations	# of cities
Case 1 – test size	12	5	10	8
Case 2 – median size	20	20	20	40
Case 3 – full size	27	28	57	143

The performances of PH algorithm against the plain solution on CPLEX 11.0 are summarized in TABLE 4.7. It is obvious that the PH algorithm significantly reduces the run time without scarifying the solution quality (with negligible difference). The benefits become more noticeable with the increase of problem size. For the full-size problem, PH yields the identical objective value but reduce the run time by 90%.

TABLE 4.7 The Performances of Solution Methods in the Three Cases

Solution methods	*Case 1 – test size*		*Case 2 – median size*		*Case 3 – full size*	
	Obj. ($)	T. (min)	Obj. ($)	T. (min)	Obj. ($)	T. (min)
CPLEX	8,221,853	0.10	10,159,171	25.52	18,584,999	1505.77
PH	8,225,807	0.27	10,178,996	5.90	18,584,999	184.10

For each algorithm, the total expected system cost (Obj. labeled columns) and run time (T. labeled columns) are reported.

4.5. Conclusions and Discussions

The study demonstrated the critical role of storage facility in risk management of biofuel supply chain. It smoothens out the impacts of the seasonality of feedstock supply and demand fluctuation to gain a better system economic and efficiency. A mixed-integer stochastic program that integrates feedstock seasonality, geographic variation, and demand fluctuation has been proposed to optimize the entire supply chain, aiming at achieving the least total system cost. The model has been used to assess the economic potential of corn stover based ethanol in California. The optimal results suggest that both feedstock and fuel storages should be included in the supply chain and that excluding the feedstock storage will result in an increase of the total system cost in a range of 3%-7%. The overall delivered cost falls between $2.03 and $2.75 per gallon, depending on the scale of the overall state demand. From modeling perspective, the planning solution is identified to be reliable in hedging against demand uncertainties.

The delivered cost in this study is higher than the $2.19 per gallon provided in the previous WGA assessment study (Parker et al., 2007) for two main reasons: (1) it considers additional storage facility layers in the supply chain for feedstock and fuel inventory; (2) through stochastic modeling, the study introduces redundancy in terms of feedstock and fuel to achieve better reliability against demand uncertainties.

An immediate extension to this study is to diversify the feedstock supply to consider a set of multiple types of lingocellulosic biomass. Although this addition will not impose additional challenge on modeling, it requests extra research efforts on data acquisition (including the feedstock and technology parameters) and improvement of solution efficiency for enlarged model scale. From risk management perspective, the non-recurrent disruptions, featuring low probability but severe consequences on energy supply chain, should be addressed in a system modeling framework, which may however require different risk management approaches from this study.

Chapter 5 Transitional Energy System Planning Under Uncertainty

Summary

Transforming to renewable energy based society involves transitional processes. Dynamics due to the evolving technologies and societal changes are the major issues. In addition, considerable uncertainty from resource supply and demand market is inevitable over the transition, which however has not been given sufficient attention in the existing research literature. The research work presented in this chapter seeks to fill this void.

A stochastic dynamic programming model that integrates the spatial and temporal dimensions is proposed for sequentially building a renewable energy production and distribution system under dynamics and uncertainties. The decision variables are the sequence and locations of the production sites and the corresponding distribution systems from supply to demand sites in hedging against uncertainty. A case study based on the hydrogen system in Northern California is included, in which the hydrogen is produced via coal gasification and transported from plant to city gates (demand sites) by cryogenic liq-

uid hydrogen trucks. Future demands for hydrogen are modeled as uncertain parameters, with an assumption that hydrogen fuel cell vehicle (HFCV) market penetration rate increases from 1% to 25% over a 20-year period. Although coal to hydrogen via gasification is not a renewable pathway, this model provides multistage decision support for long term transportation energy planning at national and regional levels, which can be adapted for renewable pathways, such as, biomass to hydrogen.

5.1 Introduction

Predicted growth in energy demand calls for additional sources of energy, especially renewable energy, to supplement traditional energy sources. Transforming to the renewable energy based society is a long-term planning process and the system will be built and expanded incrementally over time. Dynamics due to the evolving technologies and societal changes are the major issue, which however has not been studied in the existing literature. The research work presented in this chapter seeks to fill this void.

This study focuses on incorporating system dynamics into a long-term strategic planning of renewable energy systems. The problem involves both spatial and temporal dimensions. The *spatial dimension* mainly lies in the geographic distributions of the feedstock sources, the fuel demands, and the production and transportation infrastructures. The costs of feedstock, fuel production, and transport are interdependent. The *temporal di-*

mension arises in system planning with a goal of serving the long-term societal needs. The production and distribution infrastructure system will have to be expanded over time in response to the growing demand. To achieve an overall effectiveness of the system expansion, the dynamics of such an evolving process needs to be taken into consideration in the system planning. Thereby, the conventional time-independent snapshot method, as used in previous studies, is inadequate (Fiksel, 2006; Johnson, 2007).

In a recent study, a multistage mathematical model that integrates *facility spatiality* and *time variation* of demands was introduced for a strategic planning for the future bioethanol supply chain systems (Huang et al., In press). In this deterministic model, the best sequence of opening and expanding biorefineries over time is determined and the optimal bioethanol production and distribution system as a whole is sought for a given planning horizon. Lin et al. (2008) did a study of developing hydrogen supply system in Southern California in a dynamic programming Framework, but without considerations of uncertainty.

In addition, there is considerable uncertainty regarding the growth in demand over time, which requires an additional dimension in the model for handling uncertainties. The research study presented in Chapter 4 addressed uncertainties in a stochastic modeling framework but only for a span of one year. For a long-run planning, a more sophisticated modeling approach, namely multistage stochastic dynamic programming, will be used with an aimof optimizing the process of building and operating the system over the transition.

Future demand is treated as the major source of uncertainty, and is assumed to increase over time. The location and sequence of production facilities are strategic planning decisions that are usually made over a long planning period and cannot be easily modified once implemented. In addition, there are operational decisions, such as the production quantities and the deliveries between plants and demand centers, which are examined more frequently and can be adjusted according to newly acquired information. This problem feature leads to the choice of master- and sub- problem structure. The master-problem model focuses on the total expected system cost over the entire planning horizon while the sub-problem model focuses on the single-stage operational cost. The master and sub-problem models pass information between each other and are solved together iteratively. The details of this model structure will be provided in the next section.

A case study based on hydrogen system in Northern California is included, in which the hydrogen is produced via coal gasification and transported from plant to city gates (demand sites) by cryogenic liquid hydrogen trucks (Johnson, 2007). The demand for hydrogen is assumed to increase as hydrogen fuel cell vehicle (HFCV) market penetration rate increases from 1% to 25% of vehicles on the road over a 20-year period (Miller et al., 2005). Sensitivity analyses were conducted to identify important model parameters and to analyze their impacts on the design and cost-effectiveness of hydrogen infrastructure systems. It is noted that although coal to hydrogen via gasification is not a renewable pathway, this model provides multistage decision support for long term transportation energy planning at national and regional levels, which can be adapted for renewable energy pathways, such as, biomass to hydrogen (Parker, 2007a).

This chapter is organized as followings. In section 5.2, details of the problem description are given and the multistage stochastic dynamic programming model is presented. The case study of hydrogen system in Northern California is demonstrated in section 5.3. Section 5.4 briefly concludes the research work and outlines future research.

5.2 Methodology

5.2.1 Problem Description

Before the problem is formulated, the spatial and temporal dimensions of the problem are described and the possible tradeoffs between different cost components of the system are discussed, which justify the need for a system approach.

<u>Cost components:</u>

The entire system cost includes the following components:

- fixed capital cost of building production plants, which depends on the number and sizes of the plants, and the land values of the plant locations;
- operational cost associated with fuel production, which is proportional to the production quantity;
- operational cost associated with fuel transportation, which depends on the quantity of fuel and the distance that it needs to be transported between the plants and demand sites; and
- operational cost associated with the penalty associated with the fuel shortage. This is a modeling choice. The cost may be considered as the cost of outsourcing if the penalty cost is chosen equivalent to the imported fuel cost, or it may be considered as a soft constraint for satisfying demand if the penalty cost is set high.

The objective of the model is to minimize the total system cost over the entire 20-year horizon.

Spatial dimension of the problem:

The geographic layout of the production plants is critical to the efficiency of the entire system. On one hand, building centralized production plants may reduce cost by taking advantage of economy of scale and lower land value. On the other hand, transporting hydrogen can be expensive because it is a low-density gaseous fuel that must be compressed or liquefied for transport (Hamelinck and Faaij, 2002; Larson et al., 2005; Lau et al., 2003; Spath et al., 2003; Yang and Ogden, 2007). Therefore, accessing demand sites, most of which are in populated areas, may become expensive from those remote and centralized production plants. The spatial dimension of the system causes the tradeoffs between capital cost of plants and transportation cost of hydrogen, which need to be considered in the planning of process.

<u>Temporal dimension of the problem:</u>

During the transition of the system over a long planning period, building and operational decisions are likely to be made sequentially. Therefore, the entire planning horizon is divided into multiple decision stages to incorporate the time-dependent feature of those decisions. Choice of time stage interval depends on frequency of the decisions. In this problem, decisions are made annually so that the planning horizon is divided into 20 decision stages. Regarding the construction of plants, the following assumptions are made:

- Plant construction decisions are made at the beginning of each year;
- At most one new plant can be built in each time interval;
- Construction of a new plant requires two years to complete; and
- Once opened, a plant will not be shut down during the entire planning horizon.

Due to the 2-year construction lag, planning decisions for building new plants should only be made in the first 18 years of the 20-year planning period. Operational decisions are made yearly for those constructed plants. The 2-year construction lag also explains the lag in the operational costs associated with under-construction plants in our model formulation. Demand is assumed to be uncertain with an increasing trend over the planning period. Given time dynamics and demand uncertainty, there may be tradeoffs between the current cost of building and operating plants and the potential future cost of a fuel shortage. In the later part of this chapter, a case study will be used to examine the impact of imperfect information of model parameters on system cost and to highlight the value of a stochastic model compared to its deterministic counterpart.

5.2.2 Mathematical model

Basic structure of the model:

A k-year multistage process can be considered as a process of the first k-1 years plus the last k^{th} year. Given a known initial system state at the beginning of year 1, let $f_k(s_k)$ be the minimum system cost as the system transits from year 1 to the state s_k in year k. By this definition, the minimum system cost as the system transits from year 1 to the state s_{k-1} in year k-1 is $f_{k-1}(s_{k-1})$. Let x_k denote the decision variable to be made at the beginning of the k^{th} stage, which transforms the system state from s_{k-1} to s_k. Let r_k be the cost realized in the k^{th} stage, which is usually a function of x_k and s_{k-1}. In the simplest manner, the relation between the unknown functions f_k and f_{k-1} can be formulated using dynamic programming as:

$$f_k(s_k) = \min_{x_k}\{f_{k-1}(s_{k-1}) + r_k(x_k, s_{k-1})\}, \; k = 2, 3, \ldots, K, \tag{5.1}$$

where K is the entire planning horizon. The boundary condition $f_1(s_1)$ can be easily obtained based on the initial state.

Now let us add a little more complication to the above equation. Suppose there are two types of decision variables to be made in each stage, a planning decision denoted as x_k and an operational decision denoted as y_k. Equation (5.1) should be modified as:

$$f_k(s_k) = \min_{x_k, y_k}\{f_{k-1}(s_{k-1}) + r_k(x_k, y_k, s_{k-1})\},\ k = 2, 3, \ldots, K. \tag{5.2}$$

Under certain condition when y_k does not affect the transformation from s_{k-1} to s_k, using the concept of projection (sometimes also known as partitioning (Geoffrion, 1970)), Equation (5.2) can be decomposed to a master problem and a sub problem represented in equation (5.3a) and (5.3b), respectively.

$$f_k(s_k) = \min_{x_k}\{f_{k-1}(s_{k-1}) + g_k(x_k, s_{k-1})\},\ k = 2, 3, \ldots, K, \tag{5.3a}$$

where

$$g_k(x_k, s_{k-1}) = \min_{y_k}\{r_k(x_k, y_k, s_{k-1})\}. \tag{5.3b}$$

Equations (5.3a,b) provide the basic structure of the proposed model in FIGURE 5.1.

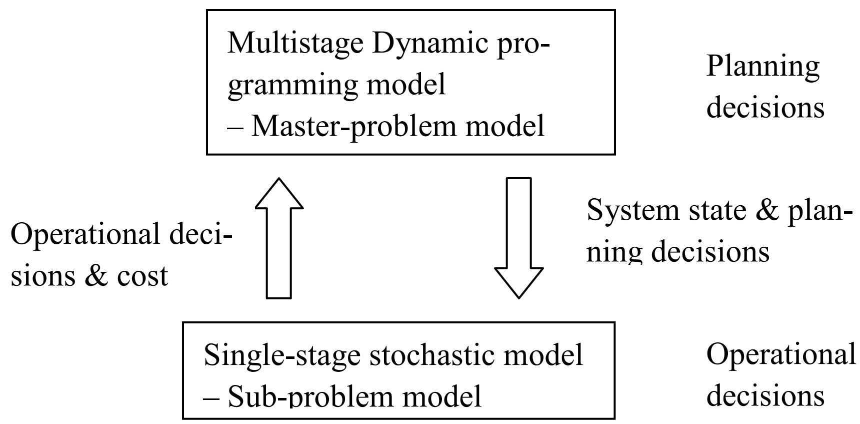


FIGURE 5.1 Structure of the Decomposed Stochastic Dynamic Programming Model

Decomposition can provide some computational advantages especially if the dimensions of decision vectors are high. It may not be common to have decomposed structure in classic dynamic programming. However, decomposition techniques based on the concept of projection are widely used for solving mixed-integer and stochastic programming problems, which has been reviewed in Chapter 2.

Mathematical formulation:

The basic structure of the proposed model formulation is similar to Equations (5.3a, b), with some modifications to incorporate the uncertainty in demand and the 2-year construction lag.

The notations used in the upper-level model are defined as following:

J: index j, set of candidate plant sites;

λ: plant construction time/lag (i.e., two years in this study);

z_j^k: planning decision variable made in stage *k*. It equals 1 if a new plant starts construction at location *j* at the beginning of time stage *k*; and 0 otherwise. This new plant becomes operational at the beginning of stage $k+\lambda$. Note that the index *k* denotes the year in which plant construction decisions are made and *k* can only be valued from 1 to 18;

$S_k \subseteq J$: state variable at stage *k*. It is the set of all chosen plants by time stage *k*. The initial state of the system is given as S_0;

F_j: annualized capital cost of a plant under construction at location *j*;

$H_{k+\lambda}(S_k)$: the total annualized capital cost of the constructed plants at time stage $k+\lambda$, given system state at stage *k* as S_k;

$O^*_{k+\lambda}(S_k)$: the minimum expected operational cost at time stage $k+\lambda$ including production cost, distribution cost and penalty cost, given system state at stage *k* as S_k. This value will be computed by the stochastic model in the sub-problem model and passed to the master-problem model;

$f_k(S_k)$: the minimum cumulative expected total system cost from the beginning of the planning horizon until the end of time stage $k+\lambda$, given system state at stage *k* as S_k. Note that under-construction plants do not impact the minimization of system operating costs during their construction time.

The complete master-problem model is included in equations (5.4) to (5.6):

$$f_k(S_k) = \min_{j \in \{S_k \cup \phi\}} \{\lambda F_j z_j^k + H_{k+\lambda}(S_k) + O_{k+\lambda}^*(S_k) + f_{k-1}(S_{k-1})\} \quad k = 2, 3, ..., 18 \tag{5.4}$$

$$S_{k-1} = \begin{cases} S_k & \text{if } j \in \phi \\ S_k - \{j\} & \text{if } j \in S_k \end{cases} \tag{5.5}$$

Boundary condition:

$$f_1(S_1) = \sum_{k=1}^{\lambda} \left(H_k^*(S_1) + O_k^*(S_1) \right) \tag{5.6}$$

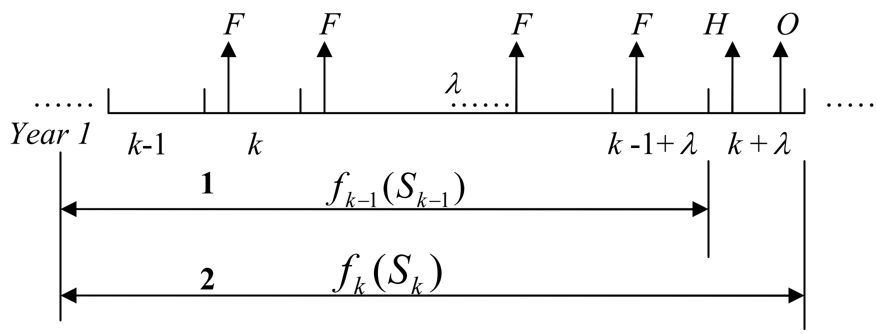


FIGURE 5.2 Recursive Relations between Time Stage k and k-1

Equation (5.4) defines the recursive relation between time stages k and k-1. FIGURE 5.2 helps to illustrate this relation. The double arrow 1 represents $f_{k-1}(S_{k-1})$, the minimum expected total system cost from the beginning of year 1 until the end of stage k-1+λ given system state at stage k-1 as S_{k-1}. Consider a feasible decision at state k as to build a new plant at location $(x_k=j)$. This decision causes three additional cost terms:

- capital cost of this under-construction plant between the k^{th} year and the $(k-1+\lambda)^{\text{th}}$ year (denoted by upward arrows Fs in FIGURE 5.2, and summed as $\lambda F_j z_j^k$ in Equation (5.4));

- the operational cost of this new plant (denoted by arrow O in the figure and $O^*_{k+\lambda}(S_k)$ in the equation), since this new plant becomes operational at stage $k+\lambda$; and
- capital cost of all operational plants (denoted by arrow H in the figure and $H_{k+\lambda}(S_k)$ in the equation).

The optimal value function $f_k(S_k)$, represented by the double arrow 2 in FIGURE 5.2, should take the minimum value of the sum of the costs associated with x_k and $f_{k-1}(S_{k-1})$. The minimization in Equation (5.4) is taken with respect to all possible $j \in \{S_k \cup \phi\}$, where ϕ means that no new plant is introduced at time stage k.

Equation (5.5) defines the state transition between the (k-1)st stage and the k^{th} stage, which explains two possibilities. If there is no new plant from stage k-1 to stage k (i.e., $j \in \phi$), the state variable does not change so that $S_{k-1} = S_k$. Otherwise, the state variable at stage k, S_k, is formed by adding the new plant j to the existing S_{k-1} of stage k-1. The boundary condition is given in equation (5.6), which is a single-stage optimization problem. The initial system state, S_0, is assumed to be an empty set. The first-year building decision is obtained from boundary condition (5.6). This plant is assumed to be operational immediately.

The complete sub-problem model is depicted in Equations (5.7-5.9), which returns the minimum expected operating cost O^* in stage k.

$$O_k^*(S_{k-\lambda}) = \min_{q,x} E_\omega \left(\sum_{j \in S_{k-\lambda}} \sum_{i \in I} \left(CP_j x_{ji}^k(\omega) + C_{ji} x_{ji}^k(\omega) \right) + \sum_{i \in I} \alpha q_i^k(\omega) \right) \qquad (5.7)$$

Subject to

$$D_i^k(\omega) - \sum_j x_{ji}^k(\omega) = q_i^k(\omega) \qquad \forall i \in I, \omega \in \Omega \qquad (5.8)$$

$$\sum_{i \in I} x_{ji}^k(\omega) \le cap_j^p \qquad \forall j \in J, \omega \in \Omega \qquad (5.9)$$

where:

I: index i, set of demand centers;

Ω: index ω ,set of demand randomness;

CP_j: hydrogen production cost at plant j (\$/tonne);

C_{ji}: delivery cost between plant j and demand center i, which includes the truck fixed and variable cost (\$/tonne);

cap_j^p: plant production capacity at plant j (tonne);

α: penalty level (i.e., cost of importing hydrogen from elsewhere) (\$/tonne);

$D_i^k(\omega)$: the hydrogen demand from center i at time stage k (tonne);

$x_{ji}^k(\omega)$: the amount of hydrogen delivered from plant j to the demand center i at time stage k (tonne);

$q_i^k(\omega)$: the amount of hydrogen shortage at demand center i at time stage k (tonne).

The decision variables include the quantity of the hydrogen shortage at each demand center $q_i^k(\omega)$ and the amount of hydrogen delivered between plants and demand centers $x_{ji}^k(\omega)$ at each stage and under each demand scenario. The objective function (5.7) is to minimize the expected operational cost at time stage k, given that plants belonging to set $S_{k-\lambda}$ are operational at stage k. Equation (5.8) defines the amount of unsatisfied demand (q_i^k) at city i at time stage k. Constraint (5.9) imposes a hydrogen production limit based on the capacity of each plant j at time stage k.

This stochastic dynamic programming model is solved iteratively as follows:

Step 1: Solve boundary condition (5.6) and obtain $f_1(S_1)$.

Step 2: Repeat for each time stage k=1 to 18:

Solve $f_k(S_k)$ in equation (5.4), where $O_{k+\lambda}^*(S_k)$ is computed using the sub problem. The detailed procedure for computing $f_k(S_k)$ for a given S_k is illustrated in TABLE 5.1, using S_k={1,2,3} as an example.

Step 3: At the final planning stage k=18, choose the minimum $f_k(S_k)$, and this $f_k(S_k)$ is the minimum cumulative expected total system cost throughout the entire 20 years. The planning decisions (i.e., the building sequence of production plants) can then be retrieved backward from S_{18}, S_{17}, …, to S_1.

Note that the iteration of the algorithm is carried over system stages. The algorithm starts from the boundary condition, which is a single stage problem that can be solved exactly. Then from the boundary condition, every time as the algorithm moves forward, one more time period is added. The problem in the new stage can still be solved exactly, because the previous stage problem is already solved. The algorithm continues to move forward until the end of the planning horizon is reached. This forward dynamic programming structure is an exact algorithm, not a heuristic procedure.

TABLE 5.1 Computation Procedure From (k-1)st to kth Stage

S_k	j	S_{k-1}	$F_j z_j^k$	$O^*_{k+\lambda}(S_k)$	$H_{k+\lambda}(S_k)$	$f_{k-1}(S_{k-1})$		$f_k(S_k)$
{1,2,3}	ϕ	1,2,3	0	O	H	g_1	$F_1 = O+H+g_1$	$\min\begin{Bmatrix} F_1 \\ F_2 \\ F_3 \\ F_4 \end{Bmatrix}$
	1	2,3	C_1	O	H	g_2	$F_2 = O+C_1+H+g_2$	
	2	1,3	C_2	O	H	g_3	$F_3 = O+C_2+H+g_3$	
	3	1,2	C_3	O	H	g_4	$F_4 = O+C_3+H+g_4$	

*The details of the computation process are interpreted as follows. Given S_k={1,2,3}, there are four possible j values (2nd column) that could transform the system from state S_{k-1} (3rd column) to S_k. The three costs associated with each j are given in columns 4, 5, 6. The value of $f_{k-1}(S_{k-1})$ for each S_{k-1} is given in the 7th column. As a result, for each possible j, the total system cost is updated from stage k-1 to k in the 8th column. The minimum value of the four Fs is $f_k(S_k)$ (last column), and the corresponding j that minimizes the total system cost is an optimal planning decision for the state S_k.

The iterative solution procedure in the master problem was implemented in MatLab and AMPL/CPLEX (Fourer et al., 2003) were used to solve the sub-problem model at each stage. The complexity of this solution algorithm is dominated by the total number of stages (K) and the number of candidate locations (N). There are three layers of iterations, which correspond to the stage index, possible states in each stage, and possible decisions at each stage. These three layers result in a complexity no worse than $K \times N^2$. Note that the sub-problem model could be solved for all possible states before running the master-problem model, or be called when it is needed during the computation procedure of the master-problem model.

In general, the complexity of a dynamic programming model depends on the size of the decision tree, while the complexity of a stochastic programming model is dominated by the size of the scenario tree. Note that three demand scenarios are assumed in each decision stage, thus forming a total of 3^{20} possible random scenarios to be considered in this problem. If a stochastic programming framework is chosen for modeling this problem, then it has to handle 3^{20} branches in the scenario tree, which will cause a major numerical challenge. In a dynamic programming framework, only the random scenarios in a single-stage are considered at a time, and the combined possibilities of the remaining process are packaged in the unknown optimal return function $f_k(S_k)$ for $k = 1, 2, \ldots, K$.

5.3 Case Study: Hydrogen System in Northern California

5.3.1 Data Preparation

It is assumed that HFCV market penetration rate increases from 1 to 25% of vehicles on the road over twenty years, as shown in **Error! Reference source not found.** (Miller et al., 2005). Given a market penetration rate in each year, a demand model was used to identify the locations and magnitudes of demand for those areas in which there is sufficient demand to warrant infrastructure investment (Johnson et al., 2005). However, under uncertain conditions, demand in each area is randomly chosen between three demand levels in each year as shown in TABLE 5.2. Random demands at different locations are assumed to be independent of each other, no geographic correlation between them is considered.

TABLE 5.2 Three Demand Levels and Associated Probabilities

	Median	*High*	*Low*
% difference from median	0	+25%	-25%
Probability	2/3	1/6	1/6

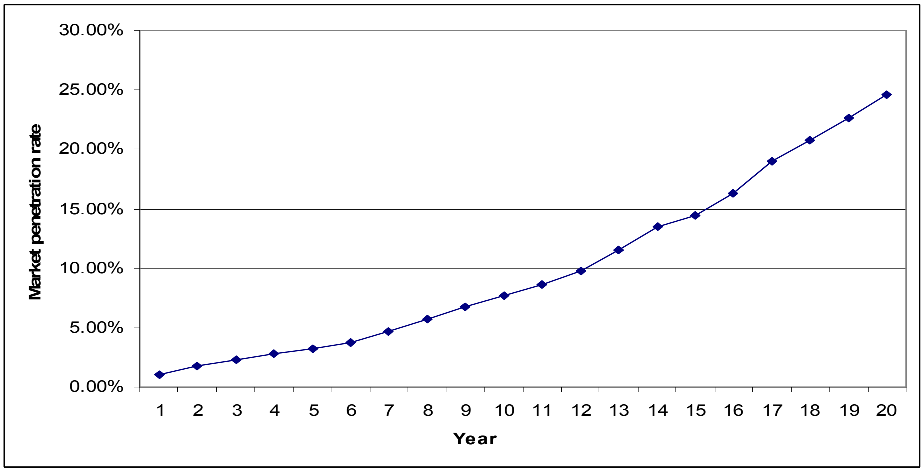


FIGURE 5.3 Market Penetration Growth Rate

The size of demand centers grows as market penetration rate increases from 1% to 25%, illustrated in FIGURE 5.4. There are five potential locations for hydrogen production sites. These sites are constrained by the locations of existing large power plants greater than 500 MW in size within the study area (USEPA, 2002). Geographic Information System (GIS) was used to identify the shortest path truck routes connecting each of the candidate production facilities to all of the demand centers. These routes form a candidate fuel delivery system. The model takes these data as inputs to identify an optimal facility building sequence that minimizes the total expected production and distribution costs.

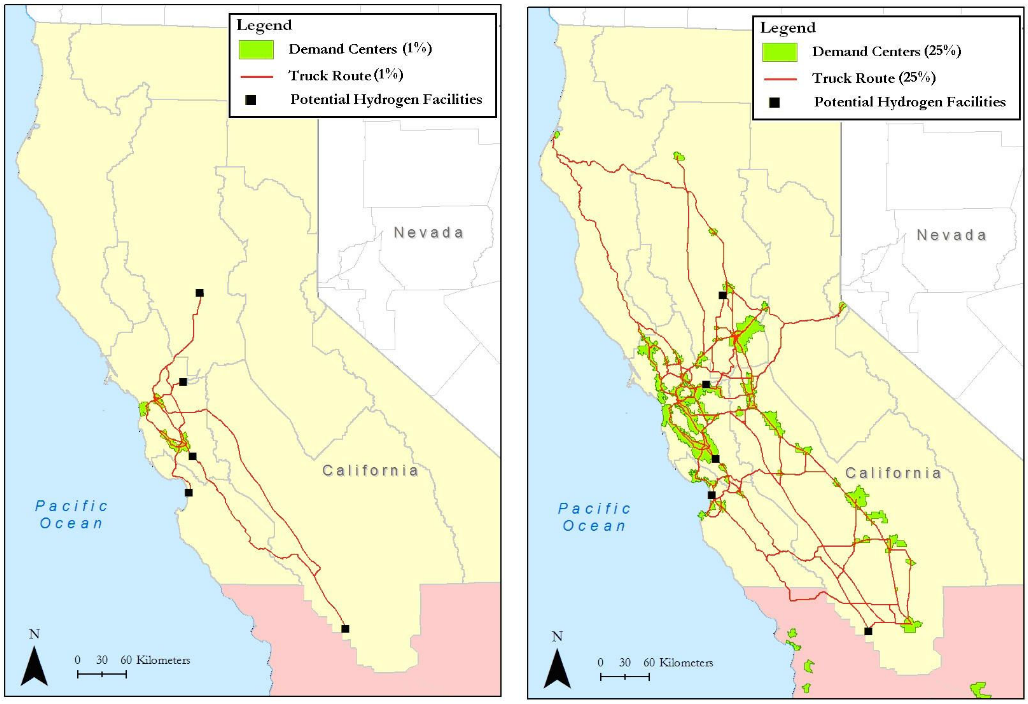


FIGURE 5.4 Demand Centers and Potential Production Facilities and Truck Routes at 1% and 25% Market Penetration Rates (Huang et al., 2009)

The plant fixed cost includes both capital and operations and maintenance (O&M) costs associated with the coal gasification plant, hydrogen liquefier, truck terminal, and on-site storage. The production capacity of each plant is set to be 500 tonnes/day based on DOE recommendations (DOE, 2006). Cost modeling conducted by DOE (2006) and Kreutz et al. (2005) was used to estimate plant fixed costs. These costs were then annualized and converted to 2005 dollar value assuming a real discount rate of 10% and a plant lifetime of 40 years. The capital cost of a plant was estimated to be \$0.28 Billion for an annualized cost.

The plant variable cost includes the coal feedstock cost, electricity cost for liquefaction, and revenue from co-production of electricity. Assuming a coal-to-hydrogen efficiency of 57%, the amount of coal required to produce a kg of H_2 is 0.198 mmBtu/kg (Chiesa et al., 2005). This number is multiplied by the price of coal ($1.29/mmBtu) to calculate the feedstock cost, which is estimated to be $0.26/kg H_2. The electricity cost is calculated assuming that 9.25 kWh/kg H_2 are required for liquefaction and an electricity cost of $0.05/kWh (DOE, 2006). The estimated cost of electricity in all cases is $0.46/kg H_2. The electricity revenue is calculated assuming that 2% of the coal input is converted to electricity and that the electricity is sold for $0.05/kWh (Chiesa et al., 2005). With these assumptions, the electricity revenue is estimated as $0.06/kg H_2. Therefore, the total plant variable cost after accounting for both costs and revenue is $0.66/kg H_2.

For hydrogen distribution via liquid trucks, it is assumed that the truck capital cost is $104,792 per year and truck capacity is 9,000 kg (DOE, 2006). The truck variable cost ($/km) is a function of fuel, labor, and fixed O&M costs. Assuming that the trucks are diesel-operated and achieve a fuel economy of 10 km per gallon, the fuel cost is calculated by dividing the fuel price ($2/gallon) by the fuel economy. As a result, the fuel cost is estimated as $0.20/km/truck. The labor cost is calculated by identifying the time it takes to travel one km (assuming an average truck speed of 60 km per hour) and multiplying this quantity by the wage ($20/hour). In addition, overhead is assumed to be 50% of labor. Therefore, the labor cost (including overhead) is estimated to be $0.50/km/truck.

The fixed O&M cost includes truck maintenance and is given as \$0.18/km/truck (DOE, 2006). The total distribution variable cost is \$0.88/km/truck.

A transport cost matrix was developed for the shortest paths between potential production facilities and all demand centers at 25% market penetration rate. Since the number of trucks required along each route will differ at each market penetration level, the desired cost metric is dollars per truck. The shortest distances provided by the GIS were converted to costs by multiplying each one-way distance by two to get a roundtrip distance and then multiplying these distances by the fuel delivery variable cost. Since the delivery variable cost is \$/km/truck, the units of the resulting transport cost matrix is \$/truck.

5.3.2 Baseline Results

The baseline scenario is defined as follows:

- all hydrogen plants have a maximum capacity of 500 tonnes H_2/day even though the actual production quantity is determined by the model;
- plant capital cost varies depending on locations (TABLE 5.3) (e.g., plants near the San Francisco Bay Area are assumed to be 20% more expensive to build due to higher land and labor costs); and
- the penalty cost for demand shortages is \$10/kg H_2, which is set significantly high to ensure sufficient instate hydrogen production.

TABLE 5.3 Annualized Plant Capital Costs (Million $/year)

Plant	Location	Annualized Capital Cost (500 tonnes/day)
Plant 1	Kern County	$ 281.3
Plant 2 (+20%)	San Jose	$ 337.6
Plant 3 (+10%)	Moss Landing	$ 309.5
Plant 4 (+20%)	Pittsburg	$ 337.6
Plant 5	Yuba City	$ 281.3

The complete results of the baseline scenario are summarized in TABLE 5.4. The first column contains the planning years and year zero denotes the time stage before the beginning of the first year. At the beginning of year 1, the plant building decision is determined by the boundary condition. The plant location pattern in each year is represented in the second column. For example, a plant at Yuba city (location ID 5) is built at the beginning of year 1 and this location pattern remains the same until the end of year 10 (or the beginning of year 11), when a new plant in Kern County (location ID 1) is built. Since it then takes two years to complete construction of a new plant, plant #1 will become operational at the beginning of year 13. During construction, the model assumes that capital payments begin on the new plant even though it is not yet operating. These additional capital costs are recorded in the third column. The fourth column contains the capital costs of the operational plants. The annual operation costs, expected hydrogen production quantity, and expected demand shortage are summarized in columns five, six and seven, respectively. The annual expected total system cost is stored in column eight, which is the summation of plant capital costs (including both under-construction and operational plants) and operational costs. The average cost of hydrogen ($/kg) is identified in column nine and is computed by dividing the total annual cost by the quantities of annual production and shortage together. Column ten records the percentage of the total system cost that results from penalties.

TABLE 5.4 indicates that the plant capital cost is significantly larger relative to the O&M costs. Since the capital costs vary by location, the model minimizes the total system cost by choosing the plants with the lowest capital cost first. In fact, these low cost plants are selected even though they are distant from the demand centers (as shown in FIGURE 5.5), which indicates that delivery costs are less important compared to plant capital costs. For example, a single plant at Yuba City is operational from year 1 to 10. As shown in column 9 of TABLE 5.4, this plant is underutilized at the beginning, resulting in high average hydrogen costs of $24.48/kg and $12.88/kg in the first two years. However, as hydrogen demand increases and the plant becomes better utilized, the average cost decreases to $2.77/kg in year 10. The model chooses to build an additional plant at Kern County in year 11 because the penalty cost on fuel shortage over weighs plant capital and fuel delivery costs by year 13. In the base model, capital cost is the main driver in selecting plant locations and determining hydrogen costs.

TABLE 5.4 Baseline Results Summary

Year	New plant location (plant ID)	Capital cost of under-construction plants (M$/year, in 2005 $)	Capital cost of operational plants (M$/year, in 2005$)	Operating cost (M$/year, in 2005 $)	Production (tonnes/year)	Shortage (ton-nes/year)	Annual total system cost (M$/year, in 2005 $)	Average H2 cost ($/kg, in 2005$)	penalty cost (%)
1	**5***		$281	$9	11,864		$290	$24.48	
2			$281	$18	23,217		$299	$12.88	
3			$281	$21	27,148		$302	$11.13	
4			$281	$30	39,350		$311	$7.91	
5			$281	$34	44,486		$315	$7.09	
6			$281	$44	57,798		$326	$5.63	
7			$281	$58	75,395		$339	$4.49	
8			$281	$73	96,187		$355	$3.69	
9			$281	$92	120,103		$373	$3.11	
10			$281	$107	140,506		$389	$2.77	
11	**1&5**	$281	$281	$145	155,957	2,620	$708	$4.37	4%
12		$281	$281	$214	174,964	8,073	$777	$3.98	10%
13			$563	$168	221,216		$731	$3.30	
14			$563	$199	261,142		$762	$2.92	
15			$563	$213	279,883		$776	$2.77	
16	**1,3 &5**	$310	$563	$289	311,329	5,089	$1,161	$3.57	4%
17		$310	$563	$464	350,416	19,578	$1,336	$3.26	15%
18			$872	$304	404,575		$1,176	$2.91	
19			$872	$350	444,073	1,597	$1,222	$2.72	1%
20			$872	$450	473,273	9,285	$1,322	$2.74	7%

Note: * Plant ID can be referred to Table 5.3 for its corresponding plant location.

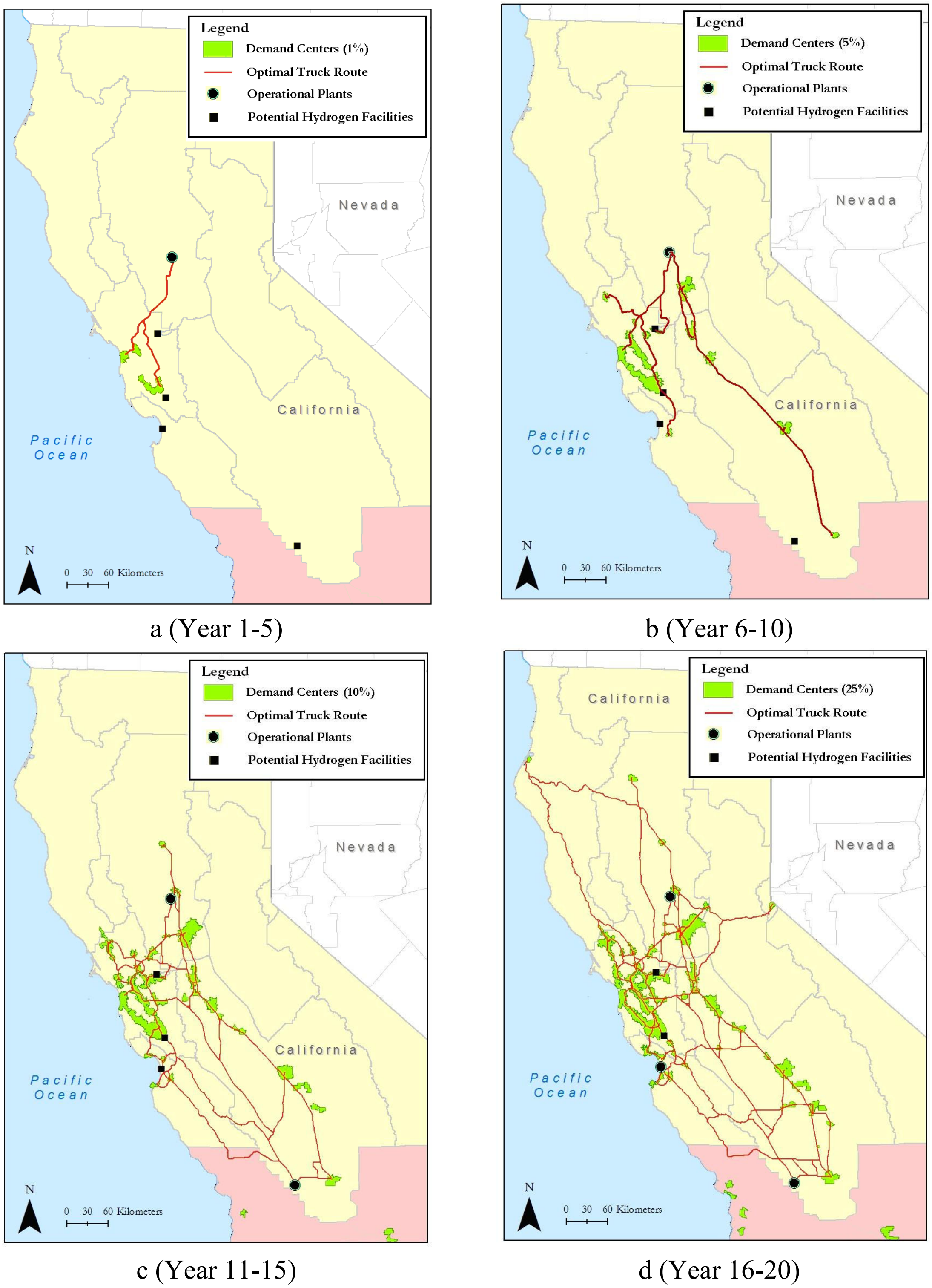


FIGURE 5.5 Hydrogen Production and Delivery System Design during Four 5-Year Periods

The sequence of building hydrogen infrastructure system is illustrated in FIGURE 5.5, with results aggregated into four 5-year periods to save space. Although the choice of plants is the same in FIGURE 5.5(a) and (b), it is noticeable that additional truck routes are needed to support the delivery of fuel to more demand centers.

In an uncertain-decision environment, a stochastic modeling method that considers the entire range of possible random scenarios often produces more reliable solution than its deterministic counterpart that considers only the expected value of random parameters. For comparison, solutions are obtained from the stochastic model and a deterministic model that uses only the expected demands of the 20-year period. These two different solutions are then evaluated under an identical set of 1000 samples of demand scenarios randomly generated using Monte Carlo simulation based on the probability distribution given in TABLE 5.2. FIGURE 5.6 shows the performance of the two solutions generated from stochastic and deterministic models under these 1000 demand scenarios. The two curves tell the cumulative probabilities of not exceeding a certain system cost, resulting from the stochastic (pink curve) and deterministic (blue curve) solutions respectively. For example, one may read that the probability of not exceeding a total system cost of 2005$14 billion is 90% following the stochastic solution and about 80% following the deterministic solution. It is clear that the stochastic solution provides better reliability on the higher end of cost thresholds, which is usually favored by risk-averse system planners especially if the system is large-scale and expensive. The stochastic solution also provides a better robustness in the worst case, with 2005$15.25 billion following the stochastic solution and 2005$16.25 billion following the deterministic solution.

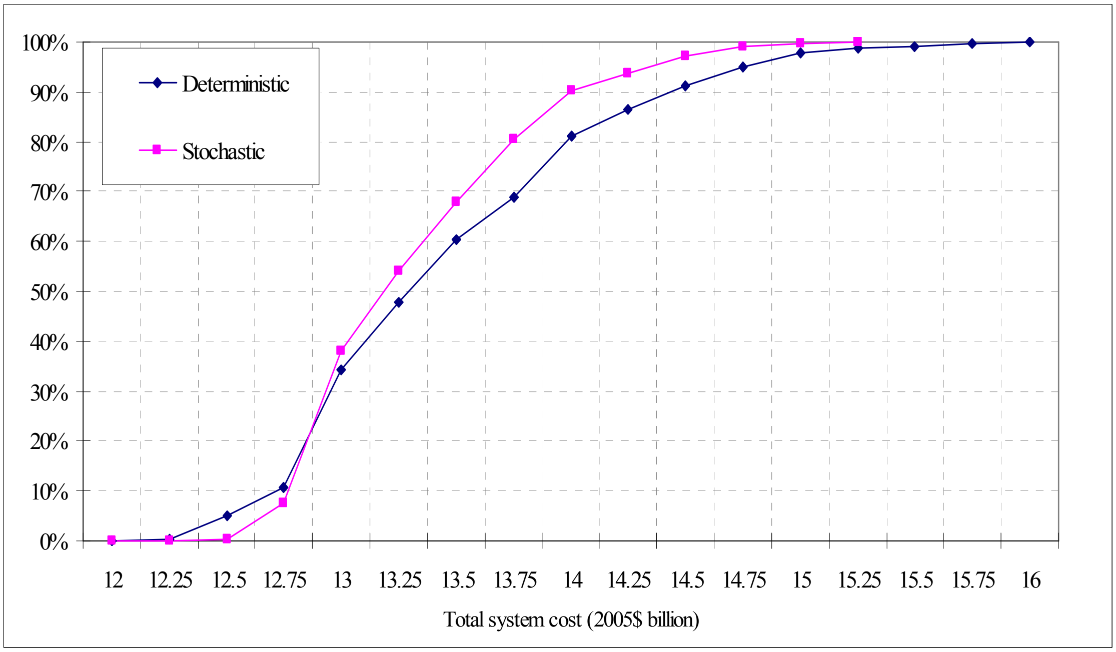


FIGURE 5.6 Comparison between Stochastic and Deterministic Methods

5.3.3 Sensitivity Analyses

Two sensitivity analyses are conducted to evaluate the impacts of basic energy feedstock (electricity, coal, and diesel) prices and the penalty cost on system layout and the total system costs.

(1) Impact of feedstock prices

The cost of hydrogen production and distribution is dependent on the costs of several energy feedstock types that are used in the process. This section analyzes the impact of changes in these feedstock costs on the model results. Three feedstock types are examined: electricity, coal and diesel fuel. Coal is gasified to produce hydrogen while significant electricity is required to liquefy hydrogen for truck transport. Finally, diesel is used to fuel the trucks that transport the hydrogen to demand centers. The impacts of changes in the prices of these feedstocks on hydrogen system costs (capital and operational) are summarized in TABLE 5.5.

TABLE 5.5 System Costs when Feedstock Costs are Varied

Scenarios	*Total system cost (2005$ billion)*	*Capital cost (2005$ billion)*	*Operating cost (2005$ billion)*
Electricity price (2005$kWh) increase from 0.05 to 0.10 (100%)	$14.85 (+12%)	$9.99 (0%)	$4.86 (+48%)
Coal price (2005$/mmbtu) increases from 1.29 to 1.50 (16%)	$13.43 (+1%)	$9.99 (0%)	$3.44 (+5%)
Diesel fuel price (2005$/gal) from 2.00 to 4.00 (100%)	$13.30 (+0%)	$9.99 (0%)	$3.31 (+1%)
Baseline scenario	$13.27	$9.99	$3.28

The results suggest that changes in feedstock prices do not affect the system capital cost. However, the system operational cost is sensitive to changes in feedstock prices. For instance, doubling the electricity cost results in about a 50% increase in the operational cost and a 12% increase in the total system cost. Compared to the electricity price, the changes in coal and diesel fuel prices have negligible impacts on the total system cost.

(2) Impact of penalty cost

The penalty cost (i.e., imported hydrogen cost) was varied from $10 to $2 per kg of H_2 to examine in theory its impact on the quantity of imported hydrogen to meet demand shortages, although based on the current hydrogen cost assessments in (National Research Council, 2008; Ogden and Yang, 2009) it is unlikely the delivered hydrogen cost will be below $3.5 per kg. It was found that if the imported fuel can be obtained for less than $2/kg, then all the demand over the 20-year planning horizon should be served by imported hydrogen. As the imported hydrogen cost increases to $4/kg, in-state production increases to 60% of the in-state demand. When the imported cost exceeds $8, it is most efficient to have all the demand satisfied by in-state production.

5.4 Conclusions and Discussions

This chapter presents a stochastic dynamic programming model to optimize the sequence of gradually building an energy system and simultaneously determine optimal production and delivery decisions in each time stage, under demand uncertainty. The proposed model integrates dynamic programming and stochastic programming methods to improve the effectiveness and flexibility of planning and operational decisions. This problem could also be formulated as a multistage stochastic programming model, as in several previous studies on the dynamic location problem mentioned in the introduction. However, the proposed model may provide some modeling flexibility such as integrating a computer simulation in the single-stage sub-problem model. It may also have computational advantages when the size of the scenario tree is the main cause for numerical difficulties.

A case study based on hydrogen system in Northern California was also examined in this paper. Numerical experiments show a clear advantage for stochastic modeling techniques in producing more reliable and robust design solutions under a highly uncertain decision environment. Based on the case study results and sensitivity analyses, some important policy implications have been identified. In general, it was found that the capital cost was the major cost driver of the total system cost and varying the electricity price could change the operational cost significantly. Sensitivity analyses on the penalty cost revealed that optimal in-state production levels correspond to different hydrogen import costs.

An immediate extension of this work would be to consider plant capacity as a planning decision variable. The dimension of planning decisions would be increased to three: location, time, and size. Also, intermediate storage facilities can be introduced into the system to store excess produced hydrogen in order to mitigate fluctuations in production cost due to changes in the supply and prices of feedstocks. Other extensions are considering more than one hydrogen distribution modes (pipeline and onsite truck) and including other sources of hydrogen (such as renewables) or CCS.

This chapter examines incorporating stochastic effects into the formalism, which is a major contribution, but more work remains to make this a realistic planning tool for H2 infrastructure because of the multiple pathways possible. These modifications would have an impact on the complexity of the problem. Developing an efficient solution algorithm for the extended work is the focus of our ongoing efforts.

Chapter 6 Conclusions and Future Work

Summary

This section highlights original contributions to the improvement of sustainability in infrastructure systems and outlines strategic research plans in the future.

6.1 Conclusions

The research effort in Critical infrastructure Protection problem has been summarized in Chapter 3 with a focus on the development of robust resource allocation strategies in an uncertain decision-making environment. Both uncertain service availability and accessibility were captured through a stochastic modeling framework that explicitly modeled random scenarios of accessibility costs, with built-in reliability constraints on service availability. It extended the existing literature in disaster mitigation and emergency service. In addition, the study has explored the performances of different modeling approaches (i.e., deterministic, stochastic programming, and robust optimization) to reflect various risk preferences. Based on the results of Singapore case study, stochastic modeling methods in general offers more robust allocation strategies compared to deterministic approaches in achieving highest possible coverage to critical infrastructures under risks. However, it has also been noticed that different modeling approach has its own emphasis of objective and different data and computational needs. Therefore, how to compare and evaluate solutions from different models is still arguable.

The research efforts in renewable energy infrastructure system for the first time bridge two knowledge domains: operations research and energy technology. The emphasis was given to energy supply chain system design and management (in Chapter 4) and transitional energy system planning (in Chapter 5). The environmental and economic sustainability and system reliability are the main measurements in the studies.

In Chapter 4, feedstock and fuel storage facilities are included in the supply chain to provide self-healing functions (via smoothing and redistribution) against unexpected system risks caused by supply seasonal variations and demand fluctuations. The study aims to seek the least-cost yet reliable infrastructure systems. A stochastic mixed-integer programming model that integrates feedstock seasonality, geographic variation, and demand fluctuation was developed, with the goal of minimizing the total expected cost of the entire supply chain from a life-cycle viewpoint. The model was evaluated using a case study considering California corn stover feedstock resources to produce biofuel. It was found that the cellulosic ethanol is cost competitive in a range between \$2.03 and \$2.75 per gallon depending on the demand. The case study also demonstrated the role of storage facilities in smoothing the negative impact of supply seasonality and demand fluctuation on the energy supply chain system.

In the process of transforming the current energy supply system to a renewable energy based society, dynamics caused by the evolving technologies and societal changes as well as uncertainties involved in resource supply and demand market fluctuations are the major issues. However, they have not been received sufficient attention in the existing research literature. The research work presented in Chapter 5 filled this void. From a modeling perspective, the conventional time-independent snapshot method was inadequate for such as transitional system planning and multistage stochastic dynamic model that integrates the spatial and temporal dimensions was proposed for sequentially building a renewable energy production and distribution system under dynamics and uncertainties. The model was applied to develop the hydrogen supply system in Northern California with the assumed hydrogen fuel cell vehicle (HFCV) market penetration rate growing from 1% to 25% over a 20-year period.

6.2 Future Work

Sustainable infrastructure system development is highly interdisciplinary, which requires addressing multiple disciplines in an integrated modeling framework. A good example is the development of energy infrastructure system, in which the energy technology was successfully integrated into an optimization modeling framework to achieve better cost competitiveness and pathway reliability. It also evokes more interdisciplinary research efforts and some of immediate research extensions are briefly discussed as follows, which mainly cluster in risk management in energy supply chains, integrated multi-energy-pathway portfolio, and interdependencies between built environment and ecosystems.

- *Develop sustainable energy infrastructure system with an emphasis on robustness and security*

To improve the system resilience against recurrent and non-recurrent risk threats, critical infrastructure protection should be addressed along with the system planning. Recurrent risks are those repeating occurrences which affect daily system operations, such as, feed-stock supply fluctuations and demand uncertainties. A key research question will be how to establish a system and maintain normal operations in an economically viable way under uncertainty. Stochastic programming method is often used to develop robust strategies for system planning and operations across all possible scenarios. In contrast, non-recurrent risks are rare but have more severe impacts on the system. Examples include disruptions in resource supply and/or on transport networks caused by natural disasters or human errors and attacks. Most existing studies focus on quantifying a disaster's impacts on energy systems in post-disaster scenarios. The results have informative policy implications but do not tell how to improve system reliability to avoid or reduce potential losses. By integrating knowledge in risk analysis, operations research (such as, stochastic programming and robust optimization), and survivable network design into the planning of a robust energy system, it is able to survive through future extreme events, such as, earthquakes and hurricanes.

- *Develop sustainable multi-energy-pathway system*

Alternative energy can come from a wide range of feedstock sources including biowastes (e.g., residues of agriculture, forestry and municipal wastes) for biofuel production as studied in the current research. Other potential natural renewable sources include but not limited to solar, wind, and water. However, different supply sources require different energy supply pathways. How to strategically integrate multiple energy systems to form a sustainable energy portfolio is another main research question to be pursued. Given the projected growth of energy demand in the future, all possible energy sources will be needed to play a collective role in sustaining future energy supply, which makes the question of sustainable energy portfolio design extremely important. A thorough assessment for all possible alternative energy technologies will be necessary.

- *Consider land-use and ecosystem impacts on energy system sustainable development*

Land-use and ecosystem impacts cannot be ignored in developing sustainable energy systems. The design of an energy system is often subject to restricted land use and affected by ecosystem interactions. For example, an economically optimal (i.e., minimum costly or maximum profitable) refinery site may not be ecologically viable or may violate land-use policies. Meanwhile, the operation of an existing energy system also impacts the evolvement of future ecosystem and land use. These interdependencies between built systems and ecosystems will be integrated into strategic energy system planning. Some key research questions to be answered through this research will include: (1) given existing land use and environmental policies, what will be a sustainable trajectory for future energy system growth? (2) how would transition of energy systems to alternative technologies impact land use and ecosystems?

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