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Operation planning for an energy service company

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For the Major Program

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For the Graduate College

To my parents

Chor-Piak Ng and Seok-Yeoh Tan

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CHAPTER 1 INTRODUCTION

The commercial incentives to re-regulate the power industry, to promote competition among companies, provides many research opportunities. One of these opportunities is studying how the regulated power industry should re-strategize itself to operate in a re-regulated, competitive environment. Given the need of business to make a profit, companies in the power industry should learn to transform their business practice to benefit from the re-regulation, should it become a reality. These factors focus this research, to investigate the operational planning of an energy service company (ESCO). In addition, this research emphasizes the contract flexibility needed at the point of delivery (with the customers and the suppliers).

1.1 RE-REGULATION AND THE ESCO MODEL

Calls for change in regulation, to allow more competition in the power industry, have spurred numerous proposals as to what needs to be changed. Most of these proposals favor breaking up the vertically integrated industry. Vernon Smith of the University of Arizona and Gerald Sheblé of Iowa State University (ISU), for instance, proposed that double auctions be used to conduct business in the new market structure [1, 2]. Previous work by Jayant Kumar and Somgiat Dekrajangpetch of ISU emphasized the feasibility, economics, and structure of auction markets, from the perspective of the independent system operator (ISO) and Energy Mercantile Association (EMA) [3, 4]. While these studies are important in encouraging the regulated industries to step into the free market, investigating how utilities under re-regulation should transform themselves to remain in business is also critical. In one proposed energy market framework [3], shown in Figure 1-1, the conventional utilities are segmented into generation, transmission, and distribution to encourage competition. In addition, energy service companies (ESCOs) are encouraged to provide energy, security, and reliability services to customers. The Federal Energy Regulatory Commission (FERC), the State Public Utility Commissions (SPUCs), and the Electric Reliability Organization (ERO) are regulatory bodies that determine the basic framework of a re-regulated energy market. The ISO, the Regional Transmission Organization (RTO), the independent contract administrator (ICA), and the EMA are companies that facilitate the buyers and sellers of electric energy in the re-regulated market. Generation companies (GENCOs), transmission companies (TRANSCOs), distribution companies (DISTCOs), broker companies (BROCOs), and ESCOs provide facilities, information, and services.

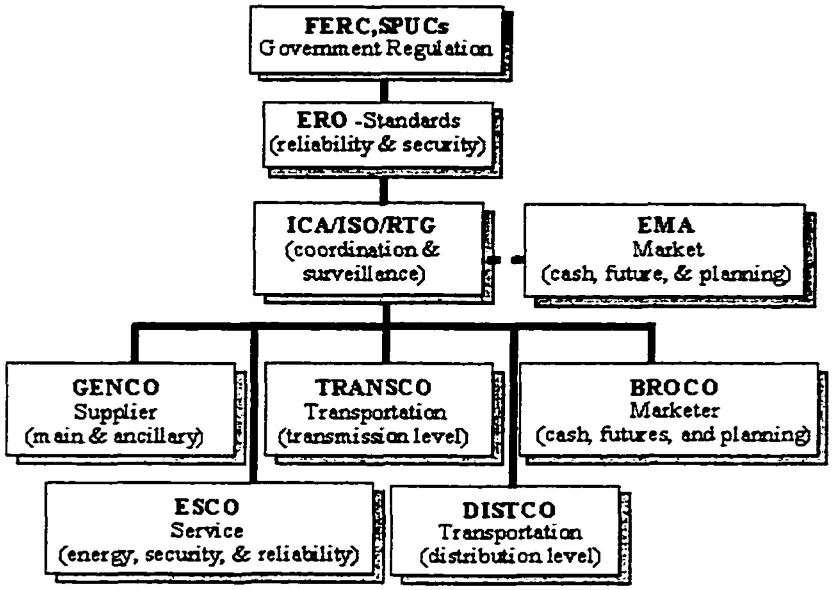

Figure 1-1. Framework of the energy market.

Based on the proposed framework, an ESCO is defined as the only entity that will have direct dealership with the end-users. An ESCO collects its revenue from distribution customers for the energy and ancillary services it has provided and acts as a wholesaler, purchasing the electric energy through the auction market and reselling it to the other market participants. To obtain the desired electric energy, an ESCO may purchase energy contracts through an auction market, utilize the reserves through the load management programs, or own the distributed generation. Finally, to keep the company operational, the ESCO incurs the cost of hiring staff to carry out the daily tasks. Figure 1-2 shows this interaction among customers, an ESCO, and other market participants.

An ESCO distinguishes itself by having direct contact with retail, wholesale and industrial customers. Since an ESCO is not required to provide facilities that generate, transmit, and distribute electricity, it incurs low capital requirement in serving customer demand. This low capital requirement allows companies easy entry into and easy exit out of the business of serving customer energy. These characteristics will increase competition among ESCOs to provide both better and cost effective service.

To provide better service at a lower cost, this dissertation focuses on three aspects of ESCO operational planning.

- How to relax customer demand using load management programs. Load management programs defer customer demand at high price periods to low price periods. These programs are important in improving the profitability of an ESCO serving customer energy and services. In this research, the load management program is modeled and used for scheduling customer demand.

- How to serve customer demand using energy contracts purchased through a re-regulated auction market. When energy is traded in an auction market where contract specifications define the details of delivered energy, learning to buy the right amount of contracts, with the right prices and the right contract specifications, is important. In this research, some aspects of energy contract specifications are modeled and incorporated into the scheduling of customer demand.
- How to manage the risks of operation and management. When information about the business environment is uncertain, risk arises. Since risk brings uncertainty as to how much profit a company can earn, it needs to be managed. To manage risk, various risk management tools are introduced, reviewed and applied.

To address the three aspects of ESCO operational planning, three factors are categorized and classified. They are market factors, customer factors, and supplementary energy factors. Market factors refer to factors that influence the cost of capital of an ESCO and purchasing strategies in the energy market to serve customer demand. Customer factors refer to factors that influence how an ESCO can attract customers purchasing energy services through the company. Finally, supplementary energy factors refer to factors that influence how controllable a customer demand is to an ESCO. Supplementary energy is equivalent to the controllable demand under the load management programs. The term "supplementary energy" is used because load management programs are not necessities, although important in improving the profitability, in serving customer demand. In this research, factors influencing an ESCO operation are classified based upon the dependency, variability, and uncertainty of the factors that influence an ESCO operation in a particular time horizon. Dependency classifies if a factor should be considered independent of other factors in a particular time horizon. Variability classifies if a factor can be influenced by an ESCO decision. Finally, uncertainty classifies if a factor is fully informed in a particular time horizon.

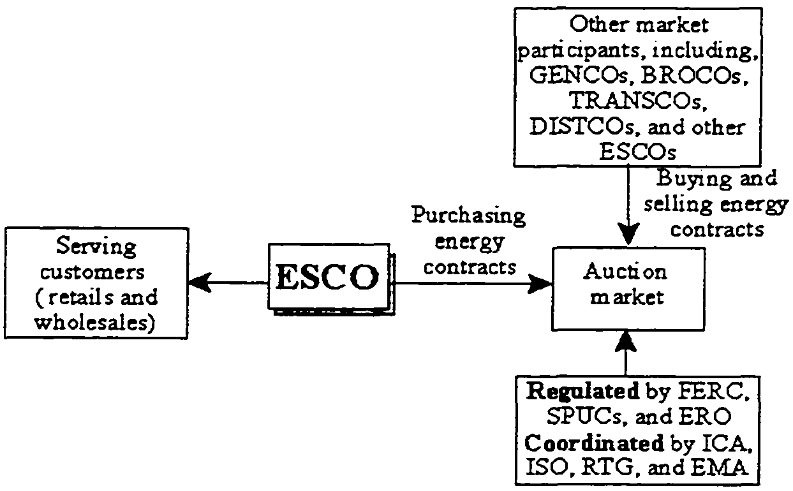

Figure 1-2. Interaction among customers, an ESCO, and other market participants.

1.2 LOAD MANAGEMENT PROGRAMS

Load management programs, introduced in the 1970s, aim to increase reliability and reduce the production cost of electric power systems. They have primarily three components: direct load control (DLC), energy storage system (ESS), and indirect load control (IDLC). Accounting for 5% to 10% of the total electrical demand, the controllable demand under load management programs allows utilities to have some degree of control over electric demand patterns. Direct load control, in general, allows utilities to shed remote customer demand unilaterally while ESS allows both utilities and customers to store and consume electric energy during scheduled duration. Because of their controllability by utilities, DLC and ESS receive the most attention when a scheduling algorithm is investigated. Indirect load control, which allows customers to control their demand independently in response to the price signals sent by the utilities, has received less attention. In this research, DLC and ESS are emphasized.

Load management programs flourished in the early 1980s. However, with the passage of time, these programs subsided. Except in states like Florida and California with insufficient generating capacity to handle the peak demand, the programs are generally not a popular option. The lack of interest in the programs is due to concern on the maturity of technologies used in the programs, lack of desirability by the utilities, and fear of utilities cross-subsidizing some customers using the programs.

Today, the advent of re-regulation sheds some light on the prospect of using load management programs. When an ESCO is driven by profitability to use load management programs, the three concerns that impede the growth of the load management program will be eliminated. If there should be any reason that load management programs were to be forfeited, it should be the unprofitable nature of the programs – nothing else!

In this research, load management programs are used extensively. First, the programs help an ESCO to develop a flexible customer demand and strengthen their purchasing power in an energy auction market. Second, scheduling customer demand using load management programs enhances the profitability of serving customer demand. Third, an ESCO with load management programs increases the service options to the customers. Fourth, load management programs also improve an ESCO cash flow by reducing the cost of purchasing energy. Finally, load management programs serve as an alternative source for ancillary services stated in the customer contracts and the system requirements.

1.3 RISK MANAGEMENT

In this research, risk management refers to decision making under uncertainty. Uncertainty in information used in decision-making results in uncertainty in profitability, which is a business risk. To an ESCO facing uncertainties in the business environment, it is important that the ESCO respond to business risk *appropriately*. However, *appropriate* response requires *appropriate* interpretation of risks. In this research, risks are defined as fuzziness (fuzzy linear programming), variance (mean-variance analysis and stochastic linear programming), and confidence level (value at risk analysis.) Various mathematical programming approaches are introduced to include the risks in decision-making. These approaches include sensitivity analysis, parametric analysis, stochastic linear programming, mean-variance analysis, fuzzy linear programming, and value at risk analysis.

Appropriate response depends on the approaches used. As future chapters will suggest, each of these mathematical programming approaches proposes different responses with a similar set of uncertain factors. The difference in their strengths and weaknesses causes different responses. Chapter 5 further discusses the applicability, technical requirements, and time requirements of these approaches.

1.4 CONTRIBUTIONS OF THIS RESEARCH

During my Master's thesis work in electrical engineering, the economics and modeling of load management programs were investigated. Improved mathematical models for load management programs using linear constraints were introduced. In addition, three economic models of load management programs were evaluated. They were: a load-based model that minimized the peak demand; a cost-based model that minimized the cost of generation; and a profit-based model that improved profitability of serving customer energy. In this research, the functions of load management programs will be further enhanced to assist an ESCO operation and management.

This research contributes toward the economics, modeling, and applications of load management programs and risk management in an ESCO operation and management. The main contributions of this research include:

- Classifying and categorizing the factors influencing an ESCO operation at various operational levels. (Chapter 2 and Chapter 7.)
  — In this research, the factors influencing an ESCO operation are categorized into market factors, customer factors, and supplementary energy factors, and classified on their dependency, variability, and uncertainty at a particular time horizon.
- Developing various mathematical models to represent load management programs (direct load control program and energy storage system in particular) – mainly my Master's thesis work. (Chapter 3.)
  — In this research, the battery energy storage developed during my Master program is generalized. In addition, the pumped-hydro storage model presented in [5] is generalized and introduced.
- Showing why and how an ESCO may utilize load management programs to service customer energy. (Chapter 4 and Chapter 6.)
  — In this research, various economic models of scheduling customer demand are presented. These include load-based, cost-based, modified cost-based, profit-based, modified profit-based, and cash

management models. The models developed for the load management programs are then included in the customer demands scheduling models.

- Developing mathematical models to meet contract specifications of the energy contracts purchased through a re-regulated energy market while servicing customer energy. (Chapter 4 and Chapter 6.)
  - In this research, the impacts of various contract specifications on scheduling and contract purchasing schemes are considered. The considered contract specifications include reliability and variability. Reliability determines the reliability of delivered energy. Variability determines how much customer energy may fluctuate during a specified duration.
- Investigating various risk management tools and introducing these tools in the ESCO operation and management. (Chapter 5 and Chapter 8.)
  - In this research, various mathematical programming models that handle uncertainties are reviewed and considered in the ESCO operation and management. They include sensitivity analysis and parametric analysis, stochastic linear programming, mean-variance analysis, fuzzy linear programming and value at risk analysis.

1.5 CONTENTS OF THIS DISSERTATION

Chapter 2 reviews a business structure for an ESCO in a re-regulated power industry. The factors influencing an ESCO operation and management also are identified and classified. Chapter 3 presents mathematical models for load management programs. A thorough literature review of mathematical models that represent load management programs is also included. Chapter 4 presents the economic models of serving customer energy using load management programs and energy contracts purchased through an auction market. Chapter 5 reviews various risk management tools that can be used in the ESCO operation and management. These tools include sensitivity analysis and parametric analysis, stochastic linear programming, fuzzy linear programming, and value at risk analysis. The pros and cons of these risk management tools are also discussed. Chapter 6 provides examples to show how load management programs may be utilized in a regulated power industry, the differences and economic implications of using various economic models, and how load management programs influence the way energy contracts are purchased to serve customer energy demand. Chapter 7 provides examples to show the different focus of ESCO operation at various time horizons. Chapter 8 provides examples to show how the risk management tools presented in Chapter 5 may be used in the ESCO operation. Chapter 9 concludes this research and proposes future work. Appendix A is included to provide information about the data used in Chapter 6 and Chapter 7 and some detailed results computed in Chapter 6. Appendix B is included to provide information about the data used in Chapter 8.

CHAPTER 2 ESCO MODEL

Regulation has nurtured the power industry for almost a hundred years. However, with more and more regulations being imposed on the utilities, these requirements are constraining the power industry corporate leaders in their decision making. Calls for competition, from the wholesale level to the retail level, has made re-regulation an attractive option around the world. New market structures were studied to search for a good alternative that would ultimately satisfy the regulatory bodies, customers, and suppliers.

The energy service company (ESCO), of the potential players in a new market structure, will be held responsible for providing energy, security, and reliability services to the distribution customers. In this chapter, the basic structure of an ESCO is reviewed. Section 2.1 summarizes the list of acronyms to be used. Section 2.2 provides a brief overview of the key players in one possible market structure [3]. The assumptions about the market are based upon Dekrajangpetch's dissertation work [4]. Section 2.3 discusses the competitions an ESCO may face in the assumed energy market framework and the factors influencing an ESCO's profitability in serving customer demand. Section 2.4 details how operational and managerial problems may be tackled by characterizing the factors influencing the ESCO operation.

2.1 NOMENCLATURE

BROCO:	Brokerage company.
CDCA:	Centralized daily commitment auction.
DEP:	Dependent factor.
DET:	Deterministic factor.
DISTCO:	Distribution company.
EMA:	Energy Mercantile Association.
ERO:	Electric Reliability Organization.
ESCO:	Energy service company.
FFO:	Forward/future/options.
GENCO:	Generation company.
ICA:	Independent contract administrator.
IND:	Independent factor.
ISO:	Independent system operator.

LRP: Long-range planning.

MRP: Middle-range planning.

NERC: National Electric Reliability Council.

PAR: Parametric factor.

PJM: Pennsylvania-New Jersey-Maryland.

PX: Power Exchange.

RS/C: Reactive scheduling/control.

RTO: Regional transmission organization.

SCH: Scheduling.

SPUC: State Public Utility Commissions.

SPCA: Single period commodity auction.

SPR: Short-range planning.

TRANSCO: Transmission company.

UNC: Uncertain factor.

VRB: Variable factor.

2.2 BROKERAGE SYSTEM AND NEW MARKET STRUCTURE

Applying the brokerage system to the power industry to encourage competition can be traced back to 1978, when Matthew Cohen and William Berry of MIT proposed several brokerage prototypes [5]. Vernon Smith has pioneered the use of experimental economics for auction markets [1, 6]. Gerald Sheblé and his students at Iowa State University have recently facilitated optimal power flow technology into the brokerage system. References [2, 7] describe the administration of a complete auction institution in the electric power industry. Figure 2-1 shows a recent proposal [2] that describes the interplay among all players. The vertically integrated power industry is broken up into several entities, with each playing a different but prominent role.

The industry consists of several companies. The vertically integrated power industry has been divided into several entities [7]. The Federal Energy Regulatory Commission (FERC) and the State Public Utility Commissions (SPUCs) are governmental bodies that regulate the industry. The Electric Reliability Organization (ERO) is a regulatory body that establishes the procedures and standards for the reliability and security of the power system operation [8]. The independent system operator (ISO) and the Regional Transmission Organization (RTO) are non-profit organizations to coordinate market participants in the present and future markets. These organizations provide surveillance to enforce all standards established by ERO on security and reliability. An energy mercantile association (EMA) may be established to provide an organized way of interchanging transaction contracts. The EMA: ensures no price distortion or market manipulation; spots illegal trading; and ensures minimal capital requirement for all members. An example is the Power

Exchanges (PXs) established in the state of California. Even though the EMA may develop contract specifications to allow the market participants to trade, the ISO and the RTO need to give approval before any transaction can be acknowledged. For this reason, the three entities, ISO, RTO and EMA, may exist as one to provide all the required services to create a good market for all market participants. The Independent Contract Administrator (ICA) represents a combined ISO, RTO and EMA.

Conventional utilities have been segmented into generation companies (GENCOs), transmission companies (TRANSCOs), and distribution companies (DISTCOs). GENCOs provide the electricity and associated ancillary services. TRANSCOs are regulated companies that provide long distance transportation of electricity over high voltage transmission lines. DISTCOs are also regulated companies that provide transportation of electricity over low voltage distribution lines. In the new structure, two additional types of companies are encouraged: broker companies (BROCOs), that provide information and negotiate contracts; and energy service companies (ESCOs), that provide energy, security, and reliability services to customers. Of all the players, the role of the ESCO in the new market structure will be the focus of this research.

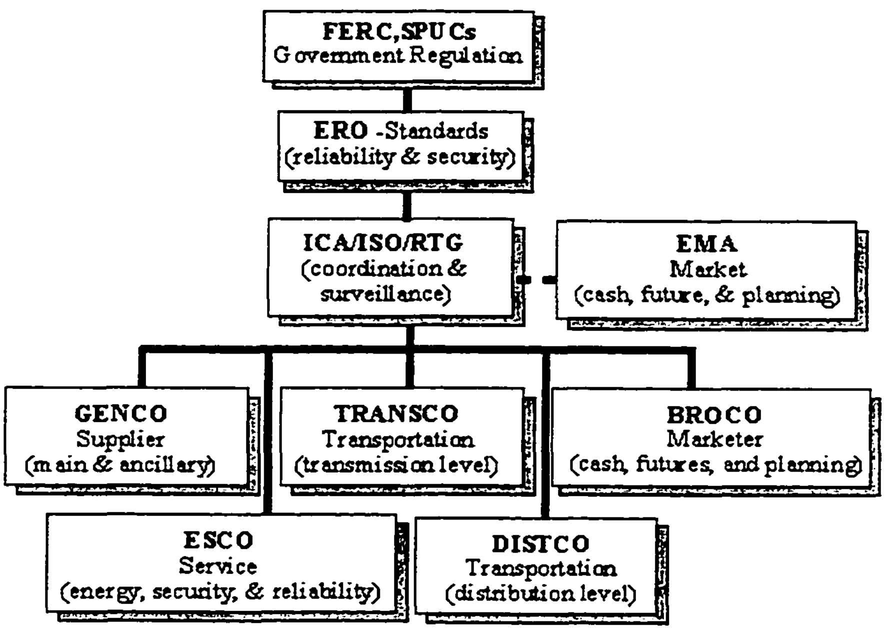

Figure 2-1. Framework of the energy market.

In Somgiat Dekrajangpetch's dissertation [4], the brokerage system can be categorized by how the auction market is implemented. First is centralized daily commitment auction (CDCA) versus single period commodity auction (SPCA). CDCA requires all involved market participants to submit their *aggregated* demand and cost function for a specific *duration*, 24 hours or 168 hours for instance. SPCA requires all involved participants to submit their *incremental* demand and price for a particular *period*, 15 minutes or an hour for instance. Second is single-sided auction versus double-sided auction. In a single-sided auction, only the buyers or the sellers can submit their offer price. In a double-sided auction, all participants, buyers or sellers, are allowed to submit their offer price. Third is uniform pricing versus discriminating pricing. Uniform pricing assures all buyers pay and all sellers receive the same price. Discriminating pricing means each seller gets paid and each buyer pays according to their bids. Fourth is heterogeneous product versus homogeneous product. In a heterogeneous product, the quality of the product differentiates the contracts. For example, in the energy market, ancillary services can be one feature that will differentiate the energy contract. In a homogeneous product, all contracts contain product of equal quality. In the energy market, the ancillary services specified in all energy contracts will be the same. In this research, the auction mechanism is assumed to be a heterogeneous, discriminating, and double-sided SPCA.

2.2.1 Regulation, Deregulation, and Re-regulation

Regulation stresses governmental control. Deregulation refers to the de-emphasis of government oversight in the private sector [9].

Regulation limits the freedom to conduct business. However, the freedom to conduct business is paramount to industrial leaders. Safety and quality are of great interest to the public. However, deregulation that frees industrial leaders of any government regulation does not require the industrial leaders to act in the interests of the public. To balance the interests of the public and the industrial leaders, government regulation is still needed.

Since the early 1900s, the ability of regulation in the power industry to maximize social welfare has been questioned. Advanced technology, a desire to lower electricity prices, and increased demand for electricity, among other forces, have driven the movement to restructure the power industry. In the process to restructure the power industry, some existing government regulation will be lifted while some new government regulation will be added. For this reason, re-regulation is a more appropriate terminology to refer to the regulatory reformation in the power industry nowadays.

2.3 ESCO

The only entity that has direct dealership with the end-users under the new market structure is the ESCO. The ESCO collects its revenue from the distribution customers for the energy and ancillary services it has provided. It also acts as a wholesaler, purchasing the electric energy through the auction market and reselling it to other ESCOs, GENCOs, etc. To obtain the desired electric energy, an ESCO may purchase energy contracts through an auction market, utilize the reserves through the load management programs, or own the distributed generation. In addition, to keep the company operational, the ESCO incurs the cost of hiring staff to carry out the daily tasks. Figure 2-2 shows the simplified diagram of an ESCO model.

The changed business structure will offer an opportunity to the ESCO. The company will be allowed to purchase the electric energy through the auction market where all GENCOs compete to sell at their best offer price. Also, the ESCO will be able to compete with the other energy service providers for business. Of course, the changed environment also means competition to the ESCO. To retain existing customers and attract new customers, the ESCO has to provide reliable services and options to the customers at competitive prices. Yet, to satisfy the investors, the ESCO has to maintain a profitable account. To provide reliable service at a competitive price while maintaining profitability for meeting customer demand, the ESCO needs to know the new market structure and takes the steps to learn the tools to manage the risk and dynamics of the auction mechanism and the customer response. More importantly, the ESCO needs to utilize fully the tools that may influence the customer demand, i.e., the load management programs, especially when the ESCO has little or no generation capability. The importance of the load management programs will be discussed further in section 2.2.3 and later chapters. Figure 2-3 relates the market, customers, and load management programs to the ESCO.

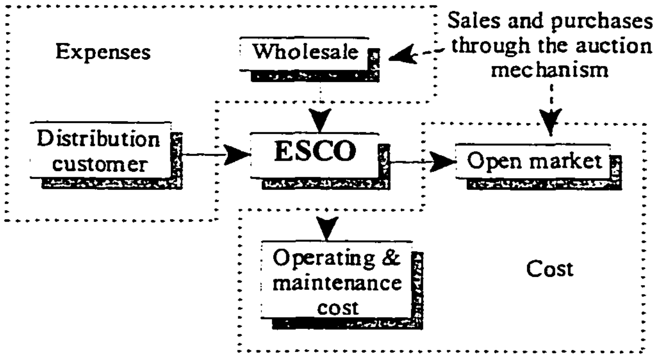

Figure 2-2. ESCO model.

The challenges ahead of the ESCO can be further explored by looking at the factors influencing the ESCO operation. These factors can be external or internal. Internal factors determine the strength, weakness, and internal cost of the firm. They include factors like leadership, productivity, marketing strength, and agility. The internal factors can be collectively called the corporate structure. The external factors can be classified into

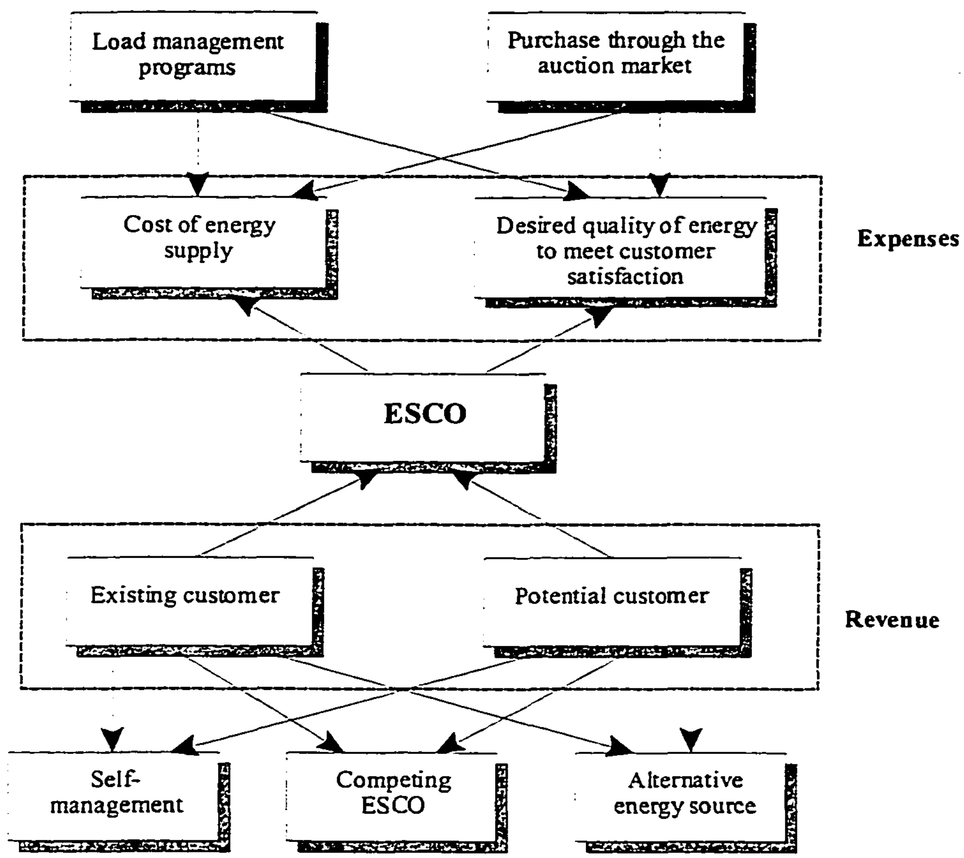

Figure 2-3. Associating the ESCO with the market, customers, and load management programs.

three components. These components are the market factors, customer factors, and supplementary energy factors. They collectively measure how well the ESCO manages the demand and supply side equation of the electric energy. Even though the corporate structure is an important, yet interesting, topic, it is not the focus of this research. Rather, it is the external factors that trigger this research. Further elaboration about these external factors follows. Figure 2-4 shows the factors that influence the ESCO operation.

2.3.1 Market Factors

This research concentrates on two distinct markets. The first is the capital market where the ESCO may raise capital to subsidize its operation or invest excess capital. The second is the auction market where the electric energy is traded. There are, as shown in Figure 2-4, three market factors that are considered in this research: the interest rate factor, the price factor, and the reliability factor.

There are two principal sources of funds when the ESCO needs to raise capital to subsidize its operation. These sources are debt and equity. The ESCO may raise debt capital by borrowing from banks and other financial institutions. The ESCO may raise equity capital by retaining part of its earning or by selling new common stock. When the ESCO accrues excess capital, it may choose, among other things, to purchase treasury bills or bonds, save in banks or similar financial institutions [10]. Whether it is raising or investing capital in debt or equity, the interest rate of the investment is what the ESCO is trying to evaluate. These equity or debt interest rates can be collectively called the interest rate factor.

In section 2.2, the auction mechanism is assumed to be a heterogeneous, discriminating, and double-sided SPCA. However, three important aspects remain to be considered in defining the factors influencing the ESCO operation in the auction market. First is how heterogeneous product is defined in this research work. Second is how the ESCO may trade in the auction market. Third is how the traded energy contract is defined.

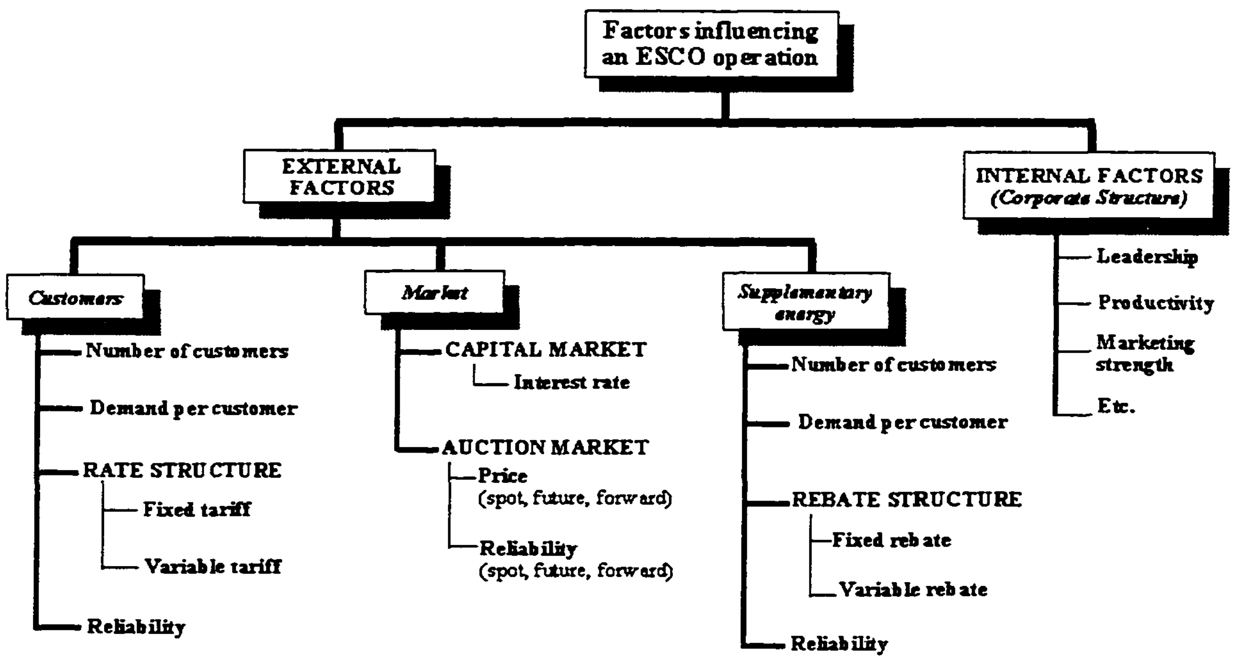

Figure 2-4. Factors influencing an ESCO operation.

There are six ancillary services that are outlined in Kumar's dissertation [3]. However, only the reliability aspect will be addressed, i.e., how reliable is the energy that is delivered to a buyer. 95% reliable energy for example, means that all the purchased energy will be delivered to the ESCO 95% of the time while no energy will be delivered 5% of the time. In addition, buyers, especially ESCOs, need to be aware of the volatility in customer demand. Volatility refers to the percentage change allowed in the demand during a specific duration. For instance, if an ESCO purchases an energy contract allowing 5% volatility, the customer demand can fluctuate within the 5% range when energy is delivered. Additional discussion on the volatility in the customer demand is presented in Chapter 4.

In the assumed auction mechanism, market participants may trade energy through four different markets. These are the spot market, the forward market, the futures market, and the options market. In the spot market, the energy for next-day delivery is traded. In the futures, forward, and options markets, the contracted energy is to be delivered in the future, ranging from within one month to several years from the date the contract is issued. The existence of the futures, forward, and options markets is to allow both buyers and sellers of energy to lock in energy prices in order to reduce the risk of business operation. A forward market is less liquid than a future market. Specifications in a forward contract are tailored to meet the needs of both the contract seller and buyer. The bilateral contract that has been used in the power industry for the past few decades is synonymous to the forward contract. A futures contract, however, is tailored to meet the needs of most players in the market. It often ends up with a cash settlement instead of actual delivery of the contracted product. In the options market, the ESCO is given the right to sell or buy energy (of which the contract specifications are similar to those in the future market) in the future.

There are four risks associated with trading in the forward, future, and option markets. They are quality risk, price risk, basis risk, and credit risk. Quality risk is the difference between contracted electric energy quality and the actually delivered electric energy quality. Since the ancillary service defines the quality of the energy, and the volatility is more of a demand-side problem, the reliability risk is equivalent to the quality risk in this research. Price risk is the adverse price movements in the spot market [11]. Basis risk is the difference between the energy spot price and the future/forward/option (FFO) energy price. This difference is a function of location, quality, and supply/demand for each [11]. In this research, no difference is assumed between the spot and FFO price, or equivalently no basis risk. Credit risk is the ability of the participants in a transaction to keep their contractual obligations. Assuming that the auction mechanism has taken great care to reduce the credit risk for all participants, the credit risk can be assumed to be minimal and ignored. Thus, the two remaining market factors that are considered in this research are the market price factor and reliability factor. Since the FFO price reflects the price and risk of the electric energy in the future, spot price and FFO price may not always be equivalent. In addition, as the next paragraph will suggest, there will be a difference in the spot and FFO markets. Thus, the market price factor is further classified as the spot price factor and the FFO price factor.

To purchase the energy, the ESCO needs to decide (1) the price of energy, (2) the quality of the energy, (3) the time of delivery, and (4) the duration for which the energy is to be delivered. The price of energy is determined based upon the demand and supply of the market. Assuming that the auction market is perfect, the price of energy will reflect the cost of generation. Again, the quality of energy is equivalent to how reliable the energy is in this research. The time of delivery is equivalent to when the energy will be delivered to the destination requested by the contract buyer. Figure 2-5 shows a sample of an ESCO demand and the different energy delivery duration the ESCO could have purchased. Type 1 duration lasts less than an hour. It is particularly useful when the peak demand is far shorter than an hour. Type 2 duration lasts for an hour. Type 3 duration lasts for a day. Type 4 duration lasts for a month. Type 5 duration lasts for more than a month. In the existing energy markets, Pennsylvania-New Jersey-Maryland (PJM) and California PX for instance, Type 2 and Type 4 duration are most common, where Type 2 duration is traded in the spot market while Type 4 duration is traded in the futures and options market. In existing markets, Type 4 duration refers to delivery during peak hours of the day only. Because of the difference in the delivery duration between the spot market and the FFO market, the FFO price is the combinatorial effect of the spot prices in multiple periods.

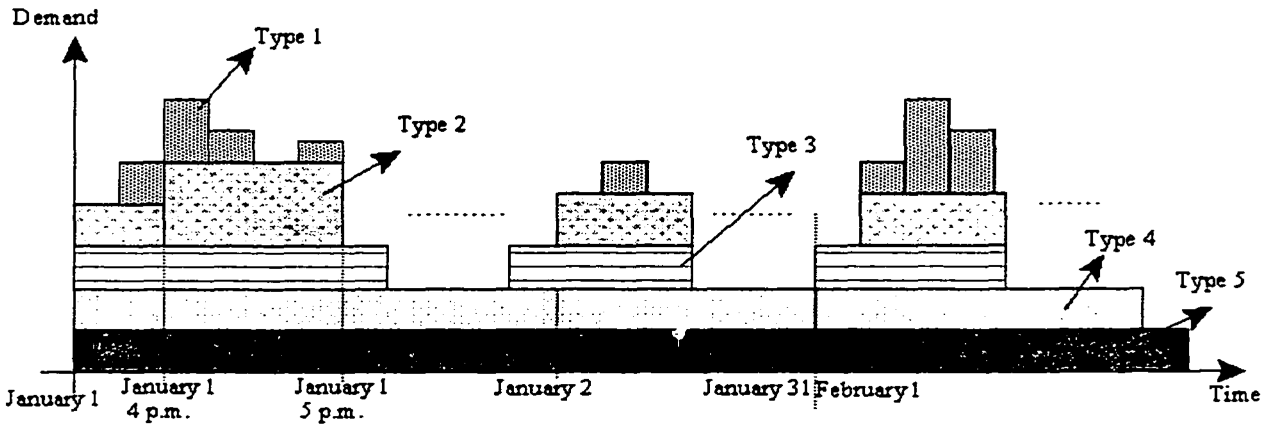

Figure 2-5. Customer demand and type of contract duration.

After a contract is agreed upon, there will be occasions when the contracts may be broken. It is assumed that the following policies will be agreed upon among all participants in the market.

- When a natural disaster occurs, the contract buyer will not receive any compensation from any party.
- When a contract is defaulted and no energy is delivered because of a system delivery problem or generation failure, the contract buyer will receive a payment from the party at fault equivalent to the contracted compensation agreement, if any.
- When the quality of energy is less than the agreed upon minimum requirement, the contract buyer will receive compensation as written in the contract. For instance, a contract seller required to deliver a 99% reliable energy delivers has to pay the contract buyer every 1% of the reliability level lower than the 99% specified.
- When a contract is broken for reasons other than physical delivery problems, ICA/ISO/RTO will purchase energy of equivalent quality and quantity and deliver it to the location specified within the contract at the expense of the party at fault. To achieve that, a clearinghouse is established to guarantee that the financial

duties of the parties involved in each transaction are fulfilled. Requiring the market participants to maintain margin accounts helps reduce the credit risk, i.e., improves the ability of the parties involved in a transaction to keep their contractual obligations.

- When a contract buyer fails to consume the energy purchased at any time, the buyer will still have to bear the cost of energy, even when the energy is not delivered for such reason.

Examples of the different contracts are presented in Table 2-1.

Table 2-1. Examples of contracts in the auction market.

Market		Spot	Future	Option	Forward
Position		Buy	Long	Long call	Long
Number of contract		5	10	2	5
Size/contract		5 MW/hr	5 MW/hr	5 MW/hr	12MW/hr
Premium		–	–	$5.00	–
Delivery price		$25.00	$23.00	$20.00	$25.00
Delivery	Begin	1/1/2000 9:00 a.m.	1/1/2000 9:00 a.m.	1/1/2000 9:00 a.m.	1/1/2000 8:00 a.m.
duration	End	1/1/2000 11:00 a.m.	1/31/2000 9:00 a.m.	1/31/2000 9:00 a.m.	1/15/2000 6:00 p.m.
Reliability level		95 %	90 %	95 %	97 %
Volatility level		5 %	10 %	5 %	10 %
Penalty per 1% reliability not meeting contract		$300.00	$25000.00	$20000.00	$12000.00

2.3.2 *Customer Factors*

There are, as shown in Figure 2-4, five customer factors that are considered in this research: the demand per customer factor, the size of customer factor, the fixed tariff factor, the variable tariff factor, and the energy reliability factor.

Prior to re-regulation, the customer demand needed to be forecasted before scheduling the electric generation. With re-regulation, a similar situation still persists. Thus, the first customer factor that the ESCO will face is the demand per customer factor. In the new business environment, the customers are free to choose their own energy service provider. Thus, the second customer factor that the ESCO will face in the advent of re-regulation is the size of customer factor.

Since the customers are the primary source of income, the ability to keep existing customers and attract new ones is important. To meet this challenge, the ESCO needs to provide competitive services at competitive rates. The terms of a service agreement between the ESCO and a customer can be viewed as a contract. Within the contract with the customer, the ESCO will specify contractual terms like: the rate structure, the quality of services, and the contract duration. A discussion follows about certain components of the contract between the customer and the ESCO, namely: the rate structure, the energy services, and the time requirement before a customer switches to another energy service provider.

In this research, the rate structure (tariff) that an ESCO may offer consists of two parts, the fixed tariff and the variable tariff. The fixed tariff is somewhat equivalent to the access fee in the telecommunication industry. It can be used to compensate the ESCO for expenses other than energy costs. It may also be used to compensate the ESCO if the ESCO decides to lower its variable tariff as the competition increases. Thus, the fixed tariff factor is the third customer factor. The variable tariff reflects the energy cost and the ancillary services that the customers have requested. Thus, the variable tariff is the fourth customer factor.

The variable tariff may come in several forms. The first form is a fixed per kWh variable tariff, regardless of the amount of energy consumed or the time of use. The second form is a time-of-use kWh variable tariff, where the electric energy consumed during the peak demand periods is charged at a higher rate. The third form is a time-varying kWh variable tariff, where the variable tariff is a function of the market price when the hour where the energy is consumed. The fourth form is a peak demand variable tariff, where the variable tariff is a function of the peak demand during a specific duration. These four forms of variable tariffs [1] not only represent customer choices, but also offer the customers options to share the uncertainty in the market price at different degree of financial risk.

Another customer factor, the energy reliability factor, is tied to the energy service. The energy service is composed of two parts. The first is the service on the quality of energy and the second is the exotic service options.

The quality of energy is equivalent to the level of ancillary service that a customer requests. Since the reliability is the only one that will be addressed in this research, reliability is defined as the quality of energy at the present time. Depending on the nature of use, different customers may request that energy be delivered at different reliability levels. Once the customer and the ESCO have agreed on the reliability level, the ESCO is responsible to keep its promises. When the reliability level is not delivered as requested, the ESCO bears the risk of losing the customer to another company. In addition, the contract term may specify how the ESCO should compensate the customer if the reliability level is not met. The ESCO will then bear additional financial cost if the compensation were to be paid to the customers [2]. Thus, the energy reliability is the fifth customer factor.

There is an enormous number of exotic service options available. Only three distinct options are presented. First is the load management option. In general, the load management programs improve the flexibility of the customer demand. From the customer perspective, the program allows customers to exchange

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[1] The time-of-use variable tariff and time-varying variable tariff are used in load management programs to indirectly control the customer demand.

[2] It is assumed that when natural disaster occurs and the contract is defaulted, the ESCO will not need to pay any compensation to the customers.

their energy demand for monetary compensation. Second is the cost-control option. In the cost-control program, the ESCO offers to provide conservation program and load management programs to minimize the customer cost of energy. For example, the ESCO may offer advice in determining the best space heating or cooling appliances to be installed at the customers' end. The ESCO receives consultation fee and possibly some percentages of savings that the customer enjoys. Third is the integration of energy, telecommunication, water, and sewage service option. This bundled service provides one stop shopping for the customers. In this research, it is assumed that the exotic service options have been reflected in the tariff and not considered as a customer factor that influences the ESCO operation.

The minimum time requirement before a customer can switch to a different energy service provider is an important aspect. The time requirement can be defined as the time needed by the ESCO to readjust its contractual positions in the auction market. For example, in PJM service territory, customers need to notify PJM a month before changing service provider. There is a possibility that the time requirement may be reduced in the future. However, this is more of a regulatory issue, which is outside the scope of this research. Despite the time requirement, the number of customers under the ESCO service will vary from one time to another. Thus, the size of customer factor will remain in the ESCO operation.

2.3.3 Supplementary Energy Factors

Supplementary energy is synonymous to the load management programs. The reason for using the term "supplementary energy" is that load management programs are not a necessity, even though they are important to improving the profitability of serving customer demand. The structure of the supplementary energy factor is similar to that of the customer factor. There are, as shown in Figure 2-4, five supplementary energy factors that are considered in this research: the supply per participation factor, the size of participation factor, the fixed rebate factor, the variable rebate factor, and the reliability factor.

The supply per participation factor refers to the amount of energy per customer participation that can be controlled by the ESCO. The size of participation factor refers to the number of customers participating in the load management programs. The fixed rebate factor and variable rebate factor refer to the rebate structure that the ESCO used to attract customer participation. The reliability factor refers to the reliability of the load management energy. The reliability of the load management energy largely depends on the reliability of the load management devices that controlled the electric energy. In addition, the trustworthiness of the customers is important in assessing the reliability of the load management devices.

Despite the similarities in their structure, the supplementary energy factors have some complexities that are not found in the customer factors. The discussion on supplementary energy is divided into the following: ownership and participation. To end the discussion, the effect of marketing and operational efficiency will be discussed.

Ownership refers to physical ownership and operational ownership. While the concern about the ownership issue has been addressed in previous work, further elaboration will be presented [12]. A physical ownership refers to who owns and is responsible for the maintenance of the appliance used for the load management programs. An operational ownership refers to who will be responsible for the daily operation of the appliance. The two parties involved in the ownership aspect are the customers and the ESCO. The two ownership aspect dictates how each of the two parties may benefit or be compensated from the load management programs. Any combination is possible. For instance, an ESCO-owned, customer-operated load management device may be loaned to a customer who doesn't have the capital to invest in the device, but wishes to benefit from the load management programs. The ESCO, on the other hand, may believe that the return on investment on the loan is so favorable that the business deserves a try. A customer-owned, ESCO-operated situation can also occur when the customer with the capital to invest in the load management device believes that the return on investment, by loaning the appliance to the utility for load management purposes, is more profitable than operating the load management device him/herself. The ESCO, on the other hand, may believe that by renting the load management devices from the customers it will reduce the capital needs while improving the flexibility of customer demand and improving the profitability of serving customers.

Participation refers to how the customers may be attracted to the load management programs. There are different ways to attract the customer. For example, the ESCO may offer the customer special treatment when there is a shortage in the energy supply. In this research, it is assumed that in attracting the customers, the potential customers are offered a two-part incentive similar to the rate structure on energy services. A fixed part is offered to customers for participating in the program. A variable part is offered to the customer each time the demand is shifted to another hour [3].

Even though with the same amount of incentive, a different marketing strategy may result in a different number of customers participating in the program. However, to realize the effect of a marketing strategy, it is important to distinguish the difference between marketing strategy and operational efficiency. A marketing strategy is employed to increase the number of customers an ESCO may attract to its company for a given revenue-cost ratio (the revenue-cost ratio is referred as the revenue that the ESCO may collect from the customer with respect to the cost of serving the customer demand.) An operational efficiency refers to the ability of the ESCO to manage the cost of energy purchased through the auction market [4]. Scheduling supplementary energy improves the operational efficiency for a given marketing effort. An efficient operation improves the profitability that eventually provides flexibility to the ESCO in the marketing effort. In short, the

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[3] A variable part of the incentive can also be the dollar per MWhr of the customer energy that is used for the load management purpose. Since the load management algorithm has been modeled for the first possibility, it will be used instead throughout the discussion.

[4] An operational efficiency can also be referred to as the efficiency of running the company. The reason for taking the first definition is to clear up the relationship among the marketing, the operational efficiency and the developed load management algorithm.

marketing effort improves sales for a given revenue-cost ratio while the operational efficiency improves revenue-cost ratio for a given sale.

2.4 OPERATION AND MANAGEMENT OF AN ESCO

As re-regulation enhances competition, each player within the market seeks to improve its profitability and strategic position. With each player driven to excel, rapid changes in the technologies and the business strategies are inevitable. This phenomenon increases the dynamics of the business environment, making it harder to differentiate the operation and management of an ESCO in the short run from the long run. Yet, to help the ESCO focus on its operation, the ability to identify the operation and management at various stages is important. This section addresses the characteristics of the factors influencing the ESCO operation, the time horizon at which these factors are considered in the decision making process, and the various possible objectives that an ESCO may have.

From section 2.2, the factors influencing the operation of the ESCO serving customer demand can be summarized as follows:

- Market – spot price, FFO price, and reliability. These market factors affect the cost of serving customer demand.
- Customers – demand per customer factor, size of customer factor, fixed tariff factor, variable tariff factor, and energy reliability factor. These customer factors affect the revenue of serving customer demand.
- Supplementary Energy – supply per participation factor, size of participation factor, fixed rebate factor, variable rebate factor, and reliability factor. The load management programs increase the ESCO capital cost, but at the same time improve the profitability of serving customer demand and relax the customer demand.

To achieve its objective, the ESCO needs to incorporate into its decision making the factors influencing its operation. However, before incorporating these factors into the decision making process, their characteristics should be identified. There is more than one way to characterize these factors. To help develop algorithms to achieve the ESCO objective, this research identifies are three major characteristics that are crucial. The first characteristic is whether the factor is dependent or independent. A dependent factor is a function of some other factors while an independent factor is not. For example, as the ESCO may offer customers with higher purchase power a lower rate, the rate structure (tariff) can be a function of the customer demand. Evaluating the factor dependency is important whether the ESCO is trying to estimate or make decision. The second characteristic is whether the factor is parametric or variable. A parametric factor refers to a factor that is known at the time of decision making. For instance, the tariff charged to a customer for the next day is known at the time of decision making and should be considered as a parameter. A variable factor refers to a factor that is not known at the time of decision making. The ESCO needs to determine the value of the variable factor at the time of decision making. For example, the ESCO needs to determine the number of spot contracts to be purchased for tomorrow's customer demand. The third characteristic is whether the factor is deterministic or uncertain. For example, since the ESCO may not know exactly how much energy a particular customer will consume, the demand per customer is an uncertain factor.

As time duration changes, the characteristics of the factors influencing the ESCO operation change as well. For instance, the ESCO knows the tariff that it can charge a customer for tomorrow, making it a parametric, independent, and deterministic factor. However, when looking into the future, the ESCO may be forced by competitors to reduce the tariff or, if energy costs increase, to increase the tariff. Then, the tariff becomes a variable, dependent, and uncertain factor. Thus, the time horizon of the operational management should first be determined to allow proper classification of the factors influencing the ESCO operation. The specification of the time horizon depends on two issues. First are the realities that influence the energy and consumer markets. For example, PJM requires the distribution customers to notify the change of their energy service providers a month ahead of time. The ESCO is assured of the number of customers that it serves within the month. Thus, the number of customers that the ESCO serves becomes an independent, parametric, and deterministic factor within the month. When the time horizon exceeds one month, the number of customers that the ESCO serves will most likely depend on the competition it faces. Then, when the time horizon exceeds one month, the number of customers that the ESCO serves becomes a dependent, variable, and uncertain factor. Second are the assumptions that the ESCO establishes to solve the intended problems. For example, the interest rate factor is uncertain most of the time. No matter how stable the economy, the traded market interest rates (treasury bonds, treasury bills, and corporate bonds) fluctuate throughout the trading hours due to the speculations of the buyers and sellers. However, in solving some short-term problems, scheduling customer demand and purchasing electric energy, for instance, the interest rates can be assumed as a parametric, independent, deterministic factor. This assumption can be supported if the ESCO has hedged against the interest rates risk in the short-term or if the economy in the near term is so stable that the fluctuation in interest rate is insignificant. As the assumptions made by each company vary, the specification of the time horizons varies from one company to another as well. Table 2-2 shows one possible way to classify the different time horizons that an ESCO may consider in its operational planning. Each of the time horizons will be discussed further.

Once the factors influencing the ESCO operation are characterized for the different time duration, the ESCO must determine what it would like to achieve within each time duration. The selected objective will govern how all the variable factors influencing ESCO operation within a time duration should behave. There are many choices for the objectives. Also, the selected objectives can affect the performance of the company as well. For example, while minimizing customer demand during peak demand hours can minimize the risk of jeopardizing the energy delivery system, the ESCO's expected profit could be significantly lowered. This is especially true if the peak energy price does not correlate well with the peak demand. Column 3 of Table 2-2 provides some objectives that the ESCO may choose during the different time horizons. In Table 2-3 through Table 2-5, the characteristics of factors influencing the ESCO operation in different time horizons are presented.

If the open market is perfect, no player should be able to influence any of the market factors. Therefore, all market factors should be parametric. Since the open market interest rate is not to be modeled, the factor is assumed to be independent. In addition, since it is assumed that the open market interest rate is stable in the near term, the factor is deterministic from the reactive scheduling/control level to the short-range planning level. In most instances, all market prices are uncertain because they are the combinatorial effect of all market players. However, in the reactive scheduling/control level, it is assumed that the ESCO must be informed of the incentive if it is to reschedule its demand. Therefore, the spot market price in the reactive scheduling/control level is assumed to be deterministic. Since the forward, futures, and options markets would most likely require all players to clear their positions prior to the beginning of contract duration, they are not available in the reactive scheduling/control level.

Table 2-2. Classification of the ESCO operational and management levels.

Level	Horizon	Examples of objectives
1. Long-range planning (LRP)	more than 2 years	Service territory expansion; determining the need to expand energy storage system and/or distribution generation capacity.
2. Middle-range planning (MRP)	1 year to 18 months	Designing the customer rate structure or rebate system; determining the size of participation in the load management programs.
3. Short-range planning (SRP)	1 month to several months	Cash flow management; risk management using FFO contracts; determining the incentives to attract/maintain new/existed customers.
4. Scheduling (SCH)	1 day to several weeks	Purchasing energy through the spot market, rescheduling customer demand and exercising future and option contracts to meet scheduling purpose.
5. Reactive scheduling/control (RS/C)	less than 1 day	Meeting system requirement as outlined by the ISO/ICA/RTG and the contracted energy demand and supply.

Since customer demand must be forecasted all the time, the demand per customer is an uncertain factor at all operational levels. Since customers need to inform the proper authority some time prior to switching their services to a different energy service company, e.g. customers in the PJM territory, factors other than the demand per customer factor are deterministic and parametric in the reactive scheduling/control and scheduling level. As the time duration increases to more than one month, customers may opt for a different energy service company for better service or prices; therefore, most factors become variable beyond the scheduling level. It is assumed that the ESCO is less likely to change its policy in the fixed part of the rate structure, therefore, fixed tariff factor remains deterministic in the short-range level. Also, It is assumed that all customer factors can be modeled to better understand the needs of the customer.

As mentioned before, the structure of the supplementary energy factors is similar to those of the customer factors. It is assumed that the customers need to inform the ESCO a month prior to discontinuing the load management programs. Thus, the first four columns of the two factors are similar. However, in this research, since no discussion will be made on the reliability of the load management devices and the trustworthiness of the customers participating in the program, the reliability factor is categorized as independent, parametric, and deterministic factor for simplicity.

Table 2-3. The characteristics of market factors.

Level	Open market (supply-side)			
	Spot price	FFO price	reliability	Interest rate
1. LRP	*DEP, PAR, UNC*	*DEP, PAR, UNC*	*DEP, PAR, UNC*	*IND, PAR, UNC*
2. MRP	*DEP, PAR, UNC*	*DEP, PAR, UNC*	*DEP, PAR, UNC*	*IND, PAR, UNC*
3. SRP	*DEP,PAR, UNC*	*DEP, PAR, UNC*	*DEP, PAR, UNC*	*IND, PAR, DET*
4. SCH	*DEP, PAR, UNC*	*DEP, PAR, UNC*	*DEP, PAR, UNC*	*IND, PAR, DET*
5. RS/C	*DEP, PAR, DET*	*Not available*	*DEP, PAR, DET*	*IND, PAR, DET*

Table 2-4. The characteristics of customer factors.

Level	Customer (demand-side)				
	Rate structure		Demand per customer	Number of customers	Energy reliability
	fixed	Variable			
1. LRP	*DEP , VRB, UNC*	DEP , VRB, UNC	*DEP , VRB, UNC*	*DEP , VRB, UNC*	*DEP , VRB, UNC*
2. MRP	*DEP, VRB, UNC*	*DEP , VRB, UNC*	*DEP , VRB, UNC*	*DEP , VRB, UNC*	*DEP , VRB, UNC*
3. SRP	*DEP, PAR, DET*	*DEP, VRB, UNC*	*DEP , VRB, UNC*	*DEP , VRB, UNC*	*DEP , VRB, UNC*
4. SCH	*DEP, PAR, DET*	*DEP, PAR, DET*	*DEP, PAR, UNC*	*DEP, PAR, DET*	*DEP, PAR, DET*
5. RS/C	*DEP, PAR, DET*	*DEP, PAR, DET*	*DEP, PAR, UNC*	*DEP, PAR, DET*	*DEP, PAR, DET*

Table 2-5. The characteristics of supplementary energy factors.

Level	Supplementary energy (load management programs)				
	Rebate structure		Supply per participation	Size of participation	Reliability
	fixed	variable			
1. LRP	*DEP, VRB, UNC*	*DEP, VRB, UNC*	*DEP, VRB, UNC*	*DEP, VRB, UNC*	*IND, PAR, DET*
2. MRP	*DEP, VRB, UNC*	*DEP, VRB, UNC*	*DEP, VRB, UNC*	*DEP, VRB, UNC*	*IND, PAR, DET*
3. SRP	*DEP, PAR, DET*	*DEP, VRB, UNC*	*DEP, VRB, UNC*	*DEP, VRB, UNC*	*IND, PAR, DET*
4. SCH	*DEP, PAR, DET*	*DEP, PAR, DET*	*DEP, PAR, UNC*	*DEP, PAR, DET*	*IND, PAR, DET*
5. RS/C	*DEP, PAR, DET*	*DEP, PAR, DET*	*DEP, PAR, UNC*	*DEP, PAR, DET*	*IND, PAR, DET*

2.4.1 Long-range Planning

At this level, there are two major concerns. The first is the market share[5] of the company. A business unit's return on the investment is directly related to its share of the market because businesses with high market shares tend to enjoy economies of scale [10]. Also, since the gain of market share is lead by the quality of services and products, it is important to consider improving the quality with attributes like added staff and service options. The second is the installation of the generation and storage systems that requires high capital cost, including energy storage system and distributed generation (if allowed). These high cost tools help the ESCO to avoid the high market risk and to manage customer demand with greater flexibility. Ultimately, the use of these tools will result in a higher profit margin in servicing the customer demand.

2.4.2 Middle-range Planning

At this level, the operation is down to 1 – 1½-year horizon. In this duration, the ESCO determines if existing customer rate structure will appropriately improve its profitability in servicing the customer demand and maintaining sufficient market share. This includes analyzing the competitions from the other ESCOs or the

[5] Having a large market share does not guarantee market power to the ESCO. A market power refers to the ability of the ESCO to control the competitive environment in which all other competing ESCOs operate. However, market share only describes the number of customers that the ESCO serves comparing to the rest ESCOs. If the ESCO is operating in a competitive market, the market share will, however, not provide any market power to the ESCO.

alternative energy source providers. In addition, it is important to consider if existing DLC and IDLC programs are appropriately maximizing the profitability of servicing the customer demand and improving the flexibility of the customer demand. The major reason for including the DLC and IDLC programs in the middle-range planning is that they are easier to set up relative to the installation of high cost yet time consuming ESS.

Comparing Tables 2-3 – 2-5, one would find that the characteristics of factors influencing the ESCO operation in both LRP and MRP are exactly the same. However, the objectives in both planning horizons are different. The difference in the objectives is a result of some high-capital investment that needs to take into account the effect in the future time. For example, a comparison between section 2.4.1 and section 2.4.2 suggests that no expansion in the distributed generation be evaluated in the MRP. Even though the expansion may take less than 1 – 1½ years to be completed, the evaluation should take into account the return on investment that often time takes more than 1 – 1½ years.

2.4.3 Short-range Planning

At this level, the ESCO operation is down to less than a year. Cyclical customer demand is relatively unchanged, other than some trend movement as a result of, say, changed weather. Except for some rebate scheme, the rate structure offered to customers does not change much during this duration. Thus, the objective at the short-range planning level is to maintain an acceptable cash flow condition, reduce the short-term risk using the futures and options contracts, and raise capital, through equity or debt, to help maintain a healthy financial condition.

2.4.4 Scheduling

At this level, the ESCO operation is down to several weeks. At this level, the customer contracts are not alterable. The number of customers participating in the load management programs and the availability of the ESS are known. Meanwhile, the rate structure agreed upon by the ESCO and the customers is set. The targeted objective (profit maximization, cost minimization, or peak load minimization) is reached by managing the controllable energy under the DLC and IDLC program, sending the proper rate signal to the customers participating in the IDLC program, purchasing energy through the auction market, and exercising the futures and options contracts.

2.4.5 Reactive Scheduling/Control

At this level, central issues are emergencies and glitches [13]. The customer demand is monitored to assure that the purchased energy and ancillary services meet the requirements stated in both the customer contracts and the regulation. Properly developed monitoring systems should help the dispatcher when contingencies occur.

CHAPTER 3 LOAD MANAGEMENT PROGRAMS

Load management programs were initiated in the 1970s to actively influence customer demand. Generally, it can be categorized into direct load control (DLC), indirect load control (IDLC), and energy storage system (ESS). Figure 3-1 shows the classification of load management programs.

This chapter focuses on modeling the DLC and ESS demand at any time duration (seconds, minutes, or hours). Section 3.1 reviews the load management programs, and includes a perspective on why load management should not be ignored in the re-regulated business environment. Section 3.2 reviews the different load management models in existing literature. Section 3.3 provides a list of variables and parameters used in modeling the DLC and ESS program. Section 3.4 presents the DLC model, while section 3.5 presents the ESS model.

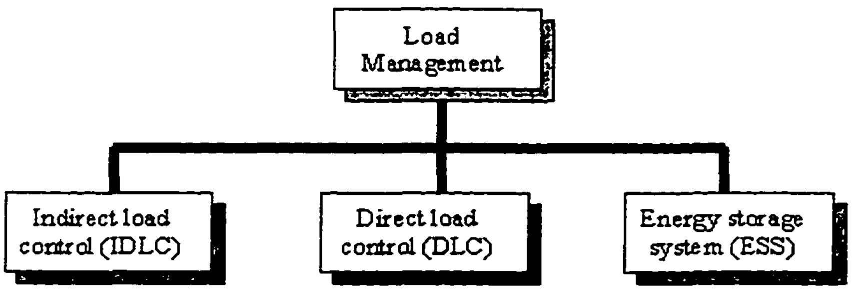

Figure 3-1. Load management programs.

3.1 LOAD MANAGEMENT PROGRAMS

The DLC allows the ESCO to shed remote customer demand unilaterally. The DLC program can be further classified, depending on the employed technology. Remote control uses the communication system to execute the load deferment or load paid back instruction. Point-of-use, however, uses devices like cyclic timers, thermostats, and time clocks to carry out the [14 – 16]. IDLC allows the customers to control their demand independently according to the price signals sent by the utilities. Both DLC and IDLC share the same concept, where controllable demands are shifted to the future where the economic values are higher. However, they differ on who has the ultimate control on the electric appliances. Finally, ESS allows both the ESCO and the customers to store energy during low-cost sessions and consume during high-cost sessions. ESS installed at the customers' end includes cool storage, storage space heating, and storage water heating. ESS installed at the providers' end includes batteries, pumped hydroelectric storage, compressed air energy storage, liquid-phase methanol with coal gasification combined-cycle, and superconducting magnetic energy storage [17].

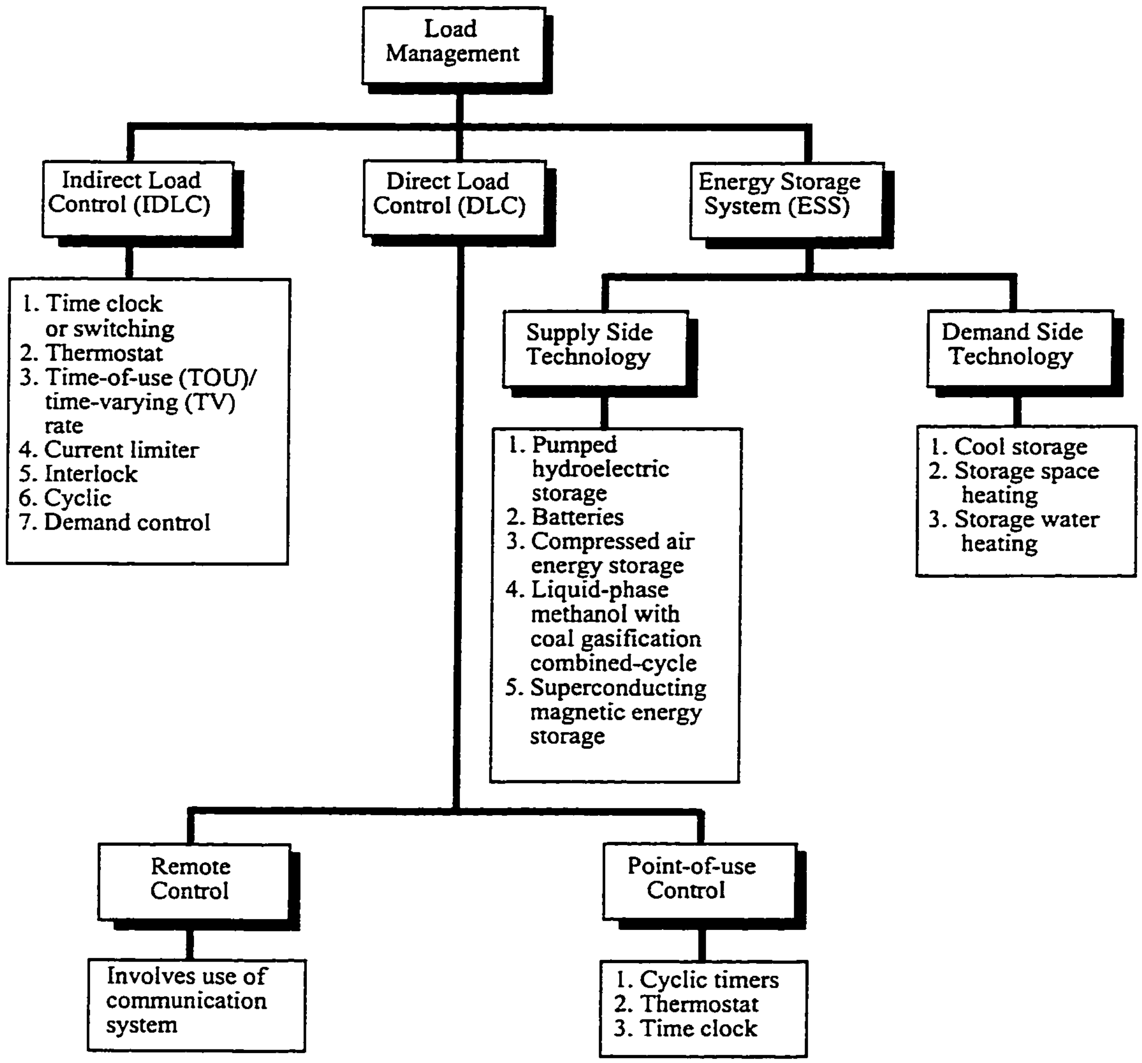

Figure 3-2. Classification of the load management programs.

Since its inception, the demand under the load management programs has accounted for 5% to 10% of the total electric demand patterns. The programs once flourished in the early 1980s. However, as time went on, interest in the program subsided. Except in states like Florida and California, with insufficient generating capacity to handle the peak demand, the programs are generally not a popular option anymore. The lack of interest in the programs is attributable to three major reasons. First, the load management programs are relatively young compared to the power industry in general. The technology has not matured enough for the utilities to feel comfortable about adopting the load management programs. Second, to a large degree, the load management programs are regulatory *forced* upon the utilities. Utilities may not see the value of the programs but still adopt them to please the regulators. With no proper incentive, the growth in adopting the programs is naturally slowed. Finally, the load management programs can be used by the utilities as a shortcut to cross subsidize some customers. Or, as Andrew Rudin put it, "the program unfairly *taxes* non-participants" [18].

The advent of re-regulation sheds some light on the prospect of adopting load management programs. At least, the three concerns that impede the growth of the load management programs can be eliminated. Since the ESCO is driven to the market by the profitability of energy services, there will be no concern on the possibility of regulatory *forced* programs. Also, since the customers are free to choose any energy service providers, even to the extent of managing the demand by themselves, the *unfair* load management programs will drive customers away. Finally, as long as the load management programs are profitable, why should one worry about the maturity of technology? If there should be any reason that the load management programs are forfeited, it should be the unprofitable nature of the programs – nothing else!

In this research, the load management programs are used extensively. First, developing a flexible customer demand and strengthening the purchasing power in the auction market helps the ESCO. Second, rescheduling the demand, from the low profit-margin periods to the high profit-margin periods, can enhance the profitability of serving customer demand. Third, increasing the service options makes the ESCO more attracting to the customer. Fourth, reducing the cost of purchasing energy from the auction market can improve the ESCO's cash flow. Finally, serving as the alternative source for the ancillary services, the load management programs diversify the ESCO portfolio of energy contracts.

3.2 LITERATURE REVIEW ON LOAD MANAGEMENT MODEL

The DLC receives the most attention of all load management tools. The program allows customers to exchange short-term discontinued electric service with rebates that reduce their bills. Various algorithms have been developed to reduce system peaks, operating costs, and spinning reserves, or improve the profitability of serving customers. The two commonly used techniques are dynamic programming [19 – 24] and linear programming [12, 25 – 28]. Algorithms using dynamic programming determine the amount of energy to be deferred/paid back at any particular time. On the other hand, algorithms using linear programming determine the number of customers to undergo load deferment/pay back. While relatively inexpensive and powerful, algorithms that used linear programming may directly determine the cost/benefit of each customer in the DLC program [12, 25].

Various ESSs exist in the literature and practice. Investigated algorithms for ESSs are commonly found on pumped hydroelectric storage [29 – 37], batteries [32, 38 – 41] and cool storage [42 – 44]. Pumped storage is the ESS that receives the most attention. Different algorithms were developed to integrate pumped storage operation with hydrothermal systems [29 – 37] or batteries [32]. Reported algorithms include dynamic programming [32, 35], gradient methods [37], Lagrangian relaxation [29, 30, 34], linear programming [31, 33], etc. Within the ESS field, battery energy storage systems (BESS) have seen significant technological advancement during the past few years. Algorithms for scheduling BESS are mostly dynamic programming [32, 39 – 41] and linear programming [12, 25]. Coordination of battery operation with others is rare except for coordinating batteries with pumped storage [32], and with DLC [12]. Research work conducted on cool storage increases each year. Reported scheduling algorithms, however, are few [42 – 44] and solved mainly using nonlinear programming techniques.

IDLC requires the knowledge of how customers would react to price versus time of day. Conceptual and theoretical models have been proposed [45 – 47]. Because the understanding of cross-time price elasticity of customer demand is limited, further study is still needed.

3.3 NOMENCLATURE

3.3.1 Parameters

$cd_{i,j,k}$: The rebate given to each customer in load group i for energy deferment of k periods beginning at period j.

cd_i : The ESS I per unit type i operating and maintenance cost when each unit begins the charging sequence.

$r_{i,j}$: The rate customers in load group i are charged at period j.

$Ed_{i,j,k}$: The deferrable energy by each customer in load group i at period j.

g_i : The maximum number of customers in load group i that is available for load deferment.

G_i : The maximum number of units in ESS II model that is available for both energy storage and release.

$\theta_{i,k}$: ESS II unit i's efficiency when $\sum_{\forall k} Pr_{i,j,k}$ is generated.

$\omega_{i,k}$: ESS II unit i's efficiency when $\sum_{\forall k} Ps_{i,j,k}$ is used.

$\overline{Pr}_{i,k}$: The maximum energy used by the ESS II unit i at the k-th linearized segment when energy is released.

$\overline{Ps}_{i,k}$: The maximum energy used by the ESS II unit i at the k-th linearized segment when energy is stored.

$sd_{i,k}$: The rate the energy stored in ESS II unit i loses at k-th amount of stored energy during the last period.

V_{min} : The minimum storage needed within ESS II.

V_{max} : The maximum storable energy within ESS II.

$u(*)$: Unit step function.

$u(*)=1$ if $*\geq 1$

$u(*)=0$ otherwise

$\alpha_{i,j,k,s}$: The energy pay back ratio for each customer in load group i at period $(j+k+s-1)$ when energy is deferred for k periods.

3.3.2 Variables

I_j : The stored energy at period j by the ESS II.

O_j : The stored energy used for discharging purpose at period j by the ESS II.

PT_{load+} : Penalty function for the increased revenue when the load increase is experienced during pay back or cold load pickup.

PT_{load-} : Penalty function for the revenue loss caused by the reduced customer energy during cold load pickup.

$PT_{revenue+}$: Penalty function for the increased revenue when the controllable demand is shifted to a high rate period.

$PT_{revenue-}$: Penalty function for the revenue loss caused by the reduced rate charged on customers during pay back.

S_j : The losses of stored energy at period j by the ESS II.

$x_{i,j,k}$: The number of customers from load group i that will undergo k periods of energy deferment beginning at period j.

$y_{i,j,k}$: The number of ESS I unit i whose storage compartment is to be fully stored at period j for k periods.

$z_{i,j,k}$: The number of ESS I unit i whose stored energy is to be fully released at period j for k periods.

$Pr_{i,j,k}$: The electric energy released by ESS II unit i at period j when the unit is operating at an efficiency level of $\theta_{i,k}$.

$Ps_{i,j,k}$: The electric energy used by ESS II unit i at period j when the unit is operating at an efficiency level of $\omega_{i,k}$.

V_j : The total stored energy at period j by the ESS II.

$V_{j,k}$: The stored energy at the k-th linearized segment at period j by the ESS II.

3.4 DLC MODEL

Appliances like air-conditioners, heaters, refrigerators and freezers are controllable. Depending on factors like energy rating, end-users energy consumption pattern, and surrounding temperatures, each appliance will perform differently. A successful DLC program requires knowledge of how the customer would behave. In particular, extensive research was conducted to study the recovery of heating and cooling loads during cold load pickup. Five major mathematical models, ranging from deterministic to stochastic models, were proposed for the task [48]. This research not only proves the feasibility of controlling the customer demand; it serves as the groundwork for designing scheduling algorithms for large-scale operation.

Potential DLC load models vary. At one end, detailed equations could be made to describe the consumption behavior of each appliance. This approach, however, requires the collection of an enormous amount of data, including energy rating, ambient weather conditions, and end-user consumption behavior. It could be timely and costly to carry out. At the other end, appliances with similar energy ratings and cycling patterns could be grouped together to enhance the predictability of controllable demand without the complete set of information.

An efficient scheduling algorithm for the DLC program requires the determination on both the duration and the amount of energy to be deferred/paid back. However, determining only the amount of energy to be deferred or paid back at any particular time leaves a hefty hidden cost, since the ESCO ultimately needs to know the number of customers that should undergo demand deferment/pay back. In addition, customers with different types of controllable demand may be offered different incentives to encourage participation, creating additional complexity in trying to figure out the profit margin of deferring the demand of a particular controllable appliance.

A more complex scheduling algorithm could be structured to directly determine the number of customer appliances and the duration for energy deferment or pay back, i.e. the load control choices. However, this technique will result in the use of an enormous number of variables. Linear programming techniques, which are well known for their computational power, are suitable to handle an enormous number of variables. To successfully use linear programming as the search medium for optimal scheduling sequences, the following criteria are required:

- Linear objective function with linear constraints. A nonlinear, convex objective function can still use the linear programming technique by successively approximating or piecewise linearizing the objective function.
- Floating point solution is allowed. The number of customer appliances for load deferment/pay back is integer in nature. However, if total controllable energy is relatively large compared to the amount of energy each controllable appliance contributes, the floating point solution will do little harm to the precision of the solution reached by linear programming. In other words, the number of controllable customer appliances should be relatively large if the floating point solution were to be permitted.

In this section, an efficient model for the DLC program is developed to capture the load control choices that the ESCO may exercise. It is a major improvement over previous research that fails to capture all load control choices [24, 28]. Prior to formulating the DLC model, the controllable customer appliances are assumed to be categorize-able, i.e., controllable demand with similar demand pattern and profitability is grouped together. The problem of modeling the DLC program is greatly simplified if the following two conditions hold:

- At each period, the ESCO determines (1) the number of customers within each group who will undergo energy deferment and (2) the duration of energy deferment for each controllable demand.
- At the end of energy deferment, the deferred energy will be paid back instantaneously.

Let $x_{i,j,k}$ (each unit representing some customer appliances that have been grouped together for higher forecast precision) be the variable representing the number of customers from load group i that will undergo k periods of energy deferment beginning at period j, ED_j, EP_j and CD_j are shown in (3.1), (3.2), and (3.3) respectively.

$$ED_j = \sum_{\forall i} \sum_{a=1}^{j} \sum_{\forall k} \left[x_{i,a,k} Ed_{i,a,k} u(a+k-j-1) \right] \tag{3.1}$$

where ED_j is the total deferred DLC demand at period j; $Ed_{i,j}$ is the deferrable energy by each controllable demand in load group i at period j; and the unit step function $u(*)$ ($*=a+k-j-1$ in (3.1)) acts as ON/OFF switch to decide if the variable $x_{i,a,k}$ is deferring energy that extends to period j.

$$EP_j = \sum_{\forall i} \sum_{a=1}^{j} \sum_{\forall k} \left[x_{i,j,k} \alpha_{i,j,k,j-a-k+1} u(j-a-k) \left(\sum_{v=1}^{k} Ed_{i,j+v-1} \right) \right] \tag{3.2}$$

where EP_j is the total paid back DLC demand at period j; $\sum_{v=1}^{k} Ed_{i,j+v-1}$ is the total deferred energy by each customer in load group i for k periods beginning at period $(j+k-1)$; $\alpha_{i,j,k,j-a-k+1}$ is the energy pay back ratio for each customer in load group i at period $(j+k+s-1)$; and the unit step function acts as ON/OFF switch to decide if the variable $x_{i,a,k}$ is paying back energy at period j.

$$CD_j = \sum_{\forall i} \sum_{\forall k} \left(x_{i,j,k} cd_{i,j,k} \right) \tag{3.3}$$

where CD_j is the total cost of controlling the DLC demand at period j; $cd_{i,j,k}$ is the rebate given to each customer in load group i for energy deferment of k periods beginning at period j.

To ensure that the controlled (deferred or paid back) customers do not exceed the existing customers enrolling in the DLC program, (3.4) and (3.5) are included in the constraints set.

$$x_{i,j,k} \geq 0 \qquad \forall i,j,k \tag{3.4}$$

which requires non-negative values for the controllable load choice, $x_{i,j,k}$.

$$\sum_{a=1}^{j}\sum_{\forall k} x_{i,a,k} u\left(a+k+q(i,a,k)-j-1\right) \leq g_i \qquad \forall i,j \tag{3.5}$$

where $q(i,a,k)$ is the maximum pay back duration when customers in load group i undergo energy deferment of k periods at period a; and the unit step function acts as ON/OFF switch to decide if the variable $x_{i,a,k}$ has a energy deferment or pay back duration that extends to period j.

In a price-based DLC program (the concept of the price-based DLC program will be explored in Chapter 4), various penalty functions may be included in the objective function to assure the customers in the DLC program that a price-based operation will not hurt them financially. Equations (3.6) and (3.7) show the penalty functions for such a purpose. In particular, (3.6) describes the penalty for the increased revenue when the load increase is experienced (total deferred energy is less than paid back energy), and (3.7) describes the penalty for the increased revenue when the demand is being shifted to a higher rate period.

$$PT_{load+} = \sum_{\forall i}\sum_{\forall j}\sum_{\forall k} x_{i,j,k}\left(\sum_{v=1}^{k} r_{i,j+v-1} Ed_{i,j+v-1}\right)\Delta e u(\Delta e)$$

where

$$\Delta e = \left(\sum_{s=1}^{q(i,j,k)} \alpha_{i,j,k,s} - 1\right) \tag{3.6}$$

where $r_{i,j+v-1} Ed_{i,j+b-1}$ represents the revenue collected from the deferred load of group i at period $(j+v-1)$; Δe represents the percentage load increase under control choice $x_{i,j,k}$; and the unit step function acts as ON/OFF switch to exclude the effect of the decreased load during load deferment process.

$$PT_{revenue+} = \sum\sum\sum \Delta f u(\Delta f)$$

where

$$\Delta f = \left\{ \left(\sum r_{i,j+v-1} Ed_{i,j+v-1} \right) \left(\sum_{s=1}^{q(i,j,k)} \alpha_{i,j,k,s} \right) - \left[\sum_{s=1}^{q(i,j,k)} \alpha_{i,j,k,s} r_{i,j+v+s-1} \left(\sum_{w=1}^{k} Ed_{i,j+w-1} \right) \right] \right\} \tag{3.7}$$

where $\sum_{w=1}^{k} Ed_{i,j+w-1}$ represents the total deferred energy under control choice $x_{i,j,k}$; the first term of the right side of Δf represents the expected revenue from the total deferred energy; the second term of the right side of Δf represents the collected revenue from the paid back energy for customer type i at period $(j+v+s-1)$; and Δf represents the increased revenue when the deferred energy has been shifted to a higher rate period.

In a cost-based DLC program (the concept of the cost-based DLC program will be explored in Chapter 4), various penalty functions may be included in the objective function to assure that the increased cost savings do not result in excessive revenue loss. Equations (3.8) and (3.9) show the penalty functions for such purpose. In particular, (3.8) describes the penalty for the revenue loss caused by the reduced customer energy during pay back or cold load pickup (total deferred energy is more than paid back energy). Equation (3.9) describes the penalty for the revenue loss caused by reduced rate charged on customers during the pay back (rate structure during energy deferlment is higher than the rate structure during energy pay back.)

$$PT_{load-} = \sum_{\forall i}\sum_{\forall j}\sum_{\forall k} x_{i,j,k} \left(\sum_{v=1}^{k} r_{i,j+v-1} Ed_{i,j+v-1} \right) \Delta e u(\Delta e)$$

where

$$\Delta e_1 = \left(1 - \sum_{s=1}^{q(i,j,k)} \alpha_{i,j,k,s} \right) \tag{3.8}$$

where Δe_1 represents the percentage load decreased under control choice, $x_{i,j,k}$.

$$PT_{revenue-} = \sum\sum\sum \Delta f u(\Delta f)$$

where

$$\Delta f_1 = \left\{ \left(\sum r_{i,j+v-1} Ed_{i,j+v-1} \right) \left(\sum_{s=1}^{q(i,j,k)} \alpha_{i,j,k,s} \right) - \left[\sum_{s=1}^{q(i,j,k)} \alpha_{i,j,k,s} r_{i,j+v+s-1} \left(\sum_{w=1}^{k} Ed_{i,j+w-1} \right) \right] \right\} \tag{3.9}$$

where Δf_1 represents the decreased revenue when deferred energy has been shifted to a lower rate period.

3.4.1 Graphical Representation

To illustrate the DLC model, Figure 3-3 is presented. The *n* pieces are lying on top of each other to represent the individual controllable customer group. For each individual piece, monitored *m* periods are listed from left to right. Listings from the top to the bottom of each piece are the load-shifting choices and how they acted throughout the time period. The gray boxes on each piece represent the periods when the load is deferred while the black boxes represent the period of paid back load.

In accordance with equation (3.1), the coefficient of each control choice, $x_{i,j,k}$, is represented by the solid boxes. By (3.2), the coefficient of each control choice, $x_{i,j,k}$, is represented by the dashed boxes. $\alpha_{i,j,k,s}$ determines how the deferred energy is paid back. It may be estimated using the historical data and the present demand pattern.

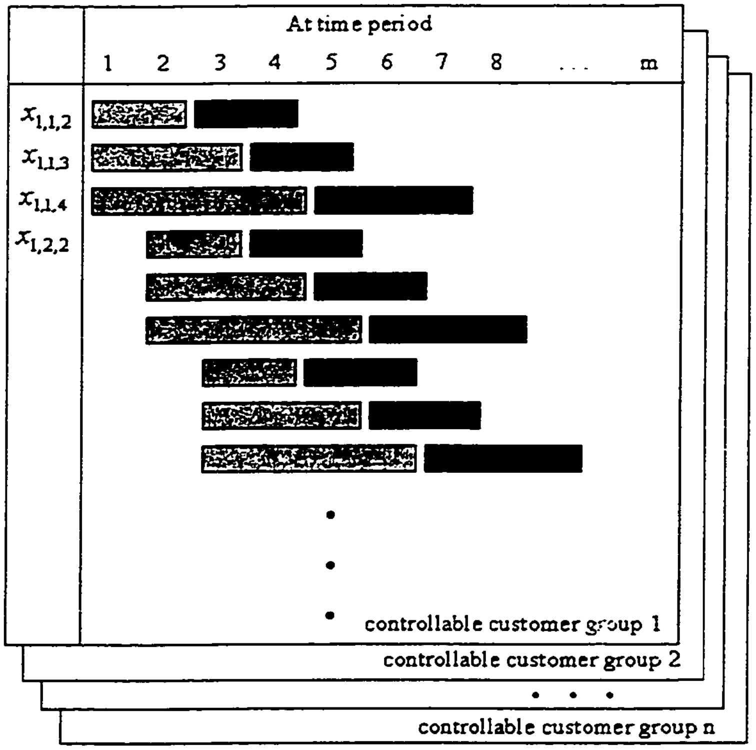

Figure 3-3. Control pattern for DLC program.

By (3.4), each control choice, $x_{i,j,k}$, has to be greater or equal to zero, i.e., $x_{1,1,1} \geq 0$, $x_{1,1,2} \geq 0$, $x_{1,1,3} \geq 0$, etc. From (3.5), the maximum control choices of any period, $x_{i,j,k}$, of any customer group i should be smaller than or equal to the maximum allowable number, g_i. At any period, for any customer group i, if the box (dashed or solid) corresponding to $x_{i,j,k}$ is extended to the observed period, $x_{i,j,k}$ is considered as one of the elements that will confine the maximum controllable groups during the period. Figure 3-4 shows an example on how ED_4 and EP_4 are related to the graphical representation in Figure 3-3.

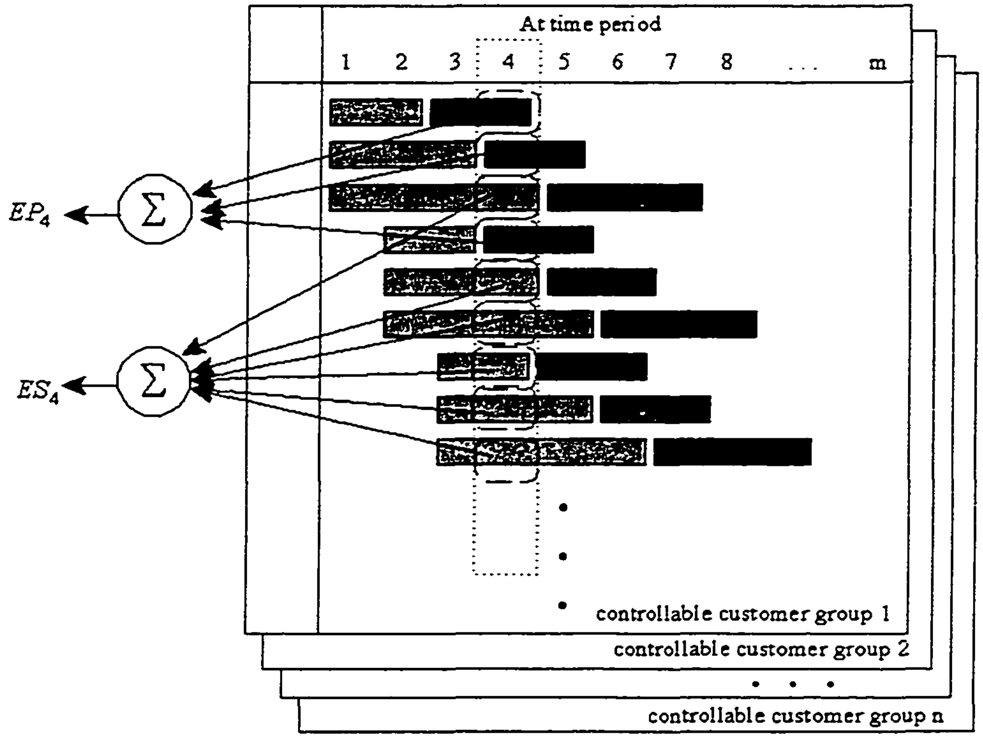

Figure 3-4. An example relating the deferred and paid back energy to the DLC model.

3.5 ESS MODEL

ESS includes pumped hydroelectric storage, batteries, cool storage, and storage space heating. Even though each device operates uniquely, they share some characteristics that make generalization possible. Electric energy is purchased from the auction market to charge/store the ESS. Energy may be stored in various form such as kinetic energy (flying wheel,) potential energy (pumped hydroelectric storage,) and chemical energy (batteries). The ESS may be composed of one (cool storage) or many (batteries) smaller units. These units may (pumped hydro) or may not (batteries) share the storage space. The number of operating units and the charging duration determine the amount of energy needed to be purchased from the auction market. If the stored energy is not used immediately after charging, the releasable energy decreases over time. The energy is dissipated through various means such as friction (flying wheel,) leakage (pumped hydro,) and diffusion (cool storage, storage space heating). During discharge, stored energy is released and sold to customers. The number of operating units and the charging duration determine the amount of energy that may be released and sold to customers.

Despite the different varieties of ESS appliances existing on the market, they share some characteristics that make generalization possible. The shared characteristics permit the existence of two generic models to represent the vast majority of ESS appliances.

ESS (ESS I) is composed of a large number of small-capacity units that operate independently of each other. The storage capacities of these units are insignificant relatively to the ESS itself. Assuming that these units have to complete a full charge (storing energy) and discharge (releasing energy), the scheduling process becomes one that determines the number of units to be charged/discharged at each instant. A good example is battery energy storage system (BESS) that consists of a large number of battery cells. The model to be presented in section 3.5.1 is a generalization shown in [12].

ESS (ESS II) is composed of single or a small number of large-capacity units. The storage capacities of these units are equivalent or large relative to the ESS appliance. By assuming that these units are one single entity, the scheduling process becomes one that determines the amount of energy to be charge/discharge at each instant. A good example is pumped hydroelectric storage that consists of a few pumps and turbines. The model to be presented in section 3.5.2 is a generalized model shown in [37].

Both models, ESS I and ESS II, are presented in section 3.5.1 and section 3.5.2 respectively.

3.5.1 Energy Storage System Type I (ESS I)

Depending on the charge/discharge characteristics, the ESS I units are categorized into different groups. The following assumptions were made in modeling ESS I:

- At each period, the ESCO determines (1) the number of units to be used for charge/discharge and (2) and the duration that each unit charge/release.
- *Full* charge/discharge of units is assumed. *Partial* charge/discharge can be achieved by assuming the next charge/discharge state as a new set of variables.

Let $y_{i,j,k}$ ($z_{i,j,k}$) be the variable that represents the number of units type i to be fully charged (released) for k periods beginning at period j. ES_j, ER_j, and CE_j are modified as in (3.10), (3.11) and (3.12) respectively.

$$ES_j = \sum_{\forall i}\sum_{a=1}^{j}\left[y_{i,a,k} Es_{i,a,j-a+1} u(j-a-k)\right] \tag{3.10}$$

$$\sum_{a=1}^{j}\left[\sum_{\forall k} y_{i,a,k} u(j-a-k)-\sum_{\forall k} z_{i,a,r}\right] \geq 0 \qquad \forall i, j \qquad (3.15)$$

which indicates that at any period, the total numbers of ESS I units should not be more than the installed units. The unit step functions act as ON/OFF switches to decide if ESS I units under control choice $y_{i,a,k}$ are fully charged at period j.

3.5.1.1 Graphical Representation

To illustrate ESS I model, Figure 3-5 is presented. The *n* sheets lying on top of each other represent units with different charge/discharge characteristics. The charging phase, with variables $y_{i,j,k}$, is shown on the left. The discharging phase, with variables $z_{i,j,r}$, is shown on the right. Governing equations connect the charge and discharge phases for different groups of ESS I units. Equations (3.14) and (3.15) are *individualized* constraints. According to (3.14), the maximum number of charge and discharge units of any group is restricted by the existing installation, G_i. Equation (3.15) further restricts the available discharge units to available fully charged units. A *group* constraint described the total energy required for charging the ESS I units and the total energy released by ESS I units. They are discussed in section 3.3 and 3.3. Figure 3-6 shows an example relating ES_4 and ER_4 to ESS I model.

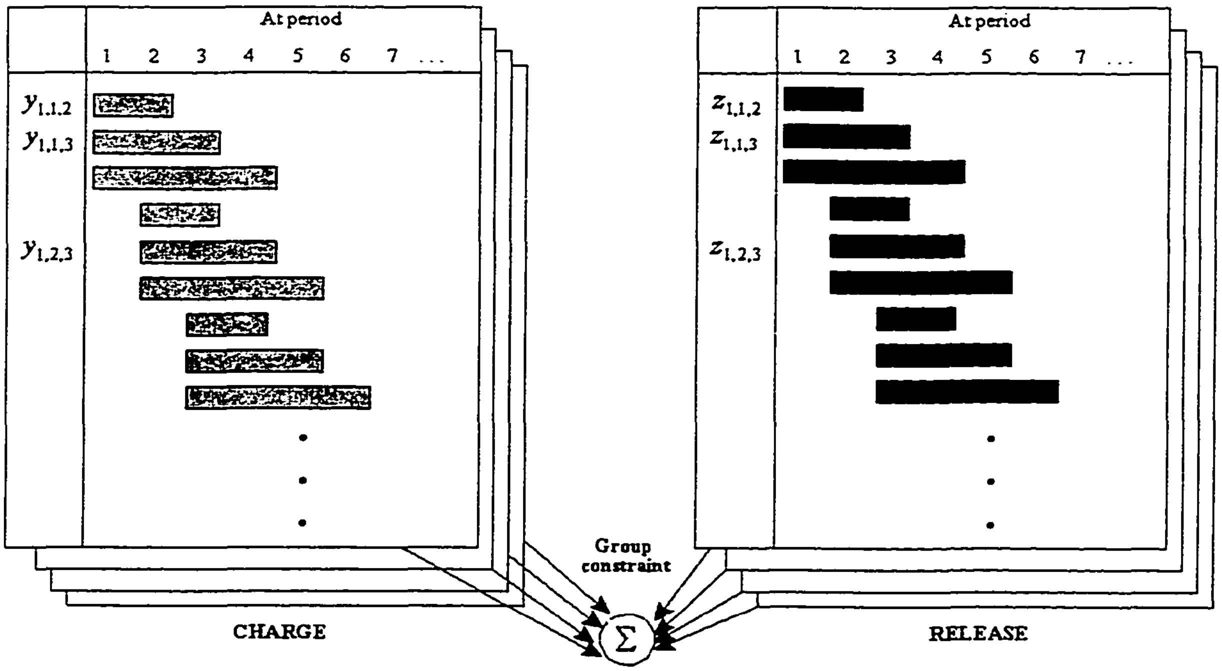

Figure 3-5. ESS type I.

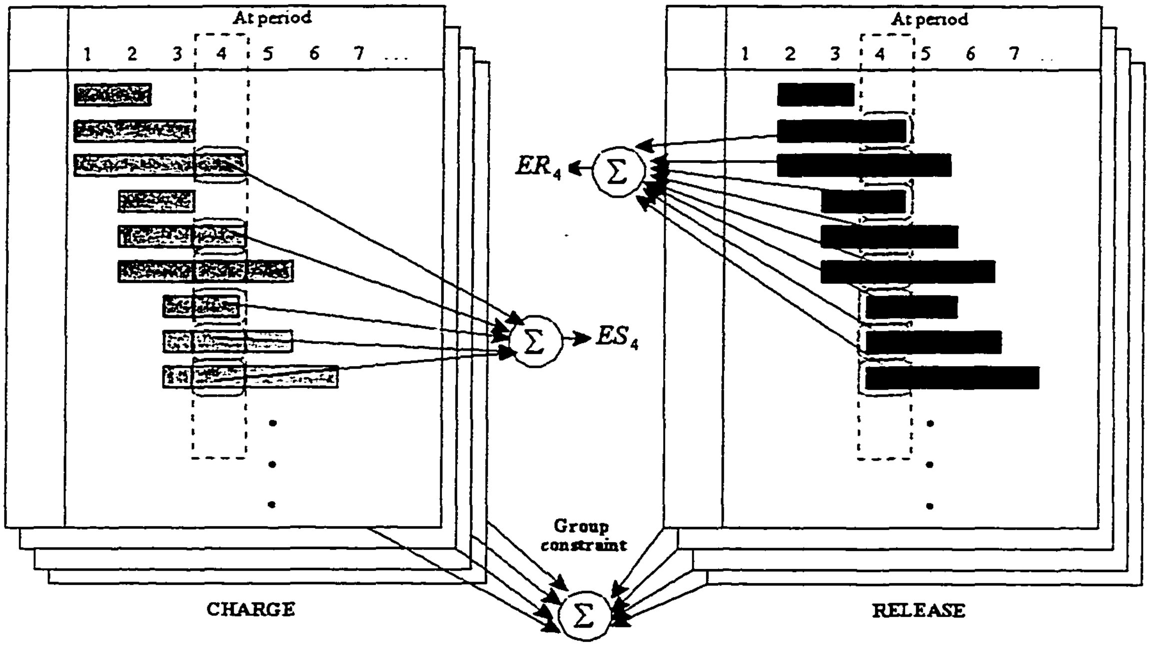

Figure 3-6. Relating the stored and released energy to the ESS I model.

3.5.2 Energy Storage System Type II (ESS II)

Each unit in ESS II has different charge/discharge characteristics that may be described as a piecewise-linearizied function. The following assumptions were made in modeling ESS II.

- Energy, ES_j, purchased from the market will be stored in another form of energy, with rate $\omega_{i,k}$ for unit i at k-th amount of energy purchased.
- During storage, the stored energy, V_j, is lost at rate $sd_{i,k}$ for unit i at k-th amount of stored energy, $V_{j-1,k}$, of last period.
- Energy, ER_j, released to the system will have rate $\theta_{i,k}$ for unit i at k-th amount of stored energy used, $Ps_{i,k}$.

Let I_j be the stored energy at period j, O_j be the energy used for discharge at period j, and V_j be the total stored energy at period j, ES_j and ER_j in ESS II are described in (3.16) and (3.17) respectively.

$$ES_j = \sum_{\forall i} \sum_{\forall k} Ps_{i,j,k} \qquad \forall j \qquad (3.16)$$

where $Ps_{i,j,k}$ is the electric energy used by unit i at period j when the unit is operating at an efficiency level of $\omega_{i,k}$; $\omega_{i,k}$ represents ESS II unit i efficiency when $\sum_{\forall k} Ps_{i,j,k}$ is used.

$$ER_j = \sum_{\forall i} \sum_{\forall k} Pr_{i,j,k} \qquad \forall j \qquad (3.17)$$

where $Pr_{i,j,k}$ is the electric energy released by unit i at period j when the unit is operating at an efficiency level of $\theta_{i,k}$; $\theta_{i,k}$ represents ESS II unit i efficiency when $\sum_{\forall k} Pr_{i,j,k}$ is generated.

Equations (3.18) and (3.19) shows the relations between stored and purchased energy.

$$I_j = \sum_{\forall i} \sum_{\forall k} \omega_{i,k} Ps_{i,j,k} \qquad \forall j \qquad (3.18)$$

$$0 \le Ps_{i,j,k} \le \overline{Ps}_{i,k} \qquad \forall i,j,k \qquad (3.19)$$

The losses of stored energy at period j, S_j, depends on the volume of water at period $(j\text{-}1)$, V_{j-1}. Equation (3.20) shows the relation.

$$S_j = \sum_{\forall k} sd_k V_{j-1,k} \qquad \forall j \qquad (3.20)$$

where

$$0 \le V_{j-1,k} \le \overline{V}_k \qquad \forall k \qquad (3.21)$$

where $sd_{i,k}$ represents leakage rate when there is $\sum_{\forall k} V_{j-1,k} (= V_{j-1})$ amount of stored energy at period $(j\text{-}1)$.

Equations (3.22) and (3.23) shows the relations between stored energy used for discharge, O_j, and released energy.

$$O_j = \sum_{\forall i} \sum_{\forall k} \theta_{i,k} \, Pr_{i,j,k} \qquad \forall j \qquad (3.22)$$

$$0 \le Pr_{i,j,k} \le \overline{Pr}_{i,k} \qquad \forall i,j,k \qquad (3.23)$$

The reservoir water at the end of period j depends on the reservoir water at the end of period j, water pumped into the reservoir, spill out, and water used for generation. Equations (3.24) and (3.25) show the relations between V_j, V_{j-1}, I_j, S_j, and O_j.

$$V_j = V_{j-1} + I_j - S_j - O_j \qquad \forall j \tag{3.24}$$

where

$$V_{min} \le V_j \le V_{max} \qquad \forall j \tag{3.25}$$

where the total stored energy at any time must remain within the limit.

To assure that the solution reached by the algorithm is also a global optimal solution, (3.26), (3.27), and (3.28) must hold.

$$\omega_{i,k} \le \omega_{i,k+1} \qquad \forall i,k \tag{3.26}$$

$$\theta_{i,k} \ge \theta_{i,k+1} \qquad \forall i,k \tag{3.27}$$

$$sd_k \ge sd_{k+1} \qquad \forall k \tag{3.28}$$

3.5.2.1 Graphical Representation

To visualize ESS II model, a graphic representation is shown in Figure 3-7. The purchased energy, ES_j, is used by the n units of ESS II. Each unit uses $Ps_{i,j}$ for storage purposes. The stored energy, I_j, depends on the amount of $Ps_{i,j}$ used and the efficiency curve that has been linearized to k segment, from. $\omega_{i,1}$ to $\omega_{i,k}$. The relationship is described by (3.18). The storage compartment has a total stored amount of V_j at period j. The outflow of stored energy, O_j, is released and sold to the customers during high cost periods. The released electric energy, ER_j, depends on the amount of stored energy, O_j used and the efficiency curve that has been linearized to k segments, from $\theta_{i,1}$ to $\theta_{i,k}$. The relationship is described by (3.20). At any period, whether the energy is stored or released, the amount of the stored energy within the storage compartment losses its potential. The amount of the energy lost, S_j, depends on the total stored amount, V_j, and the leakage rate curve that has been linearized to k segments, from sd_1 to sd_k. The relationship is described by (3.22). To assure that the solution reached by the linear programming is globally optimal, (3.26) – (3.28) set the criteria for

$\omega_{i,k}$, $\theta_{i,k}$, and sd_k respectively. Finally, (3.24) assures that the energy remained in the storage compartment will always follow the law of conservation of energy.

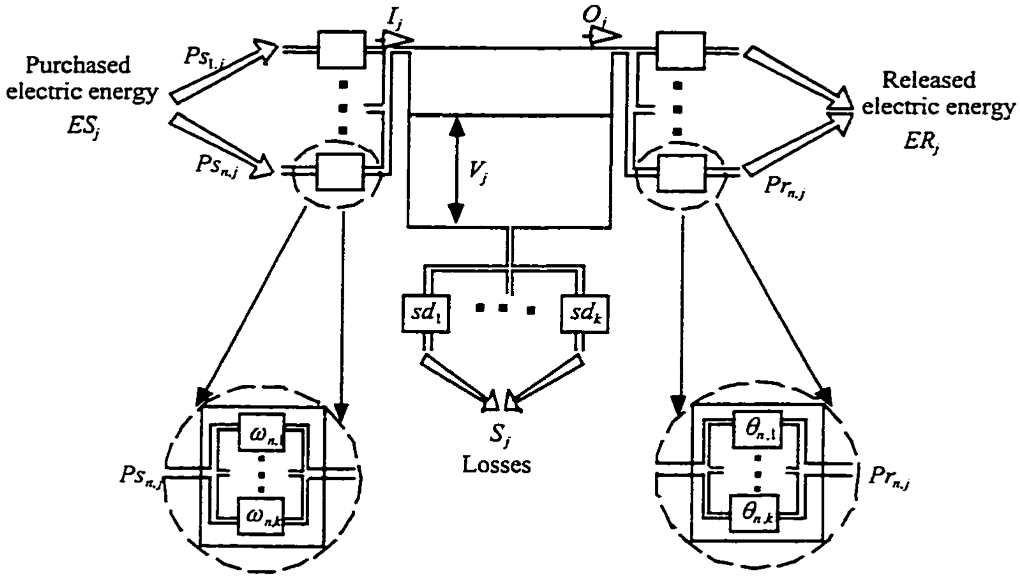

Figure 3-7. ESS II.

CHAPTER 4 SCHEDULING CUSTOMER DEMAND AND AUCTION MARKET

In Chapter 2, scheduling customer demand was emphasized in improving an ESCO's profitability. Even with Chapter 3 describing the various load management models for DLC and ESS, the *why* and *how* of scheduling customer demand are still not clear. More importantly, the interaction between scheduling customer demand and participating in the auction market has yet to be linked. In this chapter, the *why* and *how* are emphasized, i.e., why the customer demand should be scheduled and how the scheduling affects the buying and selling in the auction market.

Section 4.1 provides a list of variables and parameters used to formulate the scheduling model. Section 4.2 presents the economic models of scheduling customer demand using the DLC and ESS programs. These models include load-based, cost-based, profit-based, and cash management approaches. It will be shown that profit-maximization is in fact no different than cost-minimization. In addition, how the different approaches may be used at the different ESCO operation levels will be discussed. Section 4.3 shows the relationship between the auction market and scheduling customer demand. How the different contract specifications described in Chapter 2 can be included in the scheduling model will be shown. The limitations of the scheduling model will also be discussed.

4.1 NOMENCLATURE

4.1.1 Parameters

d^f : Energy contract delivery duration.

pr_j : Per-unit energy price on the auction market at period *j*.

pr_j^D : Per-unit energy price on the auction market at period *j* on day *D*.

q(*): Quotient of *.

r_j : The rate customers are charged at period *j*.

r_j^D : The rate customers are charged at period *j* on day *D*.

$I_{D,T}$: Rate of interest obtained from investment $X_{D,T}$ $(D < T)$.

$I_{D,T}$: Rate of interest charged on debt issued in period T and falling due in period D $(D > T)$.

size: The size of the contract in MW.

TE_j: Total customer demand at period j.

TE_j^D: Total customer demand at period j on day D.

Z: The right-hand-side value of the budget constraint. It is equivalent to net revenue (collected revenue minus all expenses) collected during the day.

α_h^{a,d^f}: The reliability level under contract type h, delivery beginning at period a, and has a d^f duration.

α_j^{TE}: The average reliability level requested by the customers at period j.

α_j^{ED}: The reliability level exhibited by the deferred energy at period j (DLC program.)

α_j^{EP}: The reliability level exhibited by the paid back energy at period j (DLC program.)

α_j^{ER}: The reliability level exhibited by the released energy at period j (ESS program.)

α_j^{ES}: The reliability level exhibited by the stored energy at period j (ESS program.)

β_h^{a,d^f}: The allowed volatility level in the customer demand by contract type h, delivery beginning at period a, and has a d^f duration.

γ_D^m: The ratio of the payments made by the customers on day D over the expected cash receipt for the energy service provided in the month m.

4.1.2 Variables

CD_j: The rebate given to the customers participating in the DLC program at period j.

CD_j^D: The rebate given to the customers participating in the DLC program at period j on day D.

CE_j: The operating cost of ESS at period j.

CE_j^D: The operating cost of ESS at period j on day D.

COY_D: The total cash outlay on day D.

E: Maximum peak demand during the scheduled duration.

EOY_D: The energy payment made to the auction market on day D for all the energy purchased during the day before day D.

ED_j: Deferred customer demand at period j.

ED_j^D : Deferred customer demand at period j on day D.

EM_j : Energy purchased from the auction market at period j.

EM_j^D : Energy purchased from the auction market at period j on day D.

EP_j : Paid back customer demand at period j.

EP_j^D : Paid back customer demand at period j on day D.

ER_j : Energy released from ESS at period j.

ER_j^D : Energy released from ESS at period j on day D.

ES_j : Energy stored at ESS at period j.

ES_j^D : Energy stored at ESS at period j on day D.

EX^+_{a,d^f} :Energy to be purchased at the auction market using contracts delivering longer than d^f duration.

EX^-_{a,d^f} :Excess energy not to be purchased at the auction market after using contracts delivering d^f duration.

L: The negative accumulation of cash at period n. (L = "loss")

NOY_D : The operating and maintenance cost of the ESS (ESCO-owned, ESCO-operated.)

P: The total buildup of cash available at period n. (P = "profit")

P_j : Energy purchased for period j.

P_j^D : Energy purchased for period j on day D.

$P_a^{d^f,\alpha_h,\beta_h}$:Energy purchased for contract type h with allowed volatility β_h^{a,d^f}, reliability level α_h^{a,d^f}, delivery beginning at period a, and has a d^f duration.

P_j^+ : Energy to be purchased at the auction market using contracts delivering longer than d^0 duration.

P_j^- : Excess energy not to be purchased at the auction market after using contracts delivering d^0 duration.

R_j : Collected revenue from serving customer demand at period j.

REV_m : Collectible revenue for the energy served during month m.

RCT_D^m : Receipt payment on day D for the energy served during month m.

$X_{D,T}$: Purchase of claim (lending) on day D, maturing on day T. ($D < T$)

$Y_{D,T}$: Issue of debt (borrowing) on day T and falling due on day D. ($D > T$)

Δs : Increased cost during the scheduled duration from the load management programs. (A negative value indicates cost saving)

$\Delta\pi$: Total increased profit during the scheduled duration from the load management programs.

$\Delta\pi_j$: Increased profit at period j from the load management programs.

π_j^{no} : The profit of serving customer demand before the implementation of the load management programs.

π_j^{yes} : The profit of serving customer demand after the implementation of the load management programs.

4.2 SCHEDULING CUSTOMER DEMAND

While maintaining the reliability of the electric power network, scheduling customer demand using the load management programs has helped utilities to reduce capital and operating costs. The two commonly perceived objectives of scheduling customer demand are peak-load shedding and cost minimization. The major reason for adopting a peak-load shedding approach is that a congested transmission poses extreme risk to the power system operation. To avoid the risk of system breakdown, the customer demand should be rescheduled to reduce the system peak. The cost-minimization approach, however, assumes that all costs, the energy cost and the breakdown risk, have been accounted for [6]. Thus, the rescheduled customer demand should immediately reduce the cost of operation.

With the advent of re-regulation and competition, two additional objectives for rescheduling customer demand emerge. The first objective, profit maximization, assumes that if proper compensation is made to the customers who participate in the load management programs, the ESCO should be allowed to profit from scheduling the customer demand. The second objective, cash management, captures the cash flow of the company and includes the effect of the cost of borrowing and lending to enhance the ESCO's ability to improve the profitability of serving customer demand.

In this section, various economic models are presented. In section 4.2.5, the cost minimization approach and the profit maximization approach are compared and discussed. In addition, in section 4.2.7, the four approaches are evaluated to tackle the ESCO operational problem at different time horizons.

4.2.1 Customer Demand and the Cost of Energy

Prior to the implementation of the DLC and ESS programs, all energy was purchased on the auction market at a per-unit energy price of pr_j. The cost of serving customer demand is $pr_j TE_j$, where TE_j is the total customer demand. The revenue collected is $r_j TE_j$, where r_j is the rate customers are charged. The profit before implementing load management is $(r_j - pr_j)TE_j$.

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[6] The cost of breakdown risk is implicitly accounted for in the cost-minimization approach. The reason is that the utility will try to serve the customer demand with the lowest-cost generation units. Thus, the cost minimization approach that schedules the customer demand at the higher cost periods to the lower cost periods will also reduce the peak demand.

When DLC and ESS are introduced, the energy to be purchased on the auction market, EM_j, is shown in (4.1).

$$EM_j = TE_j - ED_j + EP_j + ES_j - ER_j \tag{4.1}$$

ED_j is the deferred customer demand, EP_j is the paid back customer demand, ES_j is the energy stored, and ER_j is the energy released from the ESS.

4.2.2 *Load-based Approach*

The load-based approach, shown in (4.2), minimizes the maximum energy to be purchased on the auction market.

$$\begin{aligned} & \quad min \quad E \\ subject \quad to: & \\ & EM_j \le E \qquad \forall j \end{aligned} \tag{4.2}$$

E is the maximum hourly energy to be purchased on the auction market; EM_j is described in (4.1).

4.2.3 *Cost-based Approach*

The cost of serving customer demand is $pr_j TE_j$ prior to the introduction of the load management programs, and the cost of serving customer demands with the program is $pr_j EM_j$. The cost-based approach, shown in (4.3), minimizes the increased cost of load management, or, shown in (4.4), maximizes the increased savings from the program.

$$\begin{aligned} min \ \Delta s &= \sum_{\forall j} pr_j EM_j - pr_j TE_j + CD_j + CE_j \\ &= \sum_{\forall j} pr_j \left(-ED_j + EP_j + ES_j - ER_j\right) + CD_j + CE_j \end{aligned} \tag{4.3}$$

$$max \ -\Delta s = \sum_{\forall j} pr_j \left(ED_j - EP_j - ES_j + ER_j\right) - CD_j - CE_j \tag{4.4}$$

CD_j is the rebate given to the customers participating in the DLC program and CE_j is the operating cost of ESS.

4.2.4 *Profit-based Approach*

From (4.1), the profit of serving customer loads before the implementation of the DLC and ESS programs, π_j^{no}, may also be described in (4.5).

$$\begin{aligned}\pi_j^{no} &= (r_j - pr_j)TE_j \\ &= (r_j - pr_j)(EM_j + ED_j - EP_j - ES_j + ER_j)\end{aligned} \tag{4.5}$$

With DLC and ESS implemented, the cost of purchased energy is $pr_j EM_j$. The collectible revenue, R_j, is shown in (4.6).

$$R_j = r_j(EM_j - ES_j) + r_j ER_j \tag{4.6}$$

$(EM_j - ES_j)$ is the purchased energy that may generate revenue.

The profit of serving customer loads after the implementation of the load management programs is shown in (4.7).

$$\begin{aligned}\pi_j^{yes} &= R_j - pr_j EM_j - CD_j - CE_j \\ &= r_j(EM_j - ES_j + ER_j) - pr_j EM_j - CD_j - CE_j\end{aligned} \tag{4.7}$$

The profit-based approach, shown in (4.8) maximizes the gain from the load management programs.

$$max \quad \sum_{\forall j} \pi_j^{yes} \tag{4.8}$$

The increased profit from the load management programs is shown in (4.9).

$$\begin{aligned}\Delta\pi_j &= \pi_j^{yes} - \pi_j^{no} \\ &= r_j(ED_j - EP_j) - pr_j(ED_j - EP_j - ES_j + ER_j) - CD_j - CE_j\end{aligned} \tag{4.9}$$

Or, alternatively, a profit-based approach, shown in (4.10), maximizes the *net* gain from the load management programs.

$$max \qquad \Delta\pi = \sum_{\forall j} \Delta\pi_j \tag{4.10}$$

A quick glance at (4.4) and (4.10) shows a difference in changed revenue, $\sum_{\forall j} r_j(ED_j - EP_j)$, which happens only in the DLC program when customer demand is deferred/paid back. Since there is no change in ESS operational revenue, cost-based and price-based ESS operations will always reach the same optimal solution.

4.2.5 What Changes Revenue?

There are, in general, two ways that the revenue could change. First, when DLC energy is deferred to a low-rate period from a high-rate period (or vice-versa,) the ESCO experiences a reduction (increase) in the revenue due to a difference in the rate over time. Second, when paid back DLC energy is lower (higher) than the deferred energy, the ESCO experiences a reduction (increase) in the revenue due to changes in the customer demand or energy loss.

Using a simple, two-period example, Ng [12] shows that a cost-based approach and a profit-based approach differ only on the *degree* of implementation. If proper discount factors are included in the economic models, either in (4.3), (4.4), (4.8) or (4.10), a cost-based approach will be equivalent to a profit-based approach.

Because deferrable energy and paid back energy are often subject to a certain degree of uncertainty, it is hard to determine if one approach should prevail over the other. However, if re-regulation promotes competition, a profit-based approach sounds more reasonable. On the one hand, competition would drive ESCOs to compete with each other to provide the best return to the customer. On the other hand, the customers would keep track of their bill and service satisfaction to determine if the service providers had lived up to their promises.

4.2.6 Cash Management Approach

The ESCO receives payments from the customers at certain times for the services. Meanwhile, it must make payments for purchased energy, operation costs, and maintenance costs. At the end of each day, the ESCO has to decide if it has enough cash on hand to pay for tomorrow's expenses. If the ESCO should choose to raise funds, it has to determine when and how to raise that capital. Also, it must decide the expiration date for each type of capital raised. Likewise, if the ESCO should choose to invest the excess cash, it has to determine when and how to invest it. Also, it has to decide the maturity date of each investment.

The load-based, cost-based, and profit-based approaches, described in sections 4.2.2 through 4.2.4, fail to consider the complexities of these situations in the ESCO operation. First, the earning potential of the cash on hand and the cost of the borrowed funds that subsidy the ESCO operation are not included in the model. Second, the three models do not consider the possibility that the ESCO may be out of cash to fund its project. A remedy to these situations is the cash management approach. The cash management problem has been studied extensively in most industries to manage the cash flow of the corporation. Reference to the cash management model can be found in [49]. That model is extended in this section for the ESCO operation. Section 4.2.6.1 describes the cash receipts, the payments received from the customers for the energy served. Section 4.2.6.2 describes the cash outlay, the cost of serving customer demand. Section 4.2.6.3 describes the issue of debt and investment, and section 4.2.6.4 describes the deterministic cash management model. To aid the modeling process, there are equal *M* days in each month. Also, there is *N* periods in each day.

4.2.6.1 Cash Receipts

The ESCO receives payments from the customers for the energy served. However, the payment is not made until a certain time in the future. Assuming that the ESCO collected the payments from the customer once a month, (4.11) shows the revenue to be collected for each month.

$$\begin{aligned} REV_m &= \sum_{D=(m-1)*M+1}^{m*M} \left[\sum_{\forall j} r_j^D \left(EM_j^D - ES_j^D \right) + r_j^D ER_j^D - CD_j^D - CE_j^D \right] \\ &= \sum_{D=(m-1)*M+1}^{m*M} \left[\sum_{\forall j} r_j^D \left(TE_j^D - ED_j^D + EP_j^D \right) - CD_j^D - CE_j^D \right] \end{aligned} \tag{4.11}$$

$r_j^D \left(EM_j^D - ES_j^D \right) + r_j^D ER_j^D$ is the collectible revenue for energy served at period j on day D. It is a replica of (4.6), except for the added superscript D to differentiate the energy served at different day. Equation (4.11) is finally obtained by substituting EM_j^D with (4.1). CD_j^D is the rebate given the customers for participating in the DLC program at period j of day D. CE_j^D is the rebate given to the customers for rendering their energy storage system to the ESCO control at period j on day D. REV_m is the collectible revenue for energy served during month m.

Once the bills are sent to the customers, not all customers will pay at the same time. *Rather*, the payments will be spread over several days. Assuming that no late payment is made by any of the customers and that the payments will be made in full over the allowed duration, from the k^{th} day to the $(k+r)^{th}$ day after the end of each month, (4.12) shows the actual payment received on day D.

$$RCT_D^m = \gamma_D^m REV_m \qquad D = (m*M+k),\ldots,(m*M+k+r) \tag{4.12}$$

γ_D^m is the ratio of the payments made by the customers on day D over the expected cash receipt for the month m. Since all bills will be paid in full and no late payment is made, $\sum_{\forall d}\gamma_D^m$ must equal 1.

4.2.6.2 *Cash Outlays*

In serving the customer demand, the ESCO has to purchase the electric energy from the auction market. In addition, there are payments to be made to the staffs to operate and maintain the company daily operation. Equation (4.13) shows the payment made to the suppliers on day D for all the energy purchased on the day before day D.

$$EOY_D = \sum_{\forall j} pr_j^{D-1} P_j^{D-1} \tag{4.13}$$

$\sum_{\forall j} pr_j^{D-1} P_j^{D-1}$ is the cost of energy and EOY_d is the energy related cash outlay.

Shown in (4.14) is the total cash outlay on day D, COY_D. It is the sum of the energy related cash outlay, EOY_D, and the non-energy related cash outlay, NOY_D. The non-energy related cash outlay is the payments made to maintain and operate the ESCO.

$$COY_D = EOY_D + NOY_D \tag{4.14}$$

4.2.6.3 *Issue of Debt and Investment*

To subsidize the daily expenses, the ESCO has to borrow from the future. Assuming that the best offered interest rate is known, the ESCO will then have to determine the amount of money to be borrowed, the expiration date of the issued debt, and the day to incur the debt. To help the modeling process, the following assumptions are made:

- $I_{D,T}$ $(T < D)$ is the interest rate for borrowing on day T and falling due on day D.
- $Y_{D,T}$ is the amount of debt issued on day T and falling due on day D.
- The amount of money received on day T is equal to $(1 - I_{D,T})Y_{D,T}$.

At any time, when there is a surplus in its account, the ESCO may choose to invest it. Assuming that the best offered interest rate is known, the ESCO will then have to determine the amount of money to be invested, the maturity date of the investment, and the day to invest the surplus. To help the modeling process, the following assumptions are made:

- $I_{D,T}$ $(T > D)$ is the interest rate for investment made on day D and matured on day T.
- $X_{D,T}$ is the amount of investment made on day D and matured on day T.
- The amount of money received on day T is equal to $(1+I_{D,T})X_{D,T}$.

Money is either borrowed or invested at any day. All the surpluses from any daily operation will be invested. All the payments will be made in full, either using the collected revenue or the borrowed money.

4.6.6.4 Model Representation

The objective of the cash management problem is to maximize the total cash buildup at the end of the considered duration. Equation (4.15) shows the objective of the problem.

$$max \qquad P - L \tag{4.15}$$

The budget constraint in each time states that the total sum of the cash funds be coming available must equal the sum of the cash needs. Equation (4.16) shows the budget constraints.

$$\begin{aligned}
&\sum_{T=1}^{D-1}(1+I_{T,D})X_{T,D} + \sum_{t=D+1}^{n}(1-I_{T,D})Y_{T,D} - \sum_{T=1}^{D-1}X_{D,T} - \sum_{T=D+1}^{n}Y_{D,T} = -RCT_D^m + COY_D \qquad D = 1,\dots,(n-1)\\
&\sum_{T=1}^{n-1}(1+I_{T,D})X_{T,D} - \sum_{T=1}^{n-1}X_{D,T} - P + L = -RCT_n^m + COY_n \qquad D = n
\end{aligned} \tag{4.16}$$

The value of the superscript m in (4.16) can be determined using (4.17), assuming that there are M days in each month. For example, when $M = 30$, $D = 1$ yields $m = 1$, $D = 35$ yields $m = 2$, etc.

$$m = quotient\left(\frac{D+M}{M}\right) \tag{4.17}$$

The value of the superscript and subscript D used in this section can be determined using (4.18), assuming that there are N periods in each day. For example, when $N = 96, j = 1$ yields $D = 1, j = 200$ yields $D = 3$, etc.

$$D = quotient\left(\frac{j+N}{N}\right) \tag{4.18}$$

Table 4-1 is the tabular form of (4.16). Table 4-2 is the load management arcs of Table 4-1.

Table 4-1. Tabular form of Equation (4.16).

t	Load Management Arcs	Lending Arcs $(X_{1,2} \dots X_{1,n})$		...	$(X_{n-1,n})$	Borrowing Arcs $(Y_{2,1} \dots Y_{n,1})$		...	$(X_{n,n-1})$	Ultimate Gain		Constant
		(2 ... n)	(3 ... n)	...	(n-1)	(2 ... n)	(3 ... n)	...	(n)	P	L	
D = 1		(-1 ... -1)	(0 ... 0)	...	(0)	(B ... B)	(0 ... 0)	...	(0)	0	0	$= Z_1$
D = 2	Refer Table 4-2	(A)	(-1 ... -1)	...	(0)	(-1 0 ... 0)	(B ... B)	...	(0)	0	0	$= Z_2$
...			...				...			...		...
D = n-1		(A)	(A)	...	(-1)	(0 ... -1 0)	(0 ... -1 0)	...	(B)	0	0	$= Z_{n-1}$
D = n		(A)	(A)	...	(0)	(0 ...0 −1)	(0 ...0 -1)	...	(-1)	-1	1	$= Z_n$

Note: $A = (1 + I_{T,D})$ if $T = D$; $B = (1 - I_{T,D})$;

$$Z_D = NOY_D - \gamma_D^m \sum_{s=(m-1)^*M+1}^{m^*M} \left[\sum_{\forall j} r_j^s \left(TE_j^s - ED_j^s + EP_j^s \right) - CD_j^s - CE_j^s \right].$$

Table 4-2. Load management arcs.

	Load Management Arcs
D = 1	$\gamma_1^1 \sum_{s=(m-1)^*M+1}^{m^*M} \left[\sum_{\forall j} r_j^s \left(- ED_j^s + EP_j^s \right) - CD_j^s - CE_j^s \right]$ - EOY_1
D = 2	$\gamma_2^m \sum_{s=(m-1)^*M+1}^{m^*M} \left[\sum_{\forall j} r_j^s \left(- ED_j^s + EP_j^s \right) - CD_j^s - CE_j^s \right]$ - EOY_2
...	...
D = n - 1	$\gamma_{n-1}^m \sum_{s=(m-1)^*M+1}^{m^*M} \left[\sum_{\forall j} r_j^s \left(- ED_j^s + EP_j^s \right) - CD_j^s - CE_j^s \right]$ - EOY_{n-1}
D = n	$\gamma_n^m \sum_{s=(m-1)^*M+1}^{m^*M} \left[\sum_{\forall j} r_j^s \left(- ED_j^s + EP_j^s \right) - CD_j^s - CE_j^s \right]$ - EOY_n

4.2.7. Concluding Remarks

The four approaches presented to scheduling customer demand differ by what were included in the objective function. The load-based approach is the simplest of all. It attempts to reduce the peak demand. The cost-based approach advances the load-based approach to include the cost of energy. Even though the cost-based approach does not specifically reduce the peak demand, it does implicitly carrying out the task. The cost of energy, more often than not, depends on the supply and demand of energy. As energy demand increases, the cost of energy will usually increase to reflect the higher cost of production. Thus, even though the cost-based approach does not explicitly reduce the peak demand, it will usually lead to peak reduction, but less dramatically.

As suggested in section 4.2.5, the difference between the profit-based approach and the cost-based approach is due to former approach including the potential change in revenue. Since a cost-based approach implicitly reduces the peak demand, so will the profit-based approach. However, since the profit-based approach includes the potential change in the revenue to the objective function, the approach will prevent the scheduling of customer demand from hurting the ESCO profit more than the cost-based approach.

Even though the model seems complicated, the cash management approach differs from the profit-based approach only in terms of implied cash flow. The inclusion of the cost of borrowing and lending guards the ESCO against excessive lending and borrowing. It also makes the ESCO aware of the cost of borrowing. Thus, a profit-based approach that does not include the cost of lending and borrowing in the objective function may improve the profitability in the short-run, but hurt the ESCO's performance in the long run. Table 4-3 shows the different approaches and their effects on peak demand, cost, revenue, and cash flow.

Table 4-3. Scheduling customer demand and its effect.

Approaches	Factoring in			
	Peak demand	Cost	Revenue	Cash flow
Load-based	√	×	×	×
Cost-based	Implied	√	×	×
Profit-based	Implied	√	√	×
Cash management	Implied	√	√	√

Since the cash management approach includes most factors in the scheduling model, one may be inclined to suggest the cash management approach as the best approach to handle the ESCO operational problem. However, a careful study of the different models may suggest otherwise.

Since energy cost is included in the constraining equations, a nonlinear energy cost function will cause the constraints to be nonlinear as well. This will pose difficulty in solving the problem in the short time. In addition, the number of variables is also increased tremendously to reflect the opportunity to loan, $Y_{D,T}$, and invest, $X_{D,T}$, making the cash management approach harder to use than any other approach. In section 2.3, the ESCO operation was discussed for different time horizon. In evaluating the ESCO operation for a time horizon shorter than one month, it just does not seem necessary to consider the cost of borrowing and investing as significant variable factors. Thus, in this research, when evaluating the ESCO operation in the reactive scheduling/control and scheduling level, the profit-based approach will be utilized. When evaluating the ESCO operation in the short-term, mid-term, and long-term scheduling levels, the cash management approach is assumed.

Should the cost-based approach and the load-based approach be discarded when evaluating the ESCO operation? To my belief, the cost-based approach is still valuable. Ideally, in a competitive environment, the pricing mechanism should reflect the energy cost and the effectiveness of the load management programs. Thus, if the result from a cost-based approach does not match the result from a profit-based approach or cash management approach, the pricing mechanism may not have been designed properly. Or, the pricing mechanism can still be redesigned to lower the cost of serving customer demand. In short, the cost-based approach should be used as a benchmark to evaluate the effectiveness of pricing customer demand.
Since the load-based approach fails to consider the cost of energy and the collectible revenue, the potential for adopting the approach is low.

4.3 AUCTION MARKET

In chapter 2, the auction mechanism and the contract specification were discussed. In this section, the association between scheduling the customer demand and purchasing the contracts through the auction market is presented using mathematical models. In particular, the volatility and reliability specified in the contracts will be incorporated into the scheduling model. This section begins with the assumptions and criteria about the contracts, following by the contract volatility and reliability models. To end this section, the limitations of the scheduling model are discussed. Remedial approaches to the model are also presented as alternatives.

4.3.1 Assumptions and Criteria

In addition to the assumptions set forth in Chapter 2, the assumptions and criteria about the energy contracts and auction markets are added to aid the modeling process.

First, only the spot and forward contracts are modeled. Futures and options contracts are financial instruments used to hedge against the financial risk with no physical (or little chance of) delivery of energy. Since the scheduling model is intended to address the supply and demand issue in energy delivery, the futures and options contracts are not considered at current stage. Second, the energy is to be delivered equally throughout the delivery duration, except for the allowed volatility and reliability. For instance, if the size of the contract for one-month duration is 5 MW, then the energy is to be delivered is 5 MW for all instances during the month duration [7]. Third, at any instance, there is no overlap in the time of delivery with contracts of equivalent

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[7] This is different than the futures contracts traded on the New York Mercantile Exchange (NYMEX) and Chicago Board of Trade (CBOT), where energy is only contracted for delivery during peak hours.

delivery duration. For instance, if the contracts of one-month duration have a time of delivery beginning February 01, the next time of delivery on the tradable contracts of one-month duration will begin on March 01, but not for any other dates within February. Fourth, all forecasted elements (energy price, customer demand, reliability, volatility, supplementary energy) are assumed to be deterministic with no margin of error. The problems of uncertainty in the forecasted elements will be addressed in Chapter 6. Fifth, the customer demand can be forecasted for all contract delivery duration. For instance, if a contract exists for 15 minutes intervals, the customer demand is then assumed to be determinable for all 15 minutes intervals. Finally, the simplest assumption is that there are an equal days in each month. For example, there are 30 days in a month, from January to December. This assumption is intended to simplify the notation in the mathematical model.

Let $P_a^{d^f,\alpha_h,\beta_h}$ be the energy purchased for contract of α_h reliability, β_h volatility, and delivery beginning at period a with a delivery duration of d^f periods. From the second assumption, the size of the contract is then equivalent to $P_a^{d^f,\alpha_h,\beta_h} / size$, where *size* is the per contract energy to be delivered each period during delivery duration. For example, if the energy purchased is determined to be 16 MW, and the size per contract is 5 MW, the number of contracts purchased is equivalent to 3.2 (assuming that the ESCO may purchase a portion of a standardized contract.) From the third assumptions, the potential time of delivery for $P_a^{d^f,\alpha_h,\beta_h}$ is governed by (4.19).

$$a = t : d^f : t + m - d^f \tag{4.19}$$

For example, if the first contracted delivery time is at period 1, $t = 1$, the delivery duration is 5 periods, $d^f = 5$, and the schedule duration is 15 periods, $m = 15$, by (4.19), the potential time of delivery will then be at period 1, 6, and 11.

4.3.2 Meeting Customer Demand Volatility with the Purchased Contracts

There are three criteria in meeting the volatility within the purchased contract. First, the ESCO will not receive an amount of energy greater than the maximum rating $(1+\beta_h^{a,d^f})P_a^{d^f,\alpha_h,\beta_h}$, where β_h^{a,d^f} is the volatility written in the contract. Second, if the customer demand is falling below $(1-\beta_h^{a,d^f})P_a^{d^f,\alpha_h,\beta_h}$, the ESCO will not be compensated. Finally, the average energy delivered during the contracted delivery duration d should be equal to the purchased agreement, $P_a^{d^f,\alpha_h,\beta_h}$. Figure 4-1 provides an example of the customer demand patterns an ESCO serves during a particular duration and shows how the three criteria are met.

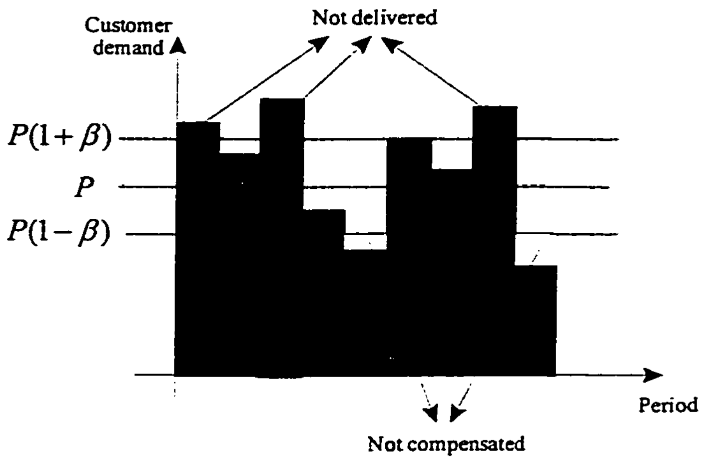

Figure 4-1. The customer demand during a particular duration.

Since, for each period, the ESCO may choose to purchase different kinds of contracts with different quality and delivery duration, the customer demand at any period should not be greater than the aggregated maximum rating. Equation (4.20) shows the relation.

$$TE_j - ED_j + EP_j + ES_j - ER_j \le \sum_{\forall h} \sum_{\forall d^f} \left(1+\beta_h^{a,d^f}\right) P_a^{d^f,\alpha_h,\beta_h} \qquad \forall j \tag{4.20}$$

The value of the superscript and subscript a used throughout section 4.3 can be determined using (4.21). $q(*)$ is the quotient of *. For instance, $q(14/4)$ is 3. For example, when $d^f = 4$ and $t = 1, j = 1$ yields $a = 1, j = 200$ yields $a = 197$, etc.

$$a = t + d^f * q\left(\frac{j-1}{d^f}\right) \tag{4.21}$$

To illustrate (4.20), if $h = 1$, $t = 1$, $d^f = 1,2,4$, at $j = 4$,

$$TE_4 - ED_4 + EP_4 + ES_4 - ER_4 \le \left(1+\beta_1^{4,1}\right)P_4^{1,\alpha_1,\beta_1} + \left(1+\beta_1^{3,2}\right)P_3^{2,\alpha_1,\beta_1} + \left(1+\beta_1^{1,4}\right)P_1^{4,\alpha_1,\beta_1} \tag{4.22}$$

By the second criterion, contracted energy that is not delivered because of the customer demand falling below the minimum rating at period j, P_j^-, is shown in (4.23).

$$TE_j - ED_j + EP_j + ES_j - ER_j - \sum_{\forall h} \sum_{\forall d^f} \left(1 - \beta_h^{a,d^f}\right) P_a^{d^f,\alpha_h,\beta_h} = P_j^+ - P_j^- \qquad \forall j \tag{4.23}$$

The third criterion requires that the average energy delivered during the contracted delivery duration d be equal to what is specified in the purchased agreement, $P_a^{d^f,\alpha_h,\beta_h}$. Satisfying this criterion takes additional work because the delivery duration of all traded contracts is not necessarily equivalent. To take this criterion into account, first assume that the contract duration is organized in incremental fashion ($d^f, f = 0,\dots,F$.) For example, for contracts with 1, 8, 4 periods, delivery duration, $d^0 = 1, d^1 = 4, d^2 = 8$ (the final contract duration is the third delivery duration, or, $F = 2$.) Then, the excess energy, EX^+_{a,d^f}, that is not satisfied by contracts of d^f delivery duration is described in (4.24) and (4.25).

$$EX^+_{a,d^0} - EX^-_{a,d^0} = \frac{1}{d^0} \sum_{j=t+(a-1)d^0}^{t+ad^0-1} \left(EM_j + P_j^-\right) - \sum_{\forall h} P_{t+(a-1)d^0}^{d^0,\alpha_h,\beta_h} \quad \forall a = t : d^f : t+m-d^f, d^f = d^0 \tag{4.24}$$

The reason for adding P_j^- in $\left(EM_j + P_j^-\right)$ is that the ESCO will have to bear the cost when the customer demand falls below the minimum rating.

$$EX^+_{a,d^f} - EX^-_{a,d^f} = \frac{d^{f-1}}{d^f} \sum_{\substack{j=t+(a-1)d^f \\ j=j+d^{f-1}}}^{t+ad^f-1} EX^+_{j,d^{f-1}} - \sum_{\forall h} P_{t+(a-1)d}^{d^f,\alpha_h,\beta_h} \quad \forall a = t : d^f : t+m-d^f, d^f \neq d^0, d^F \tag{4.25}$$

The reason for not including $EX^-_{a,d^{f-1}}$ in (4.25) is that any energy not delivered by contracts of delivery duration d^{f-1} will not bring any compensation to the ESCO. A similar argument was made in the second criterion on the volatility requirement. Equation (4.26) states that the purchased energy of delivery duration d^F must exceed the average excess energy after excluding the supply and demand of shorter delivery duration.

$$\frac{d^{F-1}}{d^F}\sum_{\substack{j=t+(a-1)d^F \\ j=j+d^{F-1}}}^{t+ad^F-1} EX^+_{j,d^{F-1}} \le \sum_{\forall h} P^{d^F,\alpha_h,\beta_h}_{t+(a-1)d^F} \qquad \forall a = t : d^f : t+m-d^f, d^f = d^F \tag{4.26}$$

4.3.3 *Meeting the Customer Reliability Requirement with the Purchased Contracts*

To meet the customer reliability requirement, the energy purchased through the auction, after excluding the maximum potential energy not delivered, should exceeds the minimum customers reliability requirement. Equation (4.26) shows the reliability criterion.

$$\begin{aligned} &TE_j\left(1-\alpha_j^{TE}\right)-ED_j\left(1-\alpha_j^{ED}\right)+EP_j\left(1-\alpha_j^{EP}\right) \\ &+ES_j\left(1-\alpha_j^{ES}\right)-ER_j\left(1-\alpha_j^{ER}\right)\le\sum_{\forall h}\sum_{\forall d}\left(1-\alpha_h^{a,d^f}\right)P_a^{d^f,\alpha_h,\beta_h} \qquad \forall j \end{aligned} \tag{4.26}$$

4.3.4 *Limitations and Remedies*

There exist some limitations to the formulations relating the auction market to scheduling customer demand. First, the cost of the purchased energy not meeting contract requirement is not included in the formulation, i.e., the payment that the ESCO may receive when the market does not deliver as promised is not considered. Second, the cost of the actual customer demand exceeding the forecasted customer demand is not accounted for in the model. Finally, since all elements within the model, including the energy price, customer demand, supplementary energy, and reliability in the delivered energy are forecasted, there is no certainty the forecasted elements will behave as predicted. The uncertainty in the forecasted elements is an important aspect and that discussion is delayed until Chapter 5 and 8.

To remedy the first limitation, one possible way is to use the reliability level of the contracts based on the *forecasted* reliability level rather than the *contract specified* reliability level. Then, the forecasted payment received by the ESCO from the different type of contracts can be included in the objective functions as described in (4.3), (4.4), (4.8) or (4.10). In Chapter 5, another approach, the value at risk approach, is presented to consider the cost of purchased energy not meeting contract requirements.

To remedy the second limitation, one way is to assume that the possibility of the cost of actual customer demand exceeding the forecasted customer demand is *high*. Then, to avoid the high cost, the higher forecast (to improve the probability that the forecasted customer demand will exceed the actual customer demand) of the customer demand should be used in the formulation. However, it is hard to determine how *high* should the forecasted customer demand be adjusted to reflect the cost of the lower forecast. In Chapter 5 and 8, the problem is addressed.

CHAPTER 5 DECISION MAKING IN THE PRESENCE OF RISK

The canonical form of a classical maximization linear programming problem can be stated as:

$$
\begin{aligned}
& \max \quad \mathbf{c}^T\mathbf{x} \\
& \text{subject to:} \\
& \quad \mathbf{Ax} \le \mathbf{b} \\
& \quad \mathbf{x} \ge \mathbf{0}
\end{aligned}
\tag{5.1}
$$

$\mathbf{c}^T$ is the vector of cost coefficients. Since (5.1) maximizes the objective, $\mathbf{c}^T$ represents the profit per unit of $\mathbf{x}$. $\mathbf{A}$ is the constraint matrix. $\mathbf{b}$ is the right-hand-side vector, representing the minimal requirements to be satisfied. All coefficients of $\mathbf{c}^T$, $\mathbf{A}$, and $\mathbf{b}$ are all known deterministically, the inequality sign, "$\le$", is not to be violated, and the objective is a strict imperative [50].

However, in real life, these conditions may not always be true. The collected data used to formulate the problem is bounded to uncertainty. *Uncertainty* is the condition in which the possibility of error exists, because we have less than the total information about our environment [51]. For instance, the forecasted market price and the forecasted customer demand used in the formulation in both Chapter 3 and Chapter 4, are estimated values. Risk arises when decision-makers and analysts attempt to make a decision based on *uncertain* information. To make a good decision, the uncertainty needs to be incorporated into the formulation. There are numerous decision algorithms commonly used in the presence of uncertainty. The first approaches are simply sensitivity analysis and parametric analysis. The second approach is mean-variance analysis that maximizes the expected profit while discounting the effect of uncertainty by including the covariance matrix of the decision factors. The third approach is stochastic linear programming. The stochastic approach has been researched since the 1950s, when it was introduced independently by Dantzig and Beale in 1955 [52]. The stochastic linear programming approach borrows its concept from statistics. More importantly, this developed approach is in the most generic form among all approaches, allowing decision-makers to consider both deterministic and uncertain parameters in $\mathbf{c}^T$, $\mathbf{A}$, and $\mathbf{b}$. However, due to the requirement of the Monte Carlo simulation and the Bender decomposition in solving a stochastic linear programming model, the size of the problem increases immensely as the number of uncertain parameter increases. The fourth approach is fuzzy linear programming. It was introduced in the 1970s with two distinct approaches, by Zimmermann [53] and Tanaka [54]. The fuzzy techniques borrow their concept from the fuzzy logic extension theory. The resulting methodology is simple and efficient. However, the fuzzy linear programming approach has an inherent difficulty in explaining the concept of aspiration level. The last technique, the value at risk [8](VaR), originated in the financial industry and seeks to improve the financial performance and to ensure an institution does not suffer unacceptable losses. The value at risk technique is a statistical measure of risk that estimates the maximum losses that may be experienced in a portfolio with a given level of confidence [55]. These five approaches collectively represent the risk management and assessment tools the decision-maker may employ to address the uncertainty in the ESCO operation and management.

In this chapter, the five risk management and assessment tools are presented to search for an optimal decision at minimum risk. Section 5.1 provides a list of variables and parameters used in this chapter. Section 5.2 presents stochastic linear programming. Section 5.3 presents mean-variance analysis. Section 5.4 presents sensitivity analysis and parametric analysis. Section 5.5 presents fuzzy linear programming. Section 5.6 presents value at risk. Finally, section 5.7 compares and contrasts the various approaches.

5.1 NOMENCLATURE

5.1.1 Abbreviations

DECIS: Decomposition and importance sampling, a software package accompanying [52].

E_*: The expectation with respect to $*$.

ENS: Energy not served.

R: The fuzzy region described by the set of fuzzy constraints.

$S(R)$: The support of fuzzy region R.

var: variance.

VaR: Value at risk.

VAR: Volt-ampere.

5.1.2 Parameters

$\mathbf{b}$: right-hand-side vector.

$\tilde{\mathbf{b}}$: The fuzzy $\mathbf{b}$.

---

[8] In the power industry, VAR is used to represent the volt-amp reactive (the reactive power). The same notation has also been used by statisticians to represent the variance and by risk managers to represents the value at risk. To avoid confusing the reader, VAR is used to represent volt-ampere, VaR to represent value at risk, and var to represent variance.

$\mathbf{b}'$: The changes in **b** to be analyzed in the sensitivity and parametric analysis.

$\mathbf{c}^T$: Vector of cost coefficients.

$\mathbf{c}^T$: Vector of cost coefficients.

c_*: The cost of utilizing technology *.

c'^T: The changes in $\mathbf{c}^T$ to be analyzed in the sensitivity and parametric analysis.

d_i: i^{th} element of the vector $\mathbf{d}$.

$\mathbf{d}$: The vector comprising of the aspiration level z and the right-hand-side vector $\mathbf{b}$.

$\mathbf{d}(\omega)$: right-hand-side vector in the recourse function that is uncertain.

eig: The eigenvalues of the correlation matrix, **C**.

$\mathbf{f}^T(\omega)$: Objective vector corresponding to **y** variables that is uncertain.

n: The vector of normally distributed random numbers.

n_k : The number of contracts purchased by the ESCO for contract type k.

p_i: The tolerance interval of the i^{th} fuzzy criteria.

pm_k: Contracted payment to be made to the ESCO by the auction market for each lowered reliability level on delivered energy for contract type k.

v: The matrix of eigenvectors corresponding to the correlation matrix, **C**.

$\mathbf{w}$: The matrix describing the width of the fuzzy number in the matrix $\widetilde{\mathbf{B}}$.

$\mathbf{w}_i$: The i^{th} row of the matrix $\mathbf{w}$.

$\mathbf{x}^*$: The solution for **x** solved in the master problem in the stochastic linear programming approach.

z: The aspiration level of the objective.

z_*: The optimal objective value using model * (refers to section 5.2.2.)

$\widetilde{z}$: The fuzzy aspiration level of the objective.

$\mathbf{A}$: constraint matrix.

$\widetilde{\mathbf{A}}$: The fuzzy $\mathbf{A}$.

$\mathbf{B}$: The matrix comprising of the $\mathbf{c}^T$ and $\mathbf{A}$.

$\widetilde{\mathbf{B}}$: The fuzzy set matrix comprising of the fuzzy cost vector, $\widetilde{\mathbf{c}}^T$, fuzzy constraint matrix, $\widetilde{\mathbf{A}}$, fuzzy aspiration level, $\widetilde{z}$, and fuzzy right-hand-side vector $\widetilde{\mathbf{b}}$.

$\mathbf{B}(\omega)$: Transition matrix corresponding to **x** variables that is uncertain.

$Cov(*_i, *_j)$: The covariance between $*_i$ and $*_j$.

C: The correlation matrix of the objective function.

$\mathbf{D}(\omega)$: Technology matrix corresponding to **y** variables that is uncertain. I_{m+l} :Identity matrix of size *(m+l)* by *(m+l)*.

M: The number of constraints.

N: The number of variables.

P: The tolerance interval vector of the fuzzy criteria.

P : The proportion or position of the assets in monetary value.

Q: The number of fuzzy constraints.

Q: The covariance matrix of the objective function.

W: The width of a fuzzy number.

α : The center of a fuzzy number.

$\boldsymbol{\alpha}$: The matrix describing the center of the fuzzy number in the matrix $\widetilde{\mathbf{B}}$.

α_i : The *I*-th row of the matrix $\boldsymbol{\alpha}$.

α_k : The contracted reliability level to be delivered by the auction market for contract type *k*.

α_k' : The reliability level delivered by the auction market for contract type *k*.

λ^* : A particular satisfaction of the criteria.

λ_* : The uncertainty level corresponding to technological advancement *.

$\lambda\mathbf{c}'/\lambda\mathbf{b}'$: The correlated random change for $\lambda\mathbf{c}'^T$ or $\lambda\mathbf{b}'$.

σ_* : The standard deviation of *.

ω : An element of the probability space.

5.1.3 Variables

x : The decision variable.

y: The decision variable to be solved in the recourse function (stochastic linear programming.)

$(\mathbf{Ax})_i$: The i^{th} row of the constraints.

$(\mathbf{Bx})_i$: The i^{th} row of the criteria.

CPST: The compensation granted to the ESCO by the auction market when the reliability level delivered by the market is below the reliability level described in the contract.

E: The expected objective function.

$Q(\mathbf{x},\omega)$: Recourse function. The second stage optimization problem containing the uncertain parameters.

V: The covariance matrix of the objective function multiplying by the square of the decision variables.

λ : The definition for λ varies from one approach to another. It in general represents the degree of monetary risk that the decision-maker is bearing as a result of uncertainty. A smaller λ means that the decision-maker is bearing a higher risk while a larger λ means that the decision-maker is bearing a lower risk.

$\mu_i(\mathbf{x})$: The fuzzy set of i^{th} fuzzy criteria.

$\mu_G(\mathbf{x})$: The transformed fuzzy set of the crisp objective function.

$\varepsilon(\mathbf{x})$: A monotonically increasing function describing $\mu_i(\mathbf{x})$.

$\sup_{S(R)} f$: Check the text for definition.

$\inf_{S(R)} f$: Check the text for definition.

Iter: The number of iteration.

Tol: The tolerance on the accuracy of the solution reached by the fuzzy linear programming approach proposed by Tanaka and Asai.

5.2 STOCHASTIC LINEAR PROGRAMMING

Stochastic linear programming is the most generic approach. In section 5.2.1, the approach is presented. In section 5.2.2, this approach is discussed, in particular, on how the model is used in the ESCO operation.

5.2.1 Model

Stochastic linear programming problem can be described as shown in (5.2).

$$\max_{\mathbf{x},\mathbf{y}} \quad z_2 = \mathbf{c}^T\mathbf{x} + \mathbf{f}^T(\omega)\mathbf{y}$$

subject to:

$$\begin{aligned} \mathbf{A}\mathbf{x} &\le \mathbf{b} \\ -\mathbf{B}(\omega)\mathbf{x} + \mathbf{D}(\omega)\mathbf{y} &\le \mathbf{d}(\omega) \\ \mathbf{x} &\ge \mathbf{0} \\ \mathbf{y} &\ge \mathbf{0} \end{aligned} \tag{5.2}$$

The matrix, $\mathbf{A}$, and vectors, $\mathbf{c}^T$ and $\mathbf{b}$, are known with certainty. The matrices, transition matrix $\mathbf{B}(\omega)$ and technology matrix $\mathbf{D}(\omega)$, objective vector $\mathbf{f}^T(\omega)$ and right-hand-side vector $\mathbf{d}(\omega)$, are uncertain. ω is an element of the probability space. Simply speaking, $\mathbf{B}(\omega)$, $\mathbf{D}(\omega)$, $\mathbf{f}^T(\omega)$, $\mathbf{d}(\omega)$, are uncertain parameters, while $\mathbf{A}$, $\mathbf{c}^T$, and $\mathbf{b}$ are deterministic parameters [52].

The classical approach to the stochastic linear programming problem described in (5.2) is a two-stage linear program with recourse [52]. It has the form shown in (5.3) and (5.4).

$$\max_{\mathbf{x}} \qquad z_2 = \mathbf{c}^T\mathbf{x} + E_\omega Q(\mathbf{x},\omega)$$

subject to:

$$\begin{aligned} \mathbf{Ax} &\le \mathbf{b} \\ \mathbf{x} &\ge \mathbf{0} \end{aligned} \tag{5.3}$$

where

$$Q(x,\omega) = \max_{y} \qquad \mathbf{f}^T(\omega)\mathbf{y}$$

subject to:

$$\begin{aligned} \mathbf{D}(\omega)\mathbf{y} &\le \mathbf{d}(\omega) + \mathbf{B}(\omega)\mathbf{x} \\ \mathbf{y} &\ge 0 \end{aligned} \tag{5.4}$$

E_ω denotes the expectation with respect to ω and the recourse function $Q(\mathbf{x},\omega)$ [52].

The requirement for a two-stage setting is due to the fact that one set of variables, $\mathbf{y}$, has only uncertain parameters associated with it, while the other set of variables, $\mathbf{x}$, has both deterministic and uncertain parameters associated with it. Thus, one part of the problem solves for the variables $\mathbf{y}$ that have only uncertain parameters associated with it, $\mathbf{D}(\omega)$, $\mathbf{f}^T(\omega)$, and $\mathbf{d}(\omega)$, as shown in (2.4), while the other part of the problem solves for the variables x with both uncertain and deterministic parameters, $\mathbf{B}(\omega)$, $\mathbf{A}$, $\mathbf{c}^T$, and $\mathbf{b}$.

Infanger uses the Benders Decomposition to solve the two-stage stochastic linear programs in (5.3) and (5.4). The approach is an iterative procedure solving the master problem and sub-problems iteratively until a particular trial solution can be declared optimal. The master problem solves for the variables $\mathbf{x}$ and θ (a variable introduced to link the master problem and sub-problems,) and consists of the Benders cuts, the deterministic coefficients ($\mathbf{A}$, $\mathbf{b}$, and $\mathbf{c}^T$) and variables ($\mathbf{x}$ and θ). The Benders cuts are the values determined by solving the sub-problems. The sub-problems solves for the variables $\mathbf{y}$ and consists of the uncertain coefficients ($\mathbf{B}(\omega)$, $\mathbf{D}(\omega)$, $\mathbf{f}^T(\omega)$, $\mathbf{d}(\omega)$, and $\mathbf{x}^*$, where $\mathbf{x}^*$ is determined in the master problem) and variables ($\mathbf{y}$). The details are presented in his book. The book is accompanied with a software, the **DECIS** (Decomposition and Importance Sampling,) that uses the Benders Decomposition technique to solve the two-stage stochastic linear programs.

5.2.2 Discussions and Extensions to the ESCO Operation

Infanger presents three decision making models [52]. The first is the "wait and see" model. In this model, uncertainty does not exist. The uncertainty is resolved prior to decision making. The second is the "here and now" model. In this model, uncertainty exists. Information leading to the decision making is incomplete. The stochastic linear programming solves problems of such nature. The third is the "expected-value" model. In this model, even though the uncertainty exists, the expected values of the uncertain parameters are used in the decision making. Let z_1, z_2, and z_3 represent the optimal objective reached under the three models, $z_2 \le z_3 \le z_1$. The expected value of perfect information is the difference between z_1 and z_3 $(z_1 - z_3)$. The value of stochastic solution is the difference between z_3 and z_2 $(z_3 - z_2)$.

The previous discussion can be generalized. In the ESCO operation, the information used in the decision making can often be improved (decreasing the standard deviation, variance, and covariance of the uncertain parameters) at the cost of technological advancement. These include upgrading the technology, improving the forecasting techniques, hiring professionals with experience and knowledge, and gathering more information. To justify the cost of such improvements, let $\lambda_\bullet$ be the uncertainty level corresponding to a level of technological advancement, $z_{\lambda^\bullet}$ be the optimal objective reached by solving the stochastic linear programming model using $\lambda_\bullet$, and $c_{\lambda^\bullet}$ be the cost of utilizing $\lambda_\bullet$. Then, in improving the uncertainty from λ_1 to λ_2, the cost of upgrading the technology is $(c_{\lambda^2} - c_{\lambda^1})$, and the benefit of upgrading the technology is $(z_{\lambda^2} - z_{\lambda^1})$. If $(z_{\lambda^2} - z_{\lambda^1}) \ge (c_{\lambda^2} - c_{\lambda^1})$, the benefit outweighs the cost of technological advancement. In addition to justifying the cost of technological advancement, the benefit frontier of technological advancements can also be traced. Let $\lambda_\bullet$ be a function of decreasing uncertainties, the net benefit corresponding to $\lambda_\bullet$, $(z_{\lambda^\bullet} - c_{\lambda^\bullet})$, is a function corresponding to the decreasing uncertainties. Then the frontier of utilizing the different technological advancement can be traced. Even though stochastic linear programming is not used in this research, Chapter 8 discusses why the presented example is not suitable for stochastic linear programming.

5.3 MEAN-VARIANCE ANALYSIS

Mean-variance analysis assumes that the decision analysis is based on the expected income on the investment and the associated variance that represents the risk of investment. In section 5.3.1, the two commonly used mean-variance analytical models are presented. In section 5.3.2, this approach is discussed, in particular, on how the model is used in the ESCO operation.

5.3.1 Models

There are various models to represent the mean-variance analysis. The two discussed models are shown in (5.5) and (5.6) respectively.

$$\max \quad \mathbf{E} - \lambda \mathbf{V}$$

subject to:

$$\begin{aligned} \mathbf{Ax} &\le \mathbf{b} \\ \mathbf{x} &\ge \mathbf{0} \end{aligned} \tag{5.5}$$

$$\min \quad \mathbf{V}$$

subject to:

$$\begin{aligned} \mathbf{c}^T\mathbf{x} &= \lambda \\ \mathbf{Ax} &\le \mathbf{b} \\ \mathbf{x} &\ge \mathbf{0} \end{aligned} \tag{5.6}$$

E and **V** are the expected value and covariance matrix of the objective function, $\mathbf{c}^T\mathbf{x}$. They are shown in (5.7) and (5.8) respectively.

$$\begin{aligned} \mathbf{E} &= \sum_{\forall i} \left(E\mathbf{c}_i^T\right)\mathbf{x}_i \\ &= \left(E\mathbf{c}^T\right)\mathbf{x} \end{aligned} \tag{5.7}$$

$$\begin{aligned} \mathbf{V} &= \sum_{\forall i}\sum_{\forall j} Cov\left(\mathbf{c}_i^T, \mathbf{c}_j^T\right)\mathbf{x}_i\mathbf{x}_j \\ &= \mathbf{x}^T\mathbf{Q}\mathbf{x} \end{aligned} \tag{5.8}$$

The notation E represents the expected value. Thus, $E\mathbf{c}^T$ is the expected value of the cost coefficients. The notation Cov represents the covariance. $Cov\left(\mathbf{c}_i^T, \mathbf{c}_j^T\right)$ is determined using (5.9) and **Q** is shown in (5.10).

$$Cov(\mathbf{c}_i^T, \mathbf{c}_j^T) = E(\mathbf{c}_i^T - E\mathbf{c}_i^T)(\mathbf{c}_j^T - E\mathbf{c}_j^T) \tag{5.9}$$

$$\mathbf{Q} = \begin{bmatrix} E(\mathbf{c}_1^T - E\mathbf{c}_1^T)(\mathbf{c}_1^T - E\mathbf{c}_1^T) & \cdots & E(\mathbf{c}_n^T - E\mathbf{c}_n^T)(\mathbf{c}_1^T - E\mathbf{c}_1^T) \\ \vdots & \ddots \quad E(\mathbf{c}_i^T - E\mathbf{c}_i^T)(\mathbf{c}_j^T - E\mathbf{c}_j^T) \quad \ddots & \vdots \\ E(\mathbf{c}_1^T - E\mathbf{c}_1^T)(\mathbf{c}_n^T - E\mathbf{c}_n^T) & \cdots & E(\mathbf{c}_n^T - E\mathbf{c}_n^T)(\mathbf{c}_n^T - E\mathbf{c}_n^T) \end{bmatrix} \tag{5.10}$$

Both (5.5) and (5.6) are quadratic programming models. Since $\mathbf{Q}$ is a positive semi-definite matrix, (5.5) and (5.6) can be solved using the modified simplex method to search for the optimal solution for the given λ value. The modified simplex method is described in [56].

5.3.2 Discussions and Extension to the ESCO Operation

On the one hand, in (5.4), λ is the parameter indicating the unwillingness of the decision-maker to assume risk. On the other hand, in (5.5), λ is the parameter indicating the targeted expected objective value. Either way, by varying λ parametrically, the optimal solution to the formulation in (5.4) and (5.5) will trace the locus of all efficient combinations of risk versus return (expected objective, $(E\mathbf{c}^T)\mathbf{x}$). An ESCO model is analyzed using this approach in Chapter 8. The model uses the MATLAB quadratic programming tool.

5.4 SENSITIVITY ANALYSIS AND PARAMETRIC ANALYSIS

Sensitivity analysis and parametric analysis are the two simplest ways to help a decision-maker in assessing and managing risk. They are post-optimality analyses that are readily available from the optimal solution reached by the linear program model in (5.1). In section 5.4.1, sensitivity analysis and parametric analysis are reviewed and the model to be used in the ESCO operation is presented. In section 5.4.2, these approaches are discussed, in particular, on how the model is used in the ESCO operation.

5.4.1 Model

Sensitivity analysis examines the effect of relaxing some of the constraints on the value of the optimal objective without having to resolve the problem. The analysis [50] includes

- Change in the cost vector, $\mathbf{c}$.
- Change in the right-hand-side vector, $\mathbf{b}$.

- Change in the constraint matrix, **A**.
- Addition of a new activity (increasing the number of row of the constraint matrix **A**).
- Addition of a new constraint (increasing the number of the column of the constraint matrix **A**).

Sensitivity analysis is used only when there are not many changes to be analyzed. Otherwise, sensitivity analysis is no different than solving a new linear programming problem. Furthermore, to conduct sensitivity analysis, the changes must be added one by one. For example, to analyze the effect on the changes in two cost coefficients, the technique requires the decision-maker to first analyze the effect of the first coefficients. Then, the decision-maker may choose to analyze the effect of the second coefficient based on the original optimal solution or the optimal solution reached after including the effect of the first coefficient.

Parametric analysis examines how the optimal solution changes as several parameters change simultaneously over some range. This analysis includes:

- Simultaneous changes in cost vector, **c**.
- Simultaneous changes in right-hand-side vector, **A**.

Parametric analysis is not suitable when the decision-maker intends to change the constraint matrix, **A**, either by changing the parametric values, or by adding new constraints and activities.

5.4.2 Discussions and Extension to the ESCO Operation

In this research, the interested subjects are the changes in the energy prices and the participation factor in the load management programs. They affect the cost vector, **c**. Even though the changes in customer demand and supplementary energy are also of interest, these changes modify the constraint matrix, A. Thus, they are not to be evaluated using sensitivity analysis or parametric analysis.

To analyze the changes in the energy prices and the participation factor in the load management programs, the techniques proposed for the parametric analysis can be used. In analyzing the changes in the cost vector **c**, the simplex method is used. In analyzing the changes in the right-hand-side vector, the revised simplex method is used. The details are presented in [50]. Equation (5.11) shows the linear programming model that analyzes the cost vector **c**. Equation (5.12) shows the linear programming model that analyzes the right-hand-side vector **b**.

In sensitivity analysis, λ is a known value. In parametric analysis, λ is the range of values to be traced for the change in the basis [9]. $\mathbf{c}'^T$ and $\mathbf{b}'$ are the changes to be analyzed. In sensitivity analysis, only one parameter in $\mathbf{c}'^T$ or $\mathbf{b}'$ is not equal to zero. In parametric analysis, however, more than one parameter in $\mathbf{c}'^T$ or $\mathbf{b}'$ is not equal to zero. In both sensitivity analysis and parametric analysis, choosing the $\mathbf{c}'$ or $\mathbf{b}'$ values

[9] Basis is the set of basic variables. Basic variables are the dependent variables obtained as the simultaneous solution of the system of equations [50, 56].

can be difficult. In this research, $\mathbf{c}'^T$ and $\mathbf{c}^T$ or $\mathbf{b}'$ and $\mathbf{b}$ are related using statistical concepts by assuming $\mathbf{c}^T$ and $\mathbf{b}$ as uncertain parameters. Equations (5.11) and (5.12) are modified respectively as shown in (5.13) and (5.14).

$$\begin{aligned} &max \quad \mathbf{c}^T\mathbf{x} + \lambda\mathbf{c}'^T\mathbf{x} \\ &\text{subject to:} \\ &\quad \mathbf{Ax} \le \mathbf{b} \\ &\quad \mathbf{x} \ge \mathbf{0} \end{aligned} \tag{5.11}$$

$$\begin{aligned} &max \quad \mathbf{c}^T\mathbf{x} \\ &\text{subject to:} \\ &\quad \mathbf{Ax} \le \mathbf{b} + \lambda\mathbf{b}' \\ &\quad \mathbf{x} \ge \mathbf{0} \end{aligned} \tag{5.12}$$

$$\begin{aligned} &max \quad E\mathbf{c}^T\mathbf{x} + \lambda\mathbf{c}'^T\mathbf{x} \\ &\text{subject to:} \\ &\quad \mathbf{Ax} \le \mathbf{b} \\ &\quad \mathbf{x} \ge \mathbf{0} \end{aligned} \tag{5.13}$$

$$\begin{aligned} &max \quad \mathbf{c}^T\mathbf{x} \\ &\text{subject to:} \\ &\quad \mathbf{Ax} \le E\mathbf{b} + \lambda\mathbf{b}' \\ &\quad \mathbf{x} \ge \mathbf{0} \end{aligned} \tag{5.14}$$

In sensitivity analysis, $\mathbf{c}'^T$ and $\mathbf{b}'$ can be treated as the standard deviation of $\mathbf{c}^T$ ($\mathbf{c}'^T = \sigma_{\mathbf{c}^T}$) and $\mathbf{b}$ ($\mathbf{b}' = \sigma_{\mathbf{b}}$) respectively. Thus, λ determines the degree the standard deviation of $\mathbf{c}$ and $\mathbf{b}$ to affect the decision-making. Comparing to model (5.4) in the mean-variance analysis, conducting sensitivity analysis as in (5.10) is equivalent to saying that there is only one parameter that is uncertain, i.e., $\mathbf{c}'^T = \sqrt{\mathbf{Q}}$ (except that in sensitivity analysis, the corresponding variable is $\mathbf{x}$ while in mean-variance analysis, the corresponding variable is $\mathbf{x}^2$.)

In parametric analysis, $\lambda\mathbf{c}'^T$ and $\lambda\mathbf{b}'$ can be treated as the correlated changes of $\mathbf{c}^T$ and $\mathbf{b}$ correspondingly. The correlated random changes for $\lambda\mathbf{c}'^T$ and $\lambda\mathbf{b}'$ can be generated using (5.15) [10].

$$
\lambda\mathbf{c}' / \lambda\mathbf{b}' = \left[\mathbf{v}\left(\mathbf{n} \bullet \sqrt{\mathbf{eig}}\right)\right] \bullet \sigma
$$

$$
\begin{bmatrix} \lambda\mathbf{c}'_1 / \kappa\mathbf{b}'_1 \\ \vdots \\ \lambda\mathbf{c}'_n / \lambda\mathbf{b}'_n \end{bmatrix} = \left(\begin{bmatrix} \mathbf{v}_{11} & & \\ & \ddots & \\ & & \mathbf{v}_{nn} \end{bmatrix} \left(\begin{bmatrix} \mathbf{n}_1 \\ \vdots \\ \mathbf{n}_n \end{bmatrix} \bullet \begin{bmatrix} \sqrt{\mathbf{eig}_1} \\ \vdots \\ \sqrt{\lambda\mathbf{eig}_n} \end{bmatrix} \right) \right) \bullet \begin{bmatrix} \sigma_1 \\ \vdots \\ \sigma_n \end{bmatrix} \tag{5.15}
$$

$\lambda\mathbf{c}' / \lambda\mathbf{b}'$ is the correlated random change for $\lambda\mathbf{c}'^T$ or $\lambda\mathbf{b}'$. $\mathbf{v}$ and $\mathbf{eig}$ are the eigenvectors and eigenvalues of the correlation matrix of $\mathbf{c}^T$ or $\mathbf{b}$. The correlation matrix of $\mathbf{c}^T$ or $\mathbf{b}$, $\mathbf{C}$, can be determined using (5.15). Equation (5.16) shows the correlation matrix for $\mathbf{c}^T$; the correlation matrix for $\mathbf{b}$ can be evaluated by replacing $\mathbf{c}^T$ in (5.16) with $\mathbf{b}$. $\mathbf{n}$ is the series of random changes generated from a normally distributed probabilistic function. Finally, σ is the standard deviation or volatility of the random cost vector, $\mathbf{c}^T$, or the random right-hand-side vector, $\mathbf{b}$.

$$
\mathbf{C} = \begin{bmatrix} \dfrac{E\left(\mathbf{c}_1^T - E\mathbf{c}_1^T\right)\left(\mathbf{c}_1^T - E\mathbf{c}_1^T\right)}{\sigma^2_{\mathbf{c}_1^T}} & \cdots & \dfrac{E\left(\mathbf{c}_n^T - E\mathbf{c}_n^T\right)\left(\mathbf{c}_1^T - E\mathbf{c}_1^T\right)}{\sigma_{\mathbf{c}_n^T}\sigma_{\mathbf{c}_1^T}} \\ \vdots & \ddots \quad \dfrac{E\left(\mathbf{c}_i^T - E\mathbf{c}_i^T\right)\left(\mathbf{c}_j^T - E\mathbf{c}_j^T\right)}{\sigma_{\mathbf{c}_i^T}\sigma_{\mathbf{c}_j^T}} \quad \ddots & \vdots \\ \dfrac{E\left(\mathbf{c}_1^T - E\mathbf{c}_1^T\right)\left(\mathbf{c}_n^T - E\mathbf{c}_n^T\right)}{\sigma_{\mathbf{c}_1^T}\sigma_{\mathbf{c}_n^T}} & \cdots & \dfrac{E\left(\mathbf{c}_n^T - E\mathbf{c}_n^T\right)\left(\mathbf{c}_n^T - E\mathbf{c}_n^T\right)}{\sigma^2_{\mathbf{c}_n^T}} \end{bmatrix} \tag{5.16}
$$

Equation (5.15) associates the change series with the random number, $\mathbf{n}$. To perform parametric analysis, however, the parameter λ needs to be included. Thus, instead of the normally distributed random number $\mathbf{n}$, it is substituted with λ, as shown in (5.17).

---

[10] The topic on the correlated random changes can be found in [55]. The expression presented in section 5.4 has been simplified.

$$\begin{bmatrix} \lambda \mathbf{c}'_1 / \kappa \mathbf{b}'_1 \\ \vdots \\ \lambda \mathbf{c}'_n / \lambda \mathbf{b}'_n \end{bmatrix} = \left(\begin{bmatrix} \mathbf{v}_{11} & & \\ & \ddots & \\ & & \mathbf{v}_{nn} \end{bmatrix} \left(\begin{bmatrix} \lambda \\ \vdots \\ \lambda \end{bmatrix} \bullet \begin{bmatrix} \sqrt{\mathbf{eig}_1} \\ \vdots \\ \sqrt{\lambda \mathbf{eig}_n} \end{bmatrix} \right) \right) \bullet \begin{bmatrix} \sigma_1 \\ \vdots \\ \sigma_n \end{bmatrix} \tag{5.17}$$

With (5.17), $\mathbf{c}'^T$ and $\mathbf{b}'$ are associated with the uncertain cost vector, $\mathbf{c}^T$, and the uncertain right-hand-side vector, $\mathbf{b}$.

5.5 FUZZY LINEAR PROGRAMMING

Fuzzy linear programming is based on the fuzzy logic extension theory, this approach is introduced last among all approaches. In section 5.2.1, the approach is discussed in general. In sections 5.2.2 and 5.2.3, two major models in fuzzy linear programming are presented. In section 5.2.4, these approaches are discussed, in particular, on how the model is used in the ESCO operation.

5.5.1 Introduction to Fuzzy Linear Programming

In describing fuzzy linear programming, the concept of *satisfaction of criteria* is important. The criteria can be either the constraints or the objectives. In general, the objective is to find the $\mathbf{x}$ that would satisfy the set of criteria or equations in (5.18).

$$\begin{aligned} -\mathbf{c}^T\mathbf{x} &\le -z \\ \mathbf{Ax} &\le \mathbf{b} \\ \mathbf{x} &\ge \mathbf{0} \end{aligned} \tag{5.18}$$

The value of z represents the aspiration level of the objective function. From an economic point of view, the goal of fuzzy linear programming is to minimize the risk of violating the set of criteria in (2.11). The formulation is similar to mean-variance analysis described in (2.7) with the exception that fuzzy set theory is utilized to formulate the problem.

There are two distinct differences between fuzzy linear programming and mean-variance analysis. First, in mean-variance analysis, the uncertainty is stochastic, and in fuzzy linear programming, the uncertainty is fuzzy. Stochastic uncertainty is used mainly to describe vagueness due to the lack of information, where the future state of the system might not be known completely. Fuzzy uncertainty is mainly used to describe vagueness concerning the description of the semantic meaning of the events, phenomena, or statements themselves [53]. Second, mean-variance analysis requires solving a quadratic programming model while fuzzy linear programming requires solving only a linear programming model. To solve fuzzy linear programming using a linear model, the fuzzy uncertainties among the criteria are assumed not correlated.

There are three fuzzy logic terms that are introduced in this section, i.e., fuzzy set, fuzzy number, and fuzzy function. A classical set is normally defined by a collection of elements. An element is either belongs to the set or not. A fuzzy set, however, is a collection of elements with a fuzzy membership function. A fuzzy membership function indicates the strength of an element's membership in a set, with 1 indicating full membership and 0 indicating non-membership. The definition of fuzzy number is very often modified. In this research, a fuzzy number is a convex normalized fuzzy set of the real line that (i) there exists exactly one element with a characteristic value of 1 and (ii) the characteristic function that describes the fuzzy number is piecewise continuous. For example, the fuzzy set {(3, 0.1), (4, 0.5), (5, 1), (6, 0.5), (7, 0.1)} describing the fuzzy statement 'approximately 5' is also a fuzzy number. However, the fuzzy set {(3, 0.1), (4, 1), (5,1), (6, 0.5), (7, 0.1)} describing the fuzzy statement 'approximately 5' is not a fuzzy number. A fuzzy function is a generalization of the concept of a classical function [53]. There are different degrees of fuzzification of the classical notion of a function that can be conceived. The various definitions of a fuzzy function can be found in [53].

In the fuzzy linear programming literature, there exist two distinct formulations. The first formulation is a research work led by H. –J. Zimmermann. The objective function and the constraints are represented by the fuzzy sets and then aggregated to derive at a maximizing decision. The second formulation is a research work led by H. Tanaka and K. Asai [53]. The coefficients, $\mathbf{A}$, $\mathbf{b}$, and $\mathbf{c}^T$, are described as fuzzy numbers and the constraints as fuzzy functions. Section 5.5.1 describes Zimmermann work and section 5.5.2 describes Tananka and Asai work.

5.5.2 *Approach 1 to Fuzzy Linear Programming [53]*

There are two variations to the Zimmermann approach. Section 5.5.2.1 describes the symmetric fuzzy linear programming, i.e., all equations in the first two sets of equations in (5.18) are fuzzy. Section 5.5.2.2 describes the non-symmetric fuzzy linear programming, i.e., some of the equations of the first two sets of equations in (5.18) are not fuzzy.

5.5.2.1 Symmetric Fuzzy Linear Programming

A symmetric fuzzy linear programming is formed when the inequality sign $\leq$ in the first two sets of equations in (5.18) are fuzzy in nature. By substituting $\mathbf{B} = \begin{pmatrix} -\mathbf{c}^T \\ \mathbf{A} \end{pmatrix}$ and $\mathbf{d} = \begin{pmatrix} -z \\ \mathbf{b} \end{pmatrix}$, (5.18) may be restated as (5.19).

$$\mathbf{Bx} \underset{\sim}{\leq} \mathbf{d}$$

$$\mathbf{x} \geq \mathbf{0} \tag{5.19}$$

Here, $\underset{\sim}{\leq}$ denotes the fuzzified version of $\leq$ and has the linguistic interpretation "essentially smaller than or equal to." The set of $(m+1)$ constraints that carries the fuzzified inequality signs, $\underset{\sim}{\leq}$, may be represented by a fuzzy set, the membership function of which is $\mu_i(\mathbf{x})$. $\mu_i(\mathbf{x})$ should be 0 if the constraints are strongly violated and 1 if strongly satisfied. In between, $\mu_i(\mathbf{x})$, shown in (5.20), is described by a nonmonotonically increasing function $\varepsilon(\mathbf{x})$ from 0 to 1 when constraint i of $\mathbf{Bx} \underset{\sim}{\leq} \mathbf{d}$ ranges from $(\mathbf{Bx})_i - d_i$ to $(\mathbf{Bx})_i - d_i + p_i$.

$$\mu_i(\mathbf{x}) = \begin{cases} 1 & \text{if } (\mathbf{Bx})_i \leq d_i \\ \varepsilon(\mathbf{x}) & \text{if } d_i \leq (\mathbf{Bx})_i \leq d_i + p_i \\ 0 & \text{if } (\mathbf{Bx})_i > d_i + p_i \end{cases} \tag{5.20}$$

Here, p_i is the tolerance interval. Using the simplest type of membership function, i.e., linearly increasing over the tolerance interval, (5.20) is rewritten as (5.21). Figure 5-1 shows the graphic representation of (5.21).

$$\mu_i(\mathbf{x}) = \begin{cases} 1 & \text{if } (\mathbf{Bx})_i \leq d_i \\ 1 - \dfrac{(\mathbf{Bx})_i - \mathbf{d}_i}{p_i} & \text{if } d_i \leq (\mathbf{Bx})_i \leq d_i + p_i \\ 0 & \text{if } (\mathbf{Bx})_i > d_i + p_i \end{cases} \tag{5.21}$$

If the risk is inversely proportional to the satisfaction of criteria, $\mu_i(\mathbf{x})$, then, to reduce the risk, the minimum $\mu_i(\mathbf{x})$ of all the criteria should be maximize. Equation (5.22) shows the mathematical representation.

$$\max_{\mathbf{x} \geq \mathbf{0}} \left\{ \min_{\forall i} \left[1 - \frac{(\mathbf{Bx})_i - d_i}{p_i} \right] \right\} \tag{5.22}$$

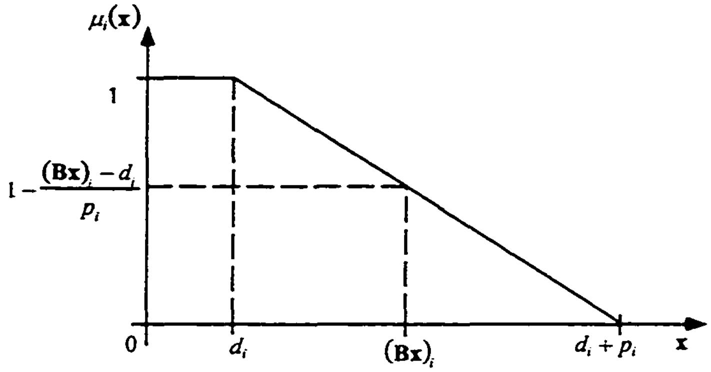

Figure 5-1. Fuzzy set $\mu_i(\mathbf{x})$.

Introducing a new variable, λ, to represent the minimum of $\left(1-\frac{(\mathbf{Bx})_i-d_i}{p_i}\right)$, (5.22) can be written as (5.23). The λ value reflects the satisfaction of criteria. λ ranges from 0 to 1. The larger the λ, the more the criteria are satisfied.

$$\max \quad \lambda$$

subject to:

$$\lambda p_i + (\mathbf{Bx})_i \le d_i + p_i \qquad i = 1,\dots,m+1$$

$$\mathbf{x} \ge 0 \tag{5.23}$$

The constraints that have to be crisp, i.e. not to be violated, can easily be added to (5.21). Equation (5.24) shows the formulation when (5.1) is a formulation consisting of a fuzzy objective, q fuzzy constraints and *(m-q)* crisp constraints.

$$\max \quad \lambda$$

subject to:

$$\lambda p_i + (\mathbf{Bx})_i \le d_i + p_i \qquad i = 1,\dots,q+1$$

$$(\mathbf{Ax})_i \le b_i \qquad i = q+1,\dots,m$$

$$\mathbf{x} \ge 0 \tag{5.24}$$

5.5.2.2 Non-symmetric Fuzzy Linear Programming

Non-symmetric fuzzy linear programming refers to the fuzzy linear programming model that has a crisp (deterministic) objective function. The problem is the determination of an extremum of a crisp function over a fuzzy domain. This problem can be solved using two approaches. They are:

1. The determination of the fuzzy set "decision."
2. The determination of a crisp "maximizing decision" by aggregating the objective function after appropriate transformations with the constraints.

1. The determination of the fuzzy set "decision."

This approach searches for the optimal objective value and decision choice $\mathbf{x}_{\lambda^*}$ from every λ^* value ranging from 0 to 1. The result is a fuzzy set and the decision-maker will have to decide which $\left(x_{\lambda^*}, \lambda^*\right)$ he considers optimal if he wants to arrive at a crisp optimal solution. The mathematical equivalent for a decision problem with a crisp objective, q fuzzy criteria, and $(m-q)$ crisp criteria is stated in (5.25).

$$\begin{aligned} & max \quad \mathbf{c}^T\mathbf{x} \\ \text{subject to:} & \\ & (\mathbf{Ax})_i \le b_i + \left(1-\lambda^*\right)p_i \qquad i = 1,\ldots,q \\ & (\mathbf{Ax})_i \le b_i \qquad i = q+1,\ldots,m \\ & \mathbf{x} \ge 0 \end{aligned} \tag{5.25}$$

2. The determination of a crisp "maximizing decision."

In this approach, a transformation is needed to determine the fuzzy set of the crisp objective function. The fuzzy set of the objective function is determined using (5.26).

$$\mu_G(\mathbf{x}) = \begin{cases} 0 & if\ \mathbf{c}^T\mathbf{x} \ge \sup\limits_{S(R)} f \\ 1 - \dfrac{\mathbf{c}^T\mathbf{x} - \inf\limits_{S(R)} f}{\sup\limits_{S(R)} f - \inf\limits_{S(R)} f} & if\ \inf\limits_{S(R)} f \le \mathbf{c}^T\mathbf{x} \le \sup\limits_{S(R)} f \\ 1 & if\ \mathbf{c}^T\mathbf{x} \le \inf\limits_{S(R)} f \end{cases} \tag{5.26}$$

R represents the fuzzy region described by the set of constraints, fuzzy and crisp. $S(R)$ is the support the fuzzy region R. $\sup_{S(R)} f$ and $\inf_{S(R)} f$ can be determined using (5.27) and (5.28) respectively.

$$\sup_{S(R)} f \equiv \max \quad \mathbf{c}^T\mathbf{x}$$

subject to:

$$\begin{aligned} (\mathbf{Ax})_i &\le b_i + p_i \qquad i = 1,\dots,q \\ (\mathbf{Ax})_i &\le b_i \qquad i = q+1,\dots,m \\ \mathbf{x} &\ge 0 \end{aligned} \tag{5.27}$$

$$\inf_{S(R)} f \equiv \max \quad \mathbf{c}^T\mathbf{x}$$

subject to:

$$\begin{aligned} (\mathbf{Ax})_i &\le b_i \qquad i = 1,\dots,m \\ \mathbf{x} &\ge 0 \end{aligned} \tag{5.28}$$

The transformed objective function results in a symmetrical fuzzy linear programming problem that can be solved using the technique developed in section 5.5.2.1. The mathematical equivalent is shown in (5.29).

$$\max \quad \lambda$$

subject to:

$$\begin{aligned} \lambda\left(\sup_{S(R)} f - \inf_{S(R)} f\right) + \mathbf{c}^T\mathbf{x} &\le -\inf_{S(R)} f \\ \lambda p_i + (\mathbf{Ax})_i &\le b_i + p_i \qquad i = 1,\dots,q \\ (\mathbf{Ax})_i &\le b_i \qquad i = q+1,\dots,m \\ \mathbf{x} &\ge 0 \end{aligned} \tag{5.29}$$

5.5.3 Approach 2 to Fuzzy Linear Programming [54]

In this approach, each element of z, $\mathbf{A}$, $\mathbf{c}^T$, and $\mathbf{b}$ are described as the fuzzy number ($\tilde{z}$, $\tilde{\mathbf{A}}$, $\tilde{\mathbf{c}}^T$, and $\tilde{\mathbf{b}}$ respectively.) These fuzzy numbers can be described by the fuzzy set with center α and width w. Figure 5-2. shows a graphic representation of the fuzzy set of the fuzzy numbers that will be used in the formulation.

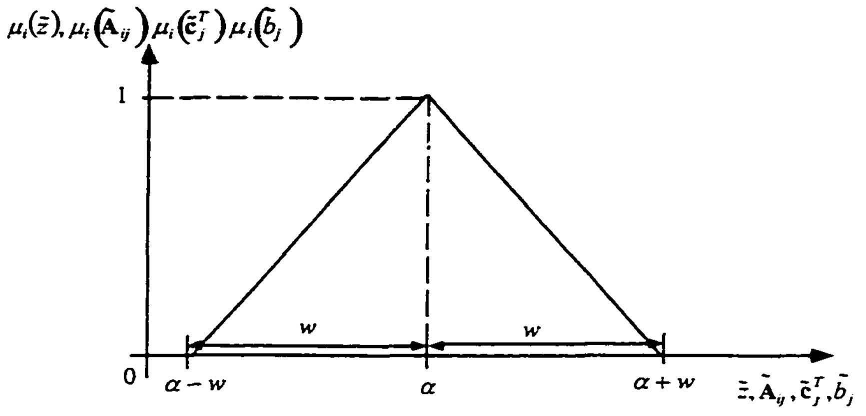

Figure 5-2. Fuzzy Set $\tilde{z}$, $\tilde{\mathbf{A}}$, $\tilde{\mathbf{c}}^T$, and $\tilde{\mathbf{b}}$.

By substituting $\tilde{\boldsymbol{B}} = \begin{pmatrix} \tilde{\boldsymbol{c}}^T & -\tilde{z} \\ -\tilde{\boldsymbol{A}} & \tilde{\boldsymbol{b}} \end{pmatrix}$, (5.17) may be restated as (5.30).

$$\begin{aligned} \tilde{\mathbf{B}}\mathbf{x} &\underset{\sim}{\geq} 0 \\ \mathbf{x} &\geq 0 \end{aligned} \tag{5.30}$$

Since $\tilde{\boldsymbol{B}}$ is a matrix comprised of fuzzy elements, it can be represented by two matrices, one, $\boldsymbol{\alpha}$, to represent the center and one, $\boldsymbol{w}$, to represent the width. The membership function, $\mu_i(\tilde{\mathbf{B}}\mathbf{x})_i$, of $(\mathbf{B}\mathbf{x})_i$ can be determined using the extension principle of fuzzy set theory. Equation (5.31) shows the resulting membership function. The proof is provided in [54].

$$\mu_i\left[(\tilde{\boldsymbol{B}}\boldsymbol{x})_i\right] = \begin{cases} 1 & \text{if } \boldsymbol{x} = 0, (\tilde{\boldsymbol{B}}\boldsymbol{x})_i = 0 \\ 1 - \dfrac{\left|(\tilde{\boldsymbol{B}}\boldsymbol{x})_i - (\boldsymbol{w}\boldsymbol{x})_i\right|}{(\boldsymbol{\alpha}\boldsymbol{x})_i} & \text{if } \boldsymbol{x} \neq 0 \\ 0 & \text{if } \boldsymbol{x} = 0, (\tilde{\boldsymbol{B}}\boldsymbol{x})_i \neq 0 \end{cases} \qquad i = 1, \ldots, m+1 \tag{5.31}$$

'$(\tilde{\mathbf{B}}\mathbf{x})_i$ is almost positive', denoted by $\tilde{\mathbf{B}}\mathbf{x} \underset{\sim}{\geq} 0$, is defined in (5.32).

$$(\tilde{\boldsymbol{B}}\boldsymbol{x})_i \underset{\sim}{\geq} 0 \quad \Leftrightarrow \quad \mu_i(0) \leq 1 - \lambda, \quad (\boldsymbol{w}\boldsymbol{x})_i \geq 0 \tag{5.32}$$

λ stands for the degree of $(\tilde{\mathbf{B}}\mathbf{x})_i \underset{\sim}{\geq} 0$, or the degree of satisfaction of criterion $(\tilde{\mathbf{B}}\mathbf{x})_i$. The larger λ is, the stronger the meaning of 'almost positive' (see Figure 5-3).

If the risk is inversely proportional to the degree of 'almost positive,' then, to reduce the risk, the minimum $\mu_i(\tilde{\mathbf{B}}\mathbf{x} = \mathbf{0})_i$ of all the criteria should be maximized. Equation (5.33) shows the mathematical representation.

$$\max_{x \geq 0}\left\{\min_{\forall i} \mu_i\left[(\tilde{B}x)_i = 0\right]\right\} \equiv \max_{x \geq 0}\left\{\min_{\forall i}\left[1 - \frac{(wx)_i}{(\alpha x)_i}\right]\right\} \tag{5.33}$$

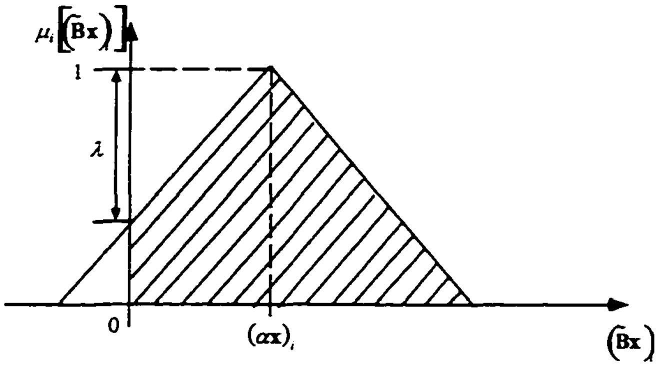

Figure 5-3. The explanation of $\tilde{\mathbf{B}}\mathbf{x} \underset{\sim}{\geq} 0$.

Equation (5.34) shows the mathematical representation after substituting (5.31) and (5.32) into (5.33).

$$\max \quad \lambda$$

subject to:

$$(w_i - \lambda\, \alpha_i)x \geq 0 \qquad i = 1, \ldots, m+1$$

$$\mathbf{x} \geq 0 \tag{5.34}$$

Since the fuzzy mathematical programming model described in (5.34) is nonlinear, the following algorithm, shown in Figure 5-4, is used to solve for the optimal decision that will maximize the satisfaction of criteria (the technique is an alteration of the technique proposed in [54].)

STEP 1	*Let* $\lambda^{*} = 0.5$, *iter* $= 1$.
STEP 2	if $(\mathbf{w} - \lambda\alpha)^{T}\mathbf{x} \geq 0$ *feasible*
	$\lambda^{*} = \lambda^{*} + 0.5/2^{iter}$
	else
	$\lambda^{*} = \lambda^{*} - 0.5/2^{iter}$
STEP 3	$iter = iter + 1$.
	if $0.5/2^{iter} \geq tol$, GO TO **STEP 2.**
	Solve for optimal decision using (5.34).

$$\begin{aligned} & max \quad \mathbf{c}^{T}\mathbf{x} \\ & \text{subject to:} \\ & (\mathbf{w}_i - \lambda^{*}\alpha_i)^{T}\mathbf{x} \geq 0 \qquad i = 1,\ldots,m+1 \\ & \mathbf{x} \geq 0 \end{aligned} \tag{5.35}$$

Figure 5-4. Iterative procedure to solve (5.22).

5.5.4 Discussions and Extension to the ESCO Operation

In general, the approaches by both Zimmermann and Tanaka are considered as the *max min* approach, i.e., the minimum satisfaction of all criteria is maximized. The resulting decision shows what the decision making can do best when uncertainty is least desired.

There are two key advantages in the Zimmermann approach. First, the fuzzy linear programming model can still be solved using linear programming techniques. In addition, the size of the problem is relatively unchanged. The number of variables is only increased by one, λ, to explain the satisfaction of criteria. The number of constraints is also increased by only one, the aspiration level of the objective function. Second, the approach has been explored by Zimmermann et al at great length to include the duality theory, sensitivity analysis, and integer fuzzy programming. Unfortunately, the approach captures only the effect of fuzziness in each of the constraints, rather than the coefficients $\mathbf{c}^{T}$, $\mathbf{A}$, and $\mathbf{b}$. As a result, the contribution of fuzziness in the coefficients can not be properly evaluated. The Zimmermann's approach on fuzzy linear programming has been used in various occasions within the power industry.

The key advantage of Tanaka and Asai approach is its ability to consider the effect of fuzziness on every element of the matrix $\widetilde{\mathbf{B}}$. The approach captures the effect of fuzziness in the fuzzy coefficients $\mathbf{c}^{T}$, $\mathbf{A}$, and $\mathbf{b}$. However, the approach results in a nonlinear mathematical model. Fortunately, the iterative procedure used to solve the nonlinear problem does not require extensive work. No publication about the technique by the authors can be found since 1984. The issues like duality and sensitivity analysis are not covered.

Notably, the two approaches, Zimmermann and Tanaka, have the difficulties of interpreting the aspiration level z when applied to the scheduling customer demand model. The problem will not be clear without an example. However, future results will reveal, the aspiration level plays an important role in the feasibility of the constraining equations.

An ESCO model is analyzed using the Zimmermann and the Tanaka approaches in Chapter 8.

5.6. VALUE AT RISK

Value at risk, VaR, is a risk assessment tool that has been used by financial institutions to evaluate the risk of holding a portfolio of assets. The VaR approach differs from all previously discussed approaches. The four approaches presented in section 5.2 through section 5.5 determine the set of actions to be taken ($\mathbf{x}$ and $\mathbf{y}$,) while including the uncertain factors (such as $\mathbf{A}$, $\mathbf{b}$, $\mathbf{c}^T$) in the decision making process. The only difference among the four approaches is how they are implemented. VaR, however, assumes that certain actions have been decided ($\mathbf{x}$ and $\mathbf{y}$ are determined.) The goal is to determine the monetary risk of taking the actions. In section 5.6.1, the concept of VaR is reviewed. In section 5.6.2, the problems of utilizing VaR to the ESCO operation are discussed. The different components of VaR in the ESCO operation are presented. Section 5.6.3 through 5.6.5 presents the techniques to evaluate the different components of VaR. Section 5.6.6 comments on the approach.

5.6.1 Introduction to VaR

VaR is the maximum amount of money that may be lost in a portfolio (given actions, $\mathbf{x}$ and $\mathbf{y}$) over a given period of time, with a given level of confidence [55]. Figure 5-5 shows the graphical representation of VaR.

There are three techniques that can be used to evaluate VaR. The first technique is the historical simulation. Historical simulation applies the historical data to evaluate the VaR. The second technique is the covariance technique. To apply the covariance technique, the correlation matrix, $\mathbf{C}$, of the uncertain factors is assumed available. The third technique is the Monte Carlo simulation. The Monte Carlo simulation involves artificially generating a very large set of events, correlated changes, from which VaR is derived [55].

The covariance technique is the easiest and fastest technique among the three. However, this technique assumes that the uncertain factors (such as $\mathbf{A}$, $\mathbf{b}$, $\mathbf{c}^T$) are normally distributed. Since normal distribution is not necessarily applicable to all situations, the technique has its limitation. The historical simulation and the Monte Carlo simulation are designed to supplement the covariance technique in this situation. Since historical simulation uses historical data to evaluate the VaR, there is no need to assume the probabilistic distribution function of the uncertain factors. However, when historical data is limited, solving the VaR using the historical simulation can be difficult. Even though the Monte Carlo simulation requires the assumption of the probabilistic distribution (usually normal distribution) of the uncertain factors, the technique is capable of handling uncertain factors that are not normally distributed. For instance, in valuing the VaR of holding the option contracts (whose price is not normally distributed), the option sensitivities (normally distributed) are used for the Monte Carlo simulation. Thus, the resulting VaR is able to consider the options contracts [55].

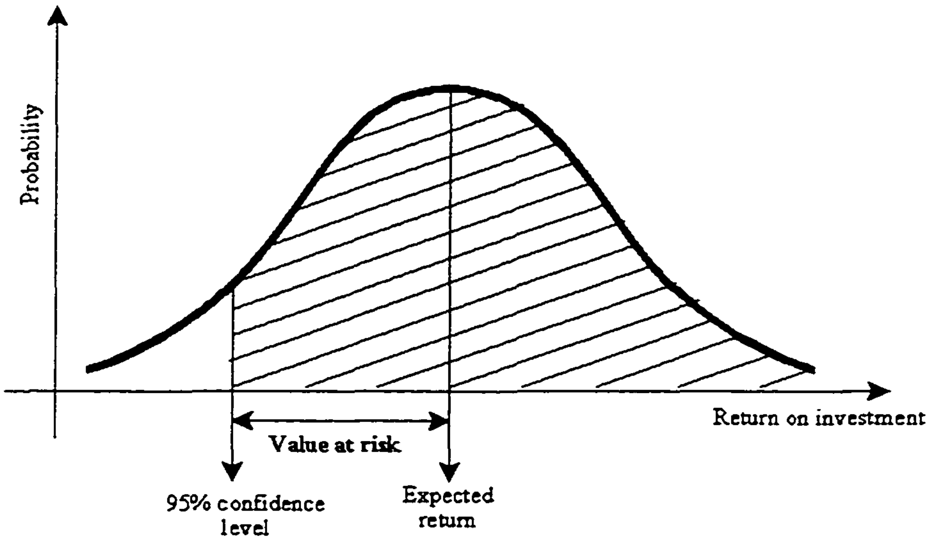

Figure 5-5. VaR at given confidence level.

5.6.2 Comments and Extension to ESCO Operation

Best describes the VaR of holding a portfolio of assets [55]. He described the VaR resulting from the assets price changes, the diversity of the portfolio (the number of assets with correlated price changes,) and the holding position of the portfolio (the amount of money invested in a particular asset.) The evaluation process is sufficient in a financial institution where the risk is primary as a result of price changes. To an ESCO, however, evaluating the VaR of the price changes is not sufficient. In addition to the risk of price fluctuation, there are two additional risks not described by Best. First, as the customer demand and the deliverability of energy are uncertain, there is a risk associated with the ESCO not being able to serve the customer with sufficient energy. In addition, since energy delivery can be a problem at times (such as transmission system failure, or generation failure) the ESCO suffers the risk of contract violations. Even after excluding the credit risk, the ESCO may still suffer monetary loss as a result of contract violations. This is due to insufficient energy to serve the customers. Figure 5-6 shows the three components of VaR in holding a particular decision for an ESCO (such as amount of supplementary energy, number of contracts, or purchased ancillary services)

In section 5.6.3, the VaR of market price fluctuation is presented. The covariance technique is used in the section. The historical simulation and Monte Carlo simulation techniques can be found in [55]. In section 5.6.4, the VaR of energy not served (ENS) is presented. In section 5.6.5, the VaR of contract violation is presented. Section 5.6.4 and 5.6.5 uses the Monte Carlo simulation technique to evaluate the VaR.

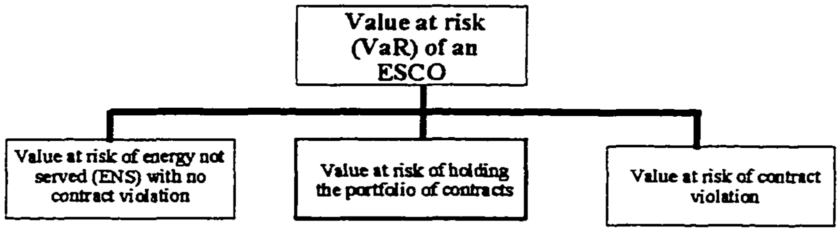

Figure 5-6. VaR of an ESCO.

5.6.3 VaR *of Market Price Fluctuation*

To evaluate the VaR of market price fluctuation, the covariance matrix of the market price fluctuation is assumed available. Historical data may be used in determining the covariance matrix. Then, the VaR of market price fluctuation is evaluated using (5.36).

$$VaR = \lambda\sqrt{\mathbf{PCP}^T} \tag{5.36}$$

$\mathbf{P}$ is the proportion or position of the assets in monetary value. λ represents the degree of volatility and determines the confidence level. For instance, when $\lambda = 1$, the confidence level is 95% [55]. The correlation matrix, **C**, is determined using (5.16).

5.6.4 VaR *of Energy Not Served (ENS)*

In Chapters 2 and 4, the reliability of energy is presented. Since the power system cannot promise a 100% deliverable energy supply, the ESCO will bear an inherent monetary risk from unreliable energy supply. The inherent monetary risk can be subdivided into two parts. The first part is the monetary risk (VaR of ENS) when the reliability level specified in the energy contract is met. The second part is the monetary risk (VaR of contract violation) when the reliability level specified in the energy contract is not met. The two VaRs measure the financial risk of the combinatorial effect of uncertainty in customer demand and supplementary energy for contracted reliability level on the delivered energy. The VaR of ENS is emphasized in this section. VaR of contract violation is discussed to section 5.6.5.

The VaR of ENS measures the financial risk of the delivery of energy and the uncertainty in customer demand and supplementary energy. Prior to evaluating the VaR of ENS, there are two issues that needed to be addressed. First, when purchased energy exceeds customer demand, what cost does the ESCO bear? Second, when the customer demand exceeds the purchased energy, how should the ESCO be penalized for not meeting the customer demand? To address the two issues, the following assumptions are made.

When there is an excess energy (purchased energy exceeds the customer demand,) the ESCO loses the opportunity to sell [11]. In this research, the average cost of energy will be used to evaluate the VaR of ENS when there is an excess energy. When there is an energy shortage (customer demand exceeds the purchased energy,) the ESCO suffers the opportunity cost to serve customer demand and the customers may refuse future services from the ESCO. The opportunity cost to serve customer demand is the rate that the customers will pay if there is no shortage of energy [12]. The opportunity cost that the customers may refuse future services is the expected cost of customers refusing the ESCO services. This opportunity cost will be a monotonically increasing function of the increased shortage in energy served.

With the opportunity cost of excess energy and shortage energy presented, the VaR of ENS can be evaluated in five steps. Figure 5-7 shows the steps in evaluating the VaR of ENS. Figure 5-8 shows the graphical representation of the VaR of ENS. An ESCO model is analyzed using this approach in Chapter 8.

5.6.5 VaR of Contract Violation

The VaR of contract violation measures the financial risk when the auction market is capable of deliverying the energy as specified in the contracts. Prior to evaluating the VaR of contract violation, there are two issues that need to be addressed. First, will the auction market compensate the ESCO when the contract specifications are not met? Second, how should the ESCO evaluate the cost of ENS when contract specifications are not met?

To address the first issue, it is assumed that the auction market will specify the compensation based on the percentage of reliability level below the contracted reliability level. The compensation to the ESCO, *CPST*, is shown in (5.37).

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[11] The opportunity to sell can be measured in various ways. First is the average cost of energy when there is an excess energy. Second is the opportunity cost of excess energy, assuming that the ESCO could have sold the excess energy at discount. The opportunity cost of excess comes in two forms, one is the average rate that the ESCO may receive, the other one is the decreasing function of excess rate (assuming that the ESCO will sell the excess energy first to buyers offering the highest discount rate.)

[12] The rate can come in two forms. First is a monotonically increasing function, assuming that customers paying higher rate will be served first. Second is an average of what customers pay, assuming that any additional energy will be partitioned equally to serve the customers.

$$CPST = \sum_{\forall k} n_k pm_k \left| \alpha'_k - \alpha_k \right| \tag{5.37}$$

pm_k is the contracted payment to be made to the ESCO for each lowered reliability level on delivered energy for contract type k. n_k is the number of contracts purchased for contract type k. α'_k is the delivered reliability level and α_k is the contracted reliability level. To address the second issue, it is assumed that the cost of ENS when contract specifications are met is the expected cost of ENS.

There are seven steps in evaluating the VaR of contract violation, as shown in Figure 5-9. Figure 5-10 shows the graphical representation of the VaR of contract violation. An ESCO model is analyzed using this approach in Chapter 8.

STEP 1	Form the probabilistic mass function [13](pmf) of purchased energy, assuming no contract violation. The technique to be used in the formation is the convolution technique [14].
STEP 2	Form the pmf of the customer demand after including the effect of supplementary energy.
STEP 3	Form the pmf of ENS by the convolution of pmf of purchased energy (described in 1) and pmf of the customer demand (described in 2.)
STEP 4	Determine the cost of ENS and its probability. This is accomplished by multiplying the ENS and with the opportunity cost of excess energy and shortage energy. The result is the pmf of the cost of ENS.
STEP 5	Based on the pmf of the cost of ENS, determine the VaR of ENS by assuming a desired confidence level.

Figure 5-7. VaR of ENS.

[13] The probabilistic function for discrete variables is called probabilistic mass function (pmf) while the probabilistic function for continuous variable is called probabilistic distribution function (pdf). Since the reliability level described in the energy contract and the number of contracts purchased are discrete (refer to Chapter 2,) pmf is used in this research. However, the described approaches can also be used for pdf.

[14] The convolution of two contracts can be solved with the following equations: $y[k] = \sum_{m=0}^{k} f[m]h[k-m]$ where $f[\bullet]$ and $h[\bullet]$ are the probability of contract 1 and 2 delivering • amount of energy while $y[\bullet]$ is the probability of the • amount energy delivered to the ESCO.

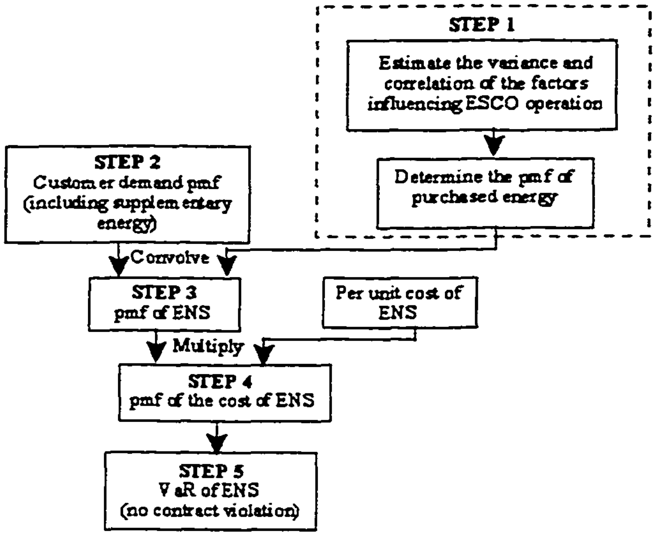

Figure 5-8. VaR of ENS.

STEP 1	Determine the eigenvalues and eigenvectors from the estimated correlation matrix of the reliability level delivered by the auction market.
STEP 2	Generate correlated random changes in the reliability level delivered using the eigenvalues and eigenvectors in **STEP 1** and (5.15). For each set of correlated random changes, go through **STEP 3** through **STEP 5**.
STEP 3	Determine the expected cost of ENS (refer to **STEP 4** of section 5.6.4.)
STEP 4	Determine the compensation based on the simulated reliability level in **STEP 2**.
STEP 5	Determine the cost of contract violation by subtracting the compensation found in **STEP 4** with the expected cost of ENS found in **STEP 3**.
STEP 6	Form the pmf of the cost of the contract violation using the simulated correlated changes in the delivered reliability level.
STEP 7	Based on the pmf of the cost of the contract violation, determine the VaR of contract violation by assuming a desired confidence level.

Figure 5-9. VaR of contract violation.

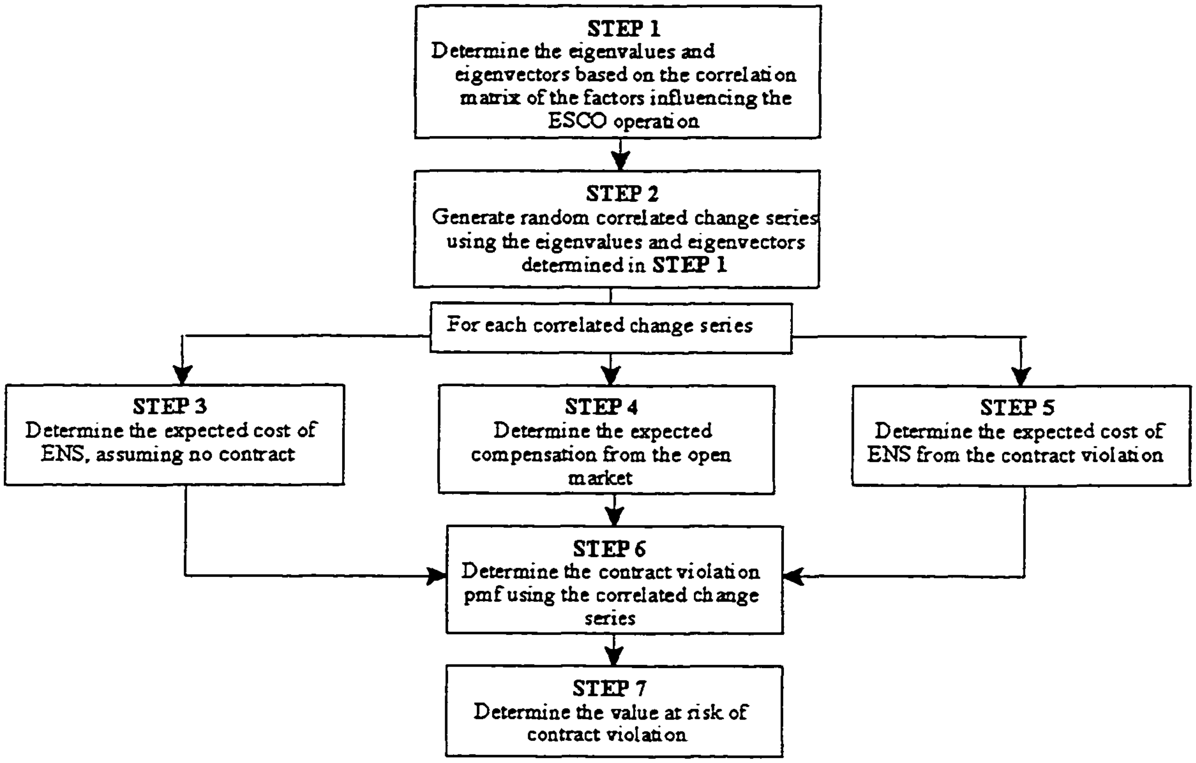

Figure 5-10. VaR of contract violation.

5.7. REMARKS

Sections 5.2 through section 5.6 present the various approaches that can be used to manage and assess the uncertainty. Each of these approaches has strengths and weaknesses. In this section, a perspective will be presented on these approaches in light of the following aspects: (1) applicability, (2) technical requirement, and (3) time requirement. Finally, section 5.7.4 provides additional discussions on uncertainty, risk, and cost of risk.

5.7.1 Applicability

Applicability refers to how easy the uncertainty may be addressed by the various approaches. The mean-variance, sensitivity analysis, and parametric analysis allow studies on the correlated changes in either the cost coefficient, **c**, or the right-hand-side vector, **b**, only. Even though the sensitivity analysis evaluates the perturbation in **c**, **A**, and **b**, it evaluates the perturbation one at a time. It would be easier to resolve the linear programming problem if too many perturbations are needed in the sensitivity analysis. The stochastic linear programming approach studies the uncertainties in **c**, **A**, and **b** simultaneously. Part of the model (**A** , **c** and **b**, in section 5.2) can be deterministic while the rest are stochastic ($\mathbf{B}(\omega)$, $\mathbf{D}(\omega)$, $\mathbf{f}^T(\omega)$, and $\mathbf{d}(\omega)$ in section 5.2). The fuzzy linear programming approach utilizes a broad range of techniques. The approach, in general, studies the changes in **c**, **A**, and **b** simultaneously. However, to use fuzzy linear programming, either all parameters within a constraining equation are considered fuzzy (i.e., being perturbed) or none are considered fuzzy. The VaR approach is capable of including risk factors that are hard to model. For example, in this research, the financial risks associated with *ENS* and contract violation are nonlinear relationships. To evaluate such financial risk using approaches other than VaR, linearizing the risk factors are needed. However, the VaR approach can determine such nonlinear financial risk without any prior simplification. Unfortunately, to evaluate the VaR, a decision choice must be made. This means that some other approaches must be used in addition to the VaR approach to provide a basis of valuation.

5.7.2 Technical Requirement

Technical requirement refers to the degree of knowledge needed in analyzing the uncertainty using the different approaches. Mean-variance, sensitivity analysis and parametric analysis, and fuzzy linear programming approaches are based on the linear programming technique. Understanding the concept of linear programming is sufficient to model an uncertain operational problem using these approaches. The fuzzy linear programming approach requires additional technical expertise as the approach borrows its concepts from fuzzy set extension theory. The approach is, nevertheless, similar to the sensitivity analysis and parametric analysis. The only exceptions are on how λ is interpreted and how applicable the approaches are (refer to section 5.7.1). To use the stochastic linear programming approach requires knowledge of Bender decomposition and Monte Carlo simulation techniques. As a result, the stochastic approach is more math-oriented than the rest. Fortunately, there are software packages available (for instance, the **DECIS** used in this research,) reducing the requirements to understand the techniques at great length. Understanding the Monte Carlo simulation technique is sufficient in the VaR approach.

5.7.3 Time Requirement

Time requirement refers to the time needed to analyze the model using the different approaches. The mean-variance, sensitivity analysis and parametric analysis, and fuzzy linear programming approaches are based on the linear programming technique. Sensitivity analysis and parametric analysis are the easiest approaches, since solving the linear programming model presented in Chapter 3 and Chapter 4 has already provided information needed to use these approaches. Mean-variance and fuzzy linear programming approaches require remodeling the models presented in Chapter 3 and Chapter 4. However, since the linear programming technique can still be used to solve the model derived from the two approaches, the time requirement is considered moderate. The stochastic linear programming and VaR approaches require the Monte Carlo simulation to obtain the random changes. The time requirements for the two approaches are considerably higher. Since the stochastic linear programming approach requires solving the model iteratively, the time requirement for this approach is the highest.

5.7.4 Uncertainty, Risk, and Cost of Risk

At the beginning of Chapter 6, *uncertainty* is defined as the condition in which the possibility of error exists, because we have less than the total information about our environment. Risk arises when decision-makers and analysts attempt to make a decision based on *uncertain* information. There are various ways to represent a risk. For example, in statistics, the risk is represented by probabilistic function, and in fuzzy set theory, the risk is represented by fuzzy membership function. In addition, risk can take various forms. In this research, two types of risk are considered, physical and financial. When an ESCO purchases energy contracts from the auction market, for example, it bears the financial risk of paying at prices higher than what it could have been offered. However, when the customer demand is uncertain, for example, an ESCO bears the risk of not serving the customers with sufficient electricity. While the ESCO still has faced the financial consequences of not meeting the customer demand, the risk is physical. In this example, the ESCO faces the physical risk of not serving the customers the requested energy demand.

The cost of risk measures the financial burden of the uncertainty. Since the financial risk is measured in monetary term, there is no difficulty in measuring the cost of financial risk. However, to measure the cost of a physical risk, the financial implication of the physical risk must first be determined. To measure the cost of ENS in section 5.6.4, for example, the opportunity cost of not serving customer energy is assumed. With the physical risk measured in terms of cost, the cost of the physical risk can be measured. In section 5.6.4, the term inherent monetary risk is used to reflect the financial implication of physical risk.

While the costs of the physical risk and the financial risk are measurable, the measurement takes various forms. One form is to use the expected financial losses resulted from the uncertainty to measure the cost of risk. It is commonly found in the field of engineering. However, in the field of economics, an expected financial loss is not a risk because it is *expected.* To economists, the cost of risk is usually measured using the variance or standard deviation of the financial risk and inherent monetary risk. In the presented risk management tools, the cost of risk has been measured using various forms. For examples, variance is used in mean-variance analysis, satisfaction of criteria is used in fuzzy linear programming, and confidence level is used in VaR analysis.

CHAPTER 6 ECONOMICS UNDERLYING ESCO OPERATION

This chapter presents several examples about the economics of scheduling customer demand and the interaction between scheduling customer demand and purchasing market contracts. All information is deterministic. Section 6.1 provides some underlying assumptions to be used throughout this chapter. Section 6.2 minimizes the cost of production using load management programs in the regulated electric industry. Section 6.3 uses the marginal costs solved in section 6.2 as the market prices to solve the different economic models of scheduling customer demand in an ESCO operation. Section 6.4 relates how scheduling customer demand may be related with the energy purchased from the auction market. Appendix A provides the data used and detailed results determined throughout this chapter.

6.1 INTRODUCTION

The following assumptions are used throughout this chapter:

- There are six months of data available for the customer demand. This data is shown in Appendix A. It is further assumed that there are six periods in each day and one day in each month.
- There are two groups of customers participating in the DLC program. Their contract specifications, controllable energy data, and pay back ratio on the controllable demand are shown in Appendix A.
- There is one ESS type I systems and one ESS type II system available in the ESS program. Their physical constraints and capabilities are shown in Appendix A.

The following assumptions are used in section 6.2 to determine the cost of production and marginal cost in the regulated electric industry:

- There are three generation units running during peak periods and two generation units running during off-peak periods. Their physical constraints and production cost functions are described in Appendix A. The allocation of the generation units has assumed the impact of the load management programs.
- The marginal cost functions during on-peak and off-peak periods are determined in Appendix A. Graphical technique is used in Appendix A to determine the marginal cost functions.
- The transmission cost and constraints are ignored in the process.

The following assumptions are used in section 6.3 to solve the various economic models for an ESCO in the re-regulated electric industry.

- The customer demand is assumed to be two tenth of the customer demand presented in Appendix A. The DLC demand is twenty four percent of that presented in Appendix A. The ESCO described in section 6.3 does not own any energy storage system.
- The market price for the electric energy is assumed to be the marginal cost solved in section 6.2. Additional assumptions on the energy contract with the sellers will be presented in section 6.4 when an ESCO tries to purchase contracts to meet its customer requirement.

6.2 SCHEDULING CUSTOMER DEMAND IN A REGULATED INDUSTRY

This section serves two purposes. The first is to show how the load management models presented in Chapter 3 may be used in the regulated power industry to reduce the production cost. The second is to use the solution reached in this section to determine market prices in future presentation.

In the tested system, the maximum controllable demand, 24.5 MW, is available during the 33rd period (or the 3rd period on the 1st day of the 6th month). The maximum controllable demand as a percentage of the total demand during that period, 8.00% of the total demand or 16 MW, is found in the 6th period (or the 6th period on the 1st day of the 1st month). The system has the highest total customer demand, 385 MW, and the highest marginal cost of production, $81.70/MW, at the 33rd period. Load management demand is comprised approximately 70 % of DLC demand, 19% of ESS type I energy, and 11% of ESS type II energy. The customer demand data, load management data, and generation cost function can be found in Appendix A.

Since there are two to three generation units that may be used for scheduling in this example, the marginal cost functions are first obtained using graphical techniques shown in Appendix A. To schedule the load management demand and generation units at the lowest production cost, an iterative procedure as shown in Appendix A is used.

Table 6-1 shows the optimal scheduling after minimizing the cost of production. The total energy produced before and after the load management scheduling are 9750 MW and 9749.02 MW respectively. The energy generated after scheduling is lower, by 0.98 MW, because the chosen DLC control sequences have a smaller paid back energy than the deferred energy, despite some inefficient energy storage systems being used. At the 10th period (or the 4th period on the 1st day of the 2nd month), the system experiences the highest level of energy being stored, 21 MW, through the load management programs. The amount of energy stored is 91.30% of the total controllable demand during that period. The highest level of energy stored as a percentage of the total load management demand, 72.73% or 12.00 MW, happens during the 5th period (or the 5th period on the 1st day of the 1st month). The maximum amount of energy is released, 21 MW, during the 10th period (or the 4th period on the 1st day of the 2nd month). The highest level of energy released as a percentage of the total load management demand, 92.56% or 19.90 MW, happens during the 3rd period (or the 3rd period on the 1st day of the 1st month). The marginal cost experiences the largest drop during the 33rd period, 4.85%, and the largest increase during the 6th period, -4.82%.

Table 6-2 shows the contributions in the increased and decreased production contributions from the three components of the load management programs, i.e., the DLC program, the ESS type I system, and the ESS type II system. Roughly 87% of the controlled demand is DLC demand, while 7.5 % and 5.5% of the controlled demands are ESS type I demand and ESS type II demand respectively. Only 97.62% of the deferred DLC demand are paid back. DLC demand contributes toward 87% of the total controlled demand. The number is higher than the DLC program' s share in the load management programs because the ESS type I system and the ESS type II system are not as effective as the DLC program. The ESS type II system is operating at 83.59% efficiency while the ESS type I system is operating at 84.09% efficiency. The higher operational efficiency of the ESS type I system contributes toward better a utilization ratio, which is 7.5%. Detailed load management demand schedule is presented in Appendix A.

The production cost before implementing the load management programs is approximately 483 thousand dollars. The production cost after implementing the load management programs is approximately 480 thousand dollars. The production cost savings is approximately three thousand dollars or 0.65% of the total production cost. Two major reasons contribute toward the relatively lower cost saving. First, the inefficient energy storage system requires that additional energy be generated to compromise for the energy lost during energy conversion. The ESS type I system is operating at 84.09% efficiency while the ESS type II system is operating at 83.59% efficiency. Second, the difference between the off-peak and on-peak marginal costs is relatively small, which is less than 20%. Load management programs are less attractive when the difference is small because the savings from deferring the on-peak demand, or storing energy during off-peak periods, will also be small. Table 6-1 shows that the largest reduction in the marginal cost happens during the 33rd period, which is a 4.85% reduction in the marginal cost when the energy produced is dropped by 3.95%.

In the tested system, the changes in the marginal costs are relatively small. Three factors contribute to the small change in the marginal costs. First, the rate of change of the marginal costs per MW energy generated is relatively small. Second, the load management demand capacity is relatively small compared to the customer demand. Finally, since there are two on-peak periods in every six periods in this tested system, the deferred customer demand, or released storage energy, are spread throughout the two periods, lowering the potential controllable demand during the two on-peak periods.

Beginning in the next section, the tested system is assumed re-regulated where energy is purchased and sold through an auction market. Assuming that competition is fierce in the energy market such that energy is priced according to the marginal cost, the marginal cost shown in Table 6-1 may then be used as the market price. This would assume that: generation companies know their cost of production and production level (and competitors' as well); market demand for energy is perfectly forecasted; and no transmission losses and congestion are happening. Even though the marginal costs before and after the load management scheduling are about the same, the marginal costs after the load management scheduling will be used as the market prices.

Table 6-1. Results from optimal scheduling.

Generation before LM in periodical order (MW)	Generation after LM (MW)	Change in generation level (MW)	% change in generation level	Marginal cost before LM ($/MW)	Marginal cost after LM ($/MW)	Change in marginal cost ($/MW)	% change in marginal cost
200	203.2000	3.2224	1.61	57.00	57.77	0.77	1.35
210	212.6047	3.2000	1.52	59.40	60.03	0.63	1.05
340	321.1000	-19.90	-5.85	76.12	73.42	-2.70	-3.54
340	320.2000	-20.49	-6.03	76.12	73.30	-2.82	-3.71
210	220.5129	12.00	5.71	59.40	61.92	2.52	4.25
200	211.4500	11.45	5.73	57.00	59.75	2.75	4.82
210	219.0001	9.36	4.46	59.40	61.56	2.16	3.64
220	227.2600	8.26	3.75	61.80	63.54	1.74	2.82
340	324.9997	-15.00	-4.41	76.12	73.98	-2.14	-2.81
350	331.1457	-21.00	-6.00	77.54	74.86	-2.68	-3.46
215	224.2852	11.12	5.17	60.60	62.83	2.23	3.68
210	220.1290	11.71	5.58	59.40	61.83	2.43	4.09
220	228.0196	7.02	3.19	61.80	63.72	1.92	3.11
225	230.9996	6.00	2.67	63.00	64.44	1.44	2.29
350	333.1738	-15.00	-4.29	77.54	75.14	-2.40	-3.09
360	342.0000	-19.00	-5.28	78.96	76.40	-2.56	-3.24
230	238.9996	9.47	4.12	64.20	66.36	2.16	3.36
220	229.6894	9.80	4.45	61.80	64.13	2.33	3.76
225	233.0422	7.58	3.37	63.00	64.93	1.93	3.06
230	236.8238	6.54	2.84	64.20	65.84	1.64	2.55
370	353.2253	-17.77	-4.80	80.39	78.00	-2.39	-2.97
360	342.0000	-19.66	-5.46	78.96	76.40	-2.56	-3.24
235	244.2449	10.24	4.36	65.40	67.62	2.22	3.39
220	229.9761	9.98	4.54	61.80	64.19	2.39	3.87
230	239.0000	9.00	3.91	64.20	66.36	2.16	3.36
240	246.9350	7.93	3.30	66.60	68.26	1.66	2.50
370	358.0000	-12.91	-3.49	80.39	78.68	-1.71	-2.13
380	362.0000	-19.85	-5.22	82.99	79.25	-3.74	-4.51
245	253.4154	9.36	3.82	67.80	69.82	2.02	2.98
250	259.0005	9.45	3.78	69.00	71.16	2.16	3.13
240	246.5684	6.48	2.70	66.60	68.18	1.58	2.37
255	259.5084	5.38	2.11	70.20	71.28	1.08	1.54
380	371.7000	-15.00	-3.95	84.74	80.63	-4.11	-4.85
380	374.1760	-6.49	-1.71	82.99	80.98	-2.01	-2.42
250	257.6000	8.60	3.44	69.00	70.82	1.82	2.64
235	243.0300	8.03	3.42	65.40	67.33	1.93	2.95

Table 6-2. The load management demands in period order during the scheduled duration.

DLC demand (MW)	DLC demand as % of the total controlled demand	ESS type I demand (MW)	ESS type I demand as % of the total controlled demand	ESS type II demand (MW)	ESS type II demand as % of the total controlled demand
0	0	2.20	68.75	1.00	31.25
0	0	2.20	84.46	0.40	15.54
-16.00	84.66	-1.90	10.05	-1.00	5.29
-17.00	85.86	-1.80	9.09	-1.00	5.05
8.91	84.75	1.60	15.25	0	0
8.25	72.05	2.20	19.21	1.00	8.73
8.25	91.67	0.60	6.63	0.15	1.70
7.26	100.00	0	0	0	0
-13.63	90.84	-0.37	2.49	-1.00	6.67
-17.50	92.82	-0.35	1.88	-1.00	5.30
8.62	92.86	0.43	4.66	0.23	2.47
8.70	85.85	0.43	4.28	1.00	9.87
7.02	87.53	0	0	1.00	12.47
6.00	100.00	0	0	0	0
-15.95	94.77	0	0	-0.88	5.23
-17.00	94.44	0	0	-1.00	5.56
9.00	100.00	0	0	0	0
8.69	89.68	0	0	1.00	10.32
7.86	97.72	0	0	0.18	2.28
6.82	100.00	0	0	0	0
-15.77	94.04	0	0	-1.00	5.96
-18.00	100.00	0	0	0	0
9.25	100.00	0	0	0	0
8.98	89.98	0	0	1.00	10.02
8.00	88.89	0	0	1.00	11.11
6.94	100.00	0	0	0	0
-11.48	95.63	0	0	-0.52	4.37
-17.48	97.13	0	0	-0.52	2.87
8.42	100.00	0	0	0	0
9.00	100.00	0	0	0	0
5.57	84.78	0	0	1.00	15.22
4.51	100.00	0	0	0	0
-11.40	85.71	-1.90	14.29	0	0
-3.61	61.98	-1.80	30.91	-0.41	7.11
7.60	100.00	0	0	0	0
7.03	87.55	0	0	1.00	12.45

6.3 ECONOMIC VALUATION OF LOAD MANAGEMENT PROGRAMS

This section is intended to provide an economic valuation of the load management programs. Even though the load management programs are used to minimize the cost of production in section 6.2 for the regulated energy market, the purpose may not serve well for an ESCO intending to profit from the auction market. Thus, the various objectives of load management scheduling presented in Chapter 4 are evaluated in this section to provide further insights into how the different objectives may influence the ESCO operation. In section 6.3.1, the ESCO is described. In section 6.3.2, the four major objectives for load management scheduling are compared. In section 6.3.3, the conflicts of maintaining system reliability and making profit using load management are discussed. In particular, the roles of ESCOs and regulated companies (ISOs and DISTCOs) in the load management programs are proposed. In section 6.3.4, the gap between a cost-based load management scheduling and a profit-based scheduling is closed, using various penalty factors formulated in section 3.4. A similar presentation was made in [12].

6.3.1 Customer Demand and Load Management Demand to an ESCO

An ESCO serves 20% of customer demand as shown in Appendix A. It also has 24% of controllable customer demand as shown in Appendix A. Additional information is shown in Appendix A, including the rate charged on the customer demand and controllable customer demand. The rebate structure given to customers participating in the DLC program is also described in Appendix A.2.2.2. In this example, the non-energy cash outlay is assumed to be zero, i.e., $NOY_D = 0$ for all D. There is no cash held by the ESCO at the beginning period, i.e., the ESCO has to decide on how much to borrow to pay for the cost of energy to serve the customers at the earlier periods. The annual percentage rate of borrowing and the annual percentage of investing are also presented in Appendix A.

6.3.2 Comparing the Various Economic Forces Behind Load Management Programs

Table 6-3 compares the results of scheduling customer demand using the load management programs with the various approaches shown in Chapter 4. Since the ESCO has to borrow to pay for the energy cost at the end of each day, while waiting for the customers to pay the cost of services at the beginning of the next month, the cash buildup is in general lower than the profit. All approaches result in a lower cost for energy and a higher profit of serving customer energy. Since the rate offered to customers is higher during peak periods and some customer demand is deferred during peak periods, the load management programs result in lower revenue.

Under the load-based approach, even though the peak demand is the lowest after scheduling, the peak demands during the various months are not always the lowest. For example, in the 1st month, the peak demand is the lowest under the cost-based approach at 65.70MW. However, during the same duration, the peak demand is higher at 68MW under the load-based approach. This is because the objective of a load-based approach minimizes the highest peak demand during the 6 months duration, which has a peak demand of 77MW in the 6th month. With this peak demand minimized to 74.91MW, the load-based approach has achieved its goal. Thus, the formulated load-based approach should be modified when there is multiple peak demand during the schedule duration.

Since a cost-based approach does not consider the impact of lowered revenue when the controllable demand during peak periods is deferred to off-peak periods, and when the paid back energy is lower than the deferred energy, the collected revenue under this approach is the lowest among all. Thus, even though the load-based approach results in the lowest cost of energy, this approach does not guarantee the highest profit.

A profit-based approach results in the highest profit, even when the cost of energy is not the lowest. By considering the impact of lowered revenue, this approach makes sure that only when the cost savings exceed the lowered revenue will energy deferment be conducted. In section 6.3.4, the cost-based approach and profit-based approach are further investigated.

Table 6-3. Results of scheduling customer demand using various objectives.

		Without load management programs	With load management programs			
			load-based	cost-based	profit-based	cash management
Maximum demand	overall	77MW	74.9081MW	77.0000MW	76.0000MW	75.8480MW
	1st month	70MW	68.0000MW	65.6960MW	66.4640MW	66.9440MW
	2nd month	72MW	70.0000MW	67.8800MW	66.4160MW	67.8880MW
	3rd month	74MW	72.0000MW	67.9200MW	70.0000MW	70.0000MW
	4th month	76MW	74.0000MW	71.4800MW	74.6960MW	74.6600MW
	5th month	77MW	73.4080MW	73.8400MW	76.0000MW	74.0000MW
	6th month	77MW	74.9081MW	77.0000MW	75.1336MW	75.8480MW
Cost of energy (including cost of rebate)		$137,449.71	$137,343.71	$137,015.96	$137,234.64	$137,182.95
Cost saving		0	$146.80	$474.55	$255.87	$307.56
Revenue		$186,820.00	$186,732.14	$186,480.74	$186,736.72	$186,753.95
Increase revenue		0	-$87.86	-$339.26	-$83.28	-$66.05
Profit (excluding interest rate factors)		$49,370.49	$49,365.51	$49,387.70	$49,435.18	$49,433.88
Increased profit		$0.00	$36.02	$58.21	$105.69	$104.39
Cash buildup		$49,283.92	$49,279.33	$ 49,302.96	$49,350.04	$49,487.00
Increased cash buildup		$0.00	$9.75	$61.54	$63.24	$245.58
DLC customers benefit		$0.00	$22.93	$77.07	$66.90	$71.70

Even though the profit reached is the highest, the profit-based approach does not guarantee the highest cash flows. In this example, the ESCO will receive the revenue at the beginning of the 3rd month after the energy is served. However, the ESCO has to pay the energy cost at the end of each day. Any cost saving made today has a higher impact than the lowered revenue. Thus, the cash management approach that includes the impact of interest payment results in higher cash flows than the profit-based approach.

In this example, there is only six periods in each day, and one day in each month. Therefore, the cost savings, increased profits, and customer benefits are relatively small. In addition, in this example, the impact of congestion cost is not considered. Thus, the market prices during peak periods are not significantly higher than during off-peak periods (less than 20%). As a result, the benefits of the load management programs are not yet fully realized.

6.3.3 Minimizing Customer Demand and Maximizing Profit: Looking into the Future

The load-based approach that minimizes peak demand is an important tool to ensure system reliability. However, as the results in Table 6-3 suggest, the load-based approach (Equation (4.2)) does not guarantee the highest profit and would not be in the best interest of an ESCO trying to maximize its profits. Given the benefit of the load management programs in maintaining a reliable system, should load management be controlled by the ESCO?

To answer that, the following issues should first be investigated. First, why would customers participate in the load management programs? Second, will market price always reflect the cost of unreliable power supply? Third, will the load-based approach that minimizes customer demand ensure a sufficient profit margin to companies investing in the load management programs?

If the power industry was re-regulated, and companies serving customer energy were allowed to make a profit, undoubtedly, customers should also be allowed to benefit from their own flexible and controllable demand. Assuming that customers were interested only in the economic benefit of their controllable demand, it is clear that they would find companies that can provide the best return for their controllable demand.

In the long run, market prices should reflect all costs and risks of an unreliable power supply in a perfectly competitive market. However, in the short run, it may not always be true in practice, even if the market is perfectly competitive. The market price may over or under reflect the cost of an unreliable power supply. Then, given the objective of the load-based approach that does not account for the cost of energy, the load-based approach definitely will not offer a company holding the load management programs as assets the best earning opportunity. Then, if a company is rational in its business practices, there is no reason why it would not choose to adopt a profit-based or cash management approach. Even if the market price reflects all costs and risks, such relationship may not always be linear. If the relationship is not linear, the load-based approach will again not perform as well as other approaches in maximizing profit. In addition, the profit margin of the load management programs may suffer from adopting the load-based approach. For an ESCO adopting the load-based approach, it is riskier to maintain a sufficient profit margin.

Since only companies that benefit most from the load management programs can provide the best return to the customers rendering their controllable demand, ESCOs that adopt the profit-based and cash management approaches are usually those who will serve the controllable demand. Certainly, that would also mean that ESCOs are willing to share the benefits of the controllable demand with the customers. Without considering the system reliability issue, it is then fair to suggest that ESCO controlled load management programs should be encouraged, or at least not prohibited. A profit-oriented ESCO will provide the customers the best return on the controllable demand while still profiting from the customer demand flexibility.

Will the nature of customers, maximizing his/her benefits, and ESCO, maximizing the return on the load management programs still guard against system instability? Undoubtedly, any rational load management programs in a rational market will improve system reliability to some degree. However, since the primary concern of a load-based approach is just to minimize peak demand, it is usually the most effective. Even though the load-based approach is the most effective approach, it is definitely not in the best interest of both an ESCO and its customers. So, to maintain the most reliable system, should regulated companies (DISTCOs and ISOs), instead of ESCOs, handle the controllable demand? Prior to addressing this question, a more fundamental question is – is practical to have regulated companies controlling the load management demand? Load management programs require the communication facilities to facilitate the control of customer demand, particularly the DLC program. When customers are free to choose any company to serve their controllable demand, the communication facilities will need to be separable so that any company can control any customer demand. If new technology becomes available, so that customer demand is easily controllable, this requirement is not a problem. However, the existing utility practice has communication facilities that usually are embedded in the distribution management system, that would be costly if they were to be separated. Thus, it is practical at the present time to have a regulated company handling the communication systems that governs the controllable demand.

If it is practical to have regulated companies handling the communications, should these regulated companies utilize the load-based approach in minimizing the risk of power supply? There is no single answer that can address this issue. It is fair to say that it will largely depend on how government regulations are established and how ISOs will interpret these regulations. If government regulations agree that the market forces are sufficient to maintain a reliable system, then, these regulated companies should practice according to what the ESCOs have requested. That means that the ESCOs will approach the customers for more flexible demand and decide on how the controllable customer demand should be scheduled, while the regulated companies, DISTCOs or ISOs, carry out the decisions made by the ESCOs.

If government regulations believe that ISOs should take additional actions, other than letting market forces determine the system reliability level, and that ISOs decide to hold some load management demand to maintain system reliability, the relationships among customers, ESCOs, and regulated companies can be complicated. One approach is for the ISOs to have ESCOs render some load management demands under ISOs discretion. In this approach, all ESCOs must have some load management demands, at least sufficient to meet the ISOs requirements. This definitely will complicate the operations of ESCOs not interested in offering load management programs to the customers. Another approach is for ISOs to establish an auction market for both customers offering load management demand and ESCOs bidding for the controllable demand. Shown in Figure 6-1, it consists of the bids from the ESCOs requiring controllable energy services at given rates and offers from the customers rendering their controllable demand at given costs. The ISOs would match the bids from the ESCOs and offers from the customers. No bids from the ESCOs should be accepted if the ESCOs bids are lower than the offers from the customers. The amount accepted for both customer offers and ESCOs bids will be controlled by the ESCO decision. To obtain the desired load management demand, ISOs will accept additional customer offers. These costs will be subsidized using the auction surplus and the monthly charges that each customer has to pay the DISTCOs for maintaining the distribution system. However, this approach has some practical difficulties. First, this approach would require every customer wishing to benefit from the flexible demand to bid in the market. Is it practical to implement? Second, given that each customer offers different load management demand, how should the controllable demand be graded and auctioned? Finally, should auction surpluses be used to compensate for the cost used to acquire additional customers?

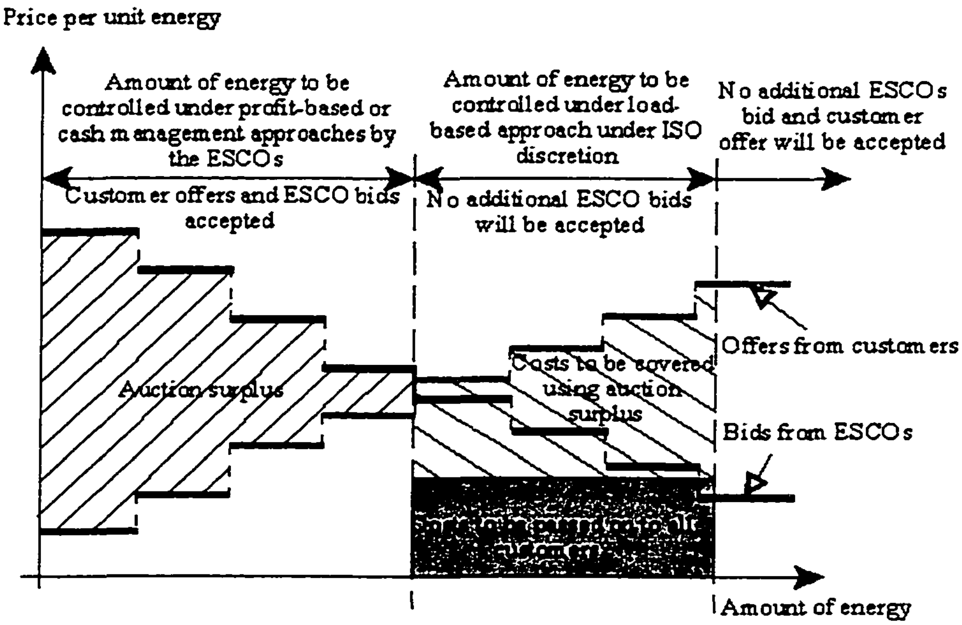

Figure 6-1. Relationships among ESCOs, ISOs, and customers using auction mechanism.

6.3.4 *Minimizing Cost and Maximizing Profit: Closing the Gap*

The differences between cost-based approach and profit-based approach are the results of energy difference between paid back energy and deferred energy and rate difference between paid back duration and deferred duration. The differences between the two approaches can be reduced by adding (3.6) and (3.7) to the profit-based approach and adding (3.8) and (3.9) to the cost-based approach. Table 6-4 shows the results after including the different remedies to the two approaches. A similar comparison has been made using different data [12]. In this example, including the penalty for any revenue increase, (3.7), does not affect the ultimate solution. This is because the deferred energy of all chosen controlling sequences of the customer demand is higher than the paid back energy.

Table 6-4. Results of scheduling customer demand using various objectives.

	Cost-based		Profit-based	
	- (3.8)	- (3.8) and (3.9)	- (3.6) and (3.7)	- (3.6)
Cost of energy (including cost of rebate)	$137,049.89	$137,149.36	$137,149.36	$137,211.48
Revenue	$186,548.70	$186,641.44	$186,641.44	$186,699.62
Profit	$49,411.20	$49,428.18	$49,428.18	$49,429.99
DLC customers benefit	$87.62	$63.90	$63.90	$58.14

6.4 MARKET CONTRACTS AND LOAD MANAGEMENT SCHEDULING

Examples in section 6.3 show the economics of scheduling customer demand. In this section, the specifications of market contracts are assumed. The ESCO presented in section 6.3 will be buying energy contracts to satisfy the customer demand while profiting from the energy service. Appendix A.3.2 shows the contract specifications and prices. Additional customers contract specifications are also presented in Appendix A.2.2.2.

Table 6-5 and Table 6-6 shows the results of contract purchasing schemes, when no load management programs are available and when the load management programs shown in section 6.3 are available, of the ESCO in section 6.3.

Even though the reliability level provided is higher and the volatility level allowed is higher, no contract type D is purchased. To meet the reliability level requested by the customers, additional contract type C is purchased. For instance, during the 5th period in Table 6-5, the customer demand is only 42MW, however, the purchased amount is 42.4421 MW (42.4421 number of contracts with each delivering 1MW). The ESCO purchase an additional 1.4981 MW of energy to meet the reliability requirement.

Similarly, contract type A and B are not favored because their prices are relatively higher than the prices for contract type C and D. Table 6-7 shows an additional case where the market price for contract type B during the 31st period is changed from \$78.81/MW to \$58.81/MW. With the changed price for contract type B, this contract is eventually purchased to serve customer energy.

Table 6-8 compares the results shown in Table 6-5 through Table 6-7. The increased profit is much higher for results in Table 6-7 because of the price drop for contract type B during the 31st period.

Table 6-5. Contract purchasing schemes of the ESCO when no load management programs are available.

Period	Demand	Contract type			
		A	B	C	D
1	40	0	0	40.4211	0
2	42	—	—	42.4421	0
3	68	—	—	68.7158	0
4	68	—	—	68.7158	0
5	42	—	—	42.4421	0
6	40	—	—	40.4211	0
7	42	0	0	42.4421	0
8	44	—	—	44.4632	0
9	68	—	—	68.7158	0
10	70	—	—	70.7368	0
11	43	—	—	43.4526	0
12	42	—	—	42.4421	0
13	44	0	0	44.4632	0
14	45	—	—	45.4737	0
15	70	—	—	70.7368	0
16	72	—	—	72.7579	0
17	46	—	—	46.4842	0
18	44	—	—	44.4632	0
19	45	0	0	45.4737	0
20	46	—	—	46.4842	0
21	74	—	—	74.7789	0
22	72	—	—	72.7579	0
23	47	—	—	47.4947	0
24	44	—	—	44.4632	0
25	46	0	0	46.4842	0
26	48	—	—	48.5053	0
27	74	—	—	74.7789	0
28	76	—	—	76.8000	0
29	49	—	—	49.5158	0
30	50	—	—	50.5263	0
31	48	0	0	48.5053	0
32	51	—	—	51.5368	0
33	77	—	—	77.8105	0
34	76	—	—	76.8000	0
35	50	—	—	50.5263	0
36	47	—	—	47.4947	0

Table 6-6. Contract purchasing schemes of the ESCO when load management programs are available.

Period	Demand after scheduling	Contract type			
		A	B	C	D
1	40.0000	0	0	40.4211	0
2	42.0000	—	—	42.4421	0
3	66.4640	—	—	67.0989	0
4	63.9200	—	—	64.4211	0
5	43.8072	—	—	44.3444	0
6	41.7712	—	—	42.2855	0
7	43.4040	0	0	43.9200	0
8	44.7920	—	—	45.2968	0
9	67.4720	—	—	68.1600	0
10	65.8000	—	—	66.3158	0
11	44.6564	—	—	45.1962	0
12	43.8960	—	—	44.4379	0
13	44.9020	0	0	45.4126	0
14	45.2720	—	—	45.7600	0
15	70.0000	—	—	70.7368	0
16	67.9200	—	—	68.4632	0
17	47.5096	—	—	48.0733	0
18	45.8768	—	—	46.4387	0
19	45.6120	0	0	46.1179	0
20	46.0000	—	—	46.4842	0
21	72.3200	—	—	73.0105	0
22	67.6800	—	—	68.2105	0
23	48.9296	—	—	49.5259	0
24	45.8888	—	—	46.4514	0
25	47.5000	0	0	48.0632	0
26	48.8520	—	—	49.4021	0
27	74.0000	—	—	74.7789	0
28	71.6800	—	—	72.2526	0
29	50.5984	—	—	51.1983	0
30	51.9872	—	—	52.6181	0
31	48.6480	0	0	49.1874	0
32	51.0000	—	—	51.5368	0
33	74.2640	—	—	74.9305	0
34	75.1336	—	—	75.8880	0
35	51.8240	—	—	52.4463	0
36	48.6872	—	—	49.2707	0

Table 6-7. Control purchasing schemes when market price for contract type B at 31st period changed.

Period	Demand after scheduling	Contract type A	B	C	D
1	40.0000	0	0	40.4211	0
2	42.0000	—	—	42.4421	0
3	66.4640	—	—	67.0989	0
4	63.9200	—	—	64.4211	0
5	43.8072	—	—	44.3444	0
6	41.7712	—	—	42.2855	0
7	43.4040	0	0	43.9200	0
8	44.7920	—	—	45.2968	0
9	68.0000	—	—	68.7158	0
10	65.8000	—	—	66.3158	0
11	44.5540	—	—	45.0884	0
12	43.9320	—	—	44.4758	0
13	44.6300	0	0	45.1263	0
14	45.0000	—	—	45.4737	0
15	70.0000	—	—	70.7368	0
16	67.9200	—	—	68.4632	0
17	47.5096	—	—	48.0733	0
18	45.8768	—	—	46.4387	0
19	45.6120	0	0	46.1179	0
20	46.0000	—	—	46.4842	0
21	73.4400	—	—	74.1895	0
22	67.6800	—	—	68.2105	0
23	48.7088	—	—	49.2935	0
24	45.9544	—	—	46.5204	0
25	46.9320	0	0	47.4653	0
26	48.2840	—	—	48.8042	0
27	69.5600	—	—	70.1053	0
28	71.6800	—	—	72.2526	0
29	51.3652	—	—	52.0055	0
30	52.1900	—	—	52.8316	0
31	50.1900	0	50.2120	0	0
32	52.9272	—	—	2.2963	0
33	74.2640	—	—	23.6614	0
34	75.1336	—	—	24.6189	0
35	51.8240	—	—	1.1772	0
36	48.6872	—	—	0	0

Table 6-8. Results of scheduling customer demand before and after using load management programs.

	Before load management programs	After load management programs: No price change	contract type B prices are changed
Cost of energy	$131,989.61	$131,634.42	$128,131.55
Revenue	$186,820.00	$186,653.73	$186,605.92
Profit	$54,830.39	$54,946.05	$58,394.13
Increased profit	0	$115.66	$356.37
DLC customer benefits	0	$73.26	$80.24

CHAPTER 7 ESCO OPERATIONAL PLANNING ISSUES

The examples presented in Chapter 6 illustrated the economic benefits of load management programs in an ESCO operation, and showed how market contracts may be selected to meet customer demand. These examples are important in establishing the fundamental operational structure of an ESCO, i.e., maximizing ESCO profit/cash flows. How the models and results described in Chapter 6 may be applied towards several ESCO operations and management is presented in this chapter. In section 7.1, various issues that an ESCO is interested in are presented. Section 7.2 through section 7.6 shows how the models and results described in Chapter 6 may be applied to address these various issues. Section 7.7 concludes this chapter by examining the limitations of using the scheduling customer demand model for decision making.

7.1 INTRODUCTION

In section 2.4, an ESCO operation and management of an ESCO was classified into various stages. Each stage defines what an ESCO had to decide, along with the characteristics of various components that influence an ESCO decision. In this chapter, the operational conditions described in Chapter 6 are applied to an ESCO operating in a re-regulated environment. Consequently, various issues that the ESCO need to address by the ESCO. They include:

- How should the ESCO react towards the changes in customer demand and market prices in the near term? This is a reactive scheduling/control issue as described in section 2.4.5. The changes in operating conditions and the ESCO's reactions are further described in section 7.2.
- Given the benefits of the DLC program, should the ESCO expand it? If yes, how should the ESCO expand the program? When the customer contracts are not alterable, this is a scheduling issue as described in section 2.4.4. The changes in operating conditions and the ESCO's reactions are further described in section 7.3. When the rebate schemes used to attract additional customers into the DLC program are alterable, this is short-range planning as described in section 2.4.3. The changes in operating conditions and the ESCO's reactions are further described in section 7.4.
- Does the ESCO gain market shares and earn sufficient profits under existing rate structure? This is middle-range planning as described in section 2.4.2. The changes in operating conditions and the ESCO reactions are further described in section 7.4.

- Should the ESCO utilize any energy storage system? Given the higher investment cost, this is long-range planning as described in section 2.4.1. The changes in operating conditions and the ESCO reactions are further described in section 7.5.

The analysis described in this chapter assumes that all factors influencing the ESCO operation and management are deterministic.

7.2 REACTIVE SCHEDULING/CONTROL

The following changes in the market conditions will be investigated:

- Prior to the beginning of the 1st period, the market prices for contract type C for the 3rd, 4th, and 5th periods increase by 20% to $84.71, $84.72, and $69.76 per MW respectively. The ESCO's reactions are described in section 7.2.1.
- Prior to the beginning of the 1st period, customer demand during the 3rd, 4th, and 5th periods increases by 20% to 82.6 MW, 81.6 MW, and 50.4 MW respectively. The ESCO's reactions are described in section 7.2.2.
- Prior to the beginning of the 1st period, controllable demand type 2 during the 3rd, 4th, and 5th periods increases by 20% to 0.1152 MW, 0.1224 MW, and 0.0792 MW respectively. The ESCO's reactions are described in section 7.2.3.

7.2.1 Changes in the Market Prices

Table 7-1 shows the changes in contract purchasing scheme given the changes in the customer demand. Table 7-2 shows the economic implications given the changes in the customer demand. Table 7-3 shows the changes in the controllable demand control scheme given the changes in the customer demand.

Due to the increases in market prices on contract type C from the 3rd period to the 5th period, the combination of market contracts type A, C and D is preferred during the first 6 periods. The purchasing scheme for the 1st, 2nd, and 6th periods is affected because contract type A delivers energy for a duration of 6 periods, beginning with the 1st period. Even though only the market prices in the 1st month have changed, the changes in the purchasing scheme extend into the 2nd month. The energy contracts purchased to serve customer energy during the 7th and 8th period have decreased by 0.6063 and 1.0004 respectively. The change in the purchasing scheme is due to a change in the load management schedule. The market price increase in the three periods makes shifting the controllable demand at the beginning of the 3rd more desirable than shifting the controllable demand at the beginning of the 4th period. Even though the total controlled duration is similar in both cases, the total rebate received by the customers, rendering controllable demand to the ESCO, increases when the market price changes because the total deferred controllable demand is higher when the market prices increase.

Table 7-1. Purchasing market contracts before and after changes in market prices.

Period	Before changes in the market prices					After changes in the market prices				
	Demand after scheduling	Contract type				Demand after scheduling	Contract type			
		A	B	C	D		A	B	C	D
1	40.0000	0	0	40.4211	0	40.0000	40.4211	0	0	0
2	42.0000	—	—	42.4421	0	42.0000	—	—	2.0211	0
3	66.4640	—	—	67.0989	0	64.1600	—	—	0	23.7526
4	63.9200	—	—	64.4211	0	63.9200	—	—	0	23.5052
5	43.8072	—	—	44.3444	0	44.1384	—	—	0	4.1839
6	41.7712	—	—	42.2855	0	41.9800	—	—	2.0842	0
7	43.4040	0	0	43.9200	0	43.9800	0	0	44.5263	0
8	44.7920	—	—	45.2968	0	45.7424	—	—	46.2973	0
9	67.4720	—	—	68.1600	0	67.4720	—	—	68.1600	0
10	65.8000	—	—	66.3158	0	65.8000	—	—	66.3158	0
11	44.6564	—	—	45.1962	0	44.6564	—	—	45.1962	0
12	43.8960	—	—	44.4379	0	43.8960	—	—	44.4379	0
13	44.9020	0	0	45.4126	0	44.9020	0	0	45.4126	0
14	45.2720	—	—	45.7600	0	45.2720	—	—	45.7600	0
15	70.0000	—	—	70.7368	0	70.0000	—	—	70.7368	0
16	67.9200	—	—	68.4632	0	67.9200	—	—	68.4632	0
17	47.5096	—	—	48.0733	0	47.5096	—	—	48.0733	0
18	45.8768	—	—	46.4387	0	45.8768	—	—	46.4387	0
19	45.6120	0	0	46.1179	0	45.6120	0	0	46.1179	0
20	46.0000	—	—	46.4842	0	46.0000	—	—	46.4842	0
21	72.3200	—	—	73.0105	0	72.3200	—	—	73.0105	0
22	67.6800	—	—	68.2105	0	67.6800	—	—	68.2105	0
23	48.9296	—	—	49.5259	0	48.9296	2—	—	49.5259	0
24	45.8888	—	—	46.4514	0	45.8888	—	—	46.4514	0
25	47.5000	0	0	48.0632	0	47.5000	0	0	48.0632	0
26	48.8520	—	—	49.4021	0	48.8520	—	—	49.4021	0
27	74.0000	—	—	74.7789	0	74.0000	—	—	74.7789	0
28	71.6800	—	—	72.2526	0	71.6800	—	—	72.2526	0
29	50.5984	—	—	51.1983	0	50.5984	—	—	51.1983	0
30	51.9872	—	—	52.6181	0	51.9872	—	—	52.6181	0
31	48.6480	0	0	49.1874	0	48.6480	0	0	49.1874	0
32	51.0000	—	—	51.5368	0	51.0000	—	—	51.5368	0
33	74.2640	—	—	74.9305	0	74.2640	—	—	74.9305	0
34	75.1336	—	—	75.8880	0	75.1336	—	—	75.8880	0
35	51.8240	—	—	52.4463	0	51.8240	—	—	52.4463	0
36	48.6872	—	—	49.2707	0	48.6872	—	—	49.2707	0

Table 7-2. Economic implications of the changes on the market prices.

	Before market price changes	After market price changes
Cost of energy	\$131,634.42	\$132,343.56
Revenue	\$186,653.73	\$186,611.39
Profit	\$54,946.05	\$54,188.82
Decreased profit	0	\$757.23
DLC customer benefits	\$73.26	\$79.02

Table 7-3. Controllable customer demand control scheme before and after changes in market prices.

Controllable customer demand			Number of customers scheduled		
Type	Beginning control at period	Deferment duration	Before changes in market prices	After changes in market prices	Net changes in market prices
1	3	2	24	24	0
1	9	2	8	8	0
1	10	1	16	16	0
1	16	1	24	24	0
1	21	2	24	24	0
1	28	1	24	24	0
1	34	1	24	24	0
2	3	2	0	24	24
2	4	1	24	0	-24
2	10	1	24	24	0
2	16	1	24	24	0
2	22	1	24	24	0
2	28	1	24	24	0
2	33	1	24	24	0

7.2.2 Changes in the Customer Demand

Table 7-4 shows the changes in contract purchasing scheme given the changes in the customer demand. Table 7-5 shows the economic implications given the changes in the customer demand. Table 7-6 shows the changes in the controllable demand control scheme given the changes in the customer demand.

Due to the increase in the customer demand, additional energy contracts type C are purchased for the increased demand in the 3rd, 4th, and 5th period. Contracts type C purchased for the 3rd, 4th, and 5th period increases by 13.7432, 13.7432, and 8.4884 respectively. Since the market prices do not change, the ESCO does not change the type of contracts it purchases. The control scheme for controllable demand does not change for two reasons. First, the market prices do not change during the scheduling duration. Second, only contracts type C with 1 period of delivery duration are purchased in this example, a demand change in the 3rd, 4th, and 5th period does not affect the purchasing scheme in other periods. Since serving customer demand at any period is always profitable in this example, an increase in customer demand increases the profit of serving the customer.

Table 7-4. Purchasing market contracts before and after changes in customer demand.

Period	Before changes in the market prices					After changes in the market prices				
	Demand after scheduling	Contract type				Demand after scheduling	Contract type			
		A	B	C	D		A	B	C	D
1	40.0000	0	0	40.4211	0	40.0000	0	0	40.4211	0
2	42.0000	—	—	42.4421	0	42.0000	—	—	42.4421	0
3	66.4640	—	—	67.0989	0	80.0640	—	—	80.8421	0
4	63.9200	—	—	64.4211	0	77.5200	—	—	78.1642	0
5	43.8072	—	—	44.3444	0	52.2072	—	—	52.8328	0
6	41.7712	—	—	42.2855	0	41.7712	—	—	42.2855	0
7	43.4040	0	0	43.9200	0	43.4040	0	0	43.9200	0
8	44.7920	—	—	45.2968	0	44.7920	—	—	45.2968	0
9	67.4720	—	—	68.1600	0	67.4720	—	—	68.1600	0
10	65.8000	—	—	66.3158	0	65.8000	—	—	66.3158	0
11	44.6564	—	—	45.1962	0	44.6564	—	—	45.1962	0
12	43.8960	—	—	44.4379	0	43.8960	—	—	44.4379	0
13	44.9020	0	0	45.4126	0	44.9020	0	0	45.4126	0
14	45.2720	—	—	45.7600	0	45.2720	—	—	45.7600	0
15	70.0000	—	—	70.7368	0	70.0000	—	—	70.7368	0
16	67.9200	—	—	68.4632	0	67.9200	—	—	68.4632	0
17	47.5096	—	—	48.0733	0	47.5096	—	—	48.0733	0
18	45.8768	—	—	46.4387	0	45.8768	—	—	46.4387	0
19	45.6120	0	0	46.1179	0	45.6120	0	0	46.1179	0
20	46.0000	—	—	46.4842	0	46.0000	—	—	46.4842	0
21	72.3200	—	—	73.0105	0	72.3200	—	—	73.0105	0
22	67.6800	—	—	68.2105	0	67.6800	—	—	68.2105	0
23	48.9296	—	—	49.5259	0	48.9296	—	—	49.5259	0
24	45.8888	—	—	46.4514	0	45.8888	—	—	46.4514	0
25	47.5000	0	0	48.0632	0	47.5000	0	0	48.0632	0
26	48.8520	—	—	49.4021	0	48.8520	—	—	49.4021	0
27	74.0000	—	—	74.7789	0	74.0000	—	—	74.7789	0
28	71.6800	—	—	72.2526	0	71.6800	—	—	72.2526	0
29	50.5984	—	—	51.1983	0	50.5984	—	—	51.1983	0
30	51.9872	—	—	52.6181	0	51.9872	—	—	52.6181	0
31	48.6480	0	0	49.1874	0	48.6480	0	0	49.1874	0
32	51.0000	—	—	51.5368	0	51.0000	—	—	51.5368	0
33	74.2640	—	—	74.9305	0	74.2640	—	—	74.9305	0
34	75.1336	—	—	75.8880	0	75.1336	—	—	75.8880	0
35	51.8240	—	—	52.4463	0	51.8240	—	—	52.4463	0
36	48.6872	—	—	49.2707	0	48.6872	—	—	49.2707	0

Table 7-5. Economic implications of the changes in customer demand.

	Before market price changes	After market price changes
Cost of energy	$131,634.42	$ 134,234.66
Revenue	$186,653.73	$ 190,207.92
Profit	$54,946.05	$ 55,934.34
Increased profit	0	$ 1042.17
DLC customer benefits	$73.26	$38.92

Table 7-6. Controllable customer demand control scheme before and after changes in customer demand.

Controllable customer demand			Number of customers scheduled		
Type	Beginning control at period	Deferment duration	Before changes in market prices	After changes in market prices	Net changes in market prices
1	3	2	24	24	0
1	9	2	8	8	0
1	10	1	16	16	0
1	16	1	24	24	0
1	21	2	24	24	0
1	28	1	24	24	0
1	34	1	24	24	0
2	4	1	24	24	0
2	10	1	24	24	0
2	16	1	24	24	0
2	22	1	24	24	0
2	28	1	24	24	0
2	33	1	24	24	0

7.2.3 Changes in the controllable demand

Table 7-7 shows the changes in the contract purchasing schemes given the changes in the controllable demand. Table 7-8 shows the economic implications given the changes in the controllable demand. Table 7-9 shows the changes in the controllable demand control scheme given the changes in the controllable demand.

In this example, increases in the controllable demand reduce the number of contracts type C purchased for the 4th period by 0.5154 units, but increase the number of contracts type C purchased for the 5th, 6th, and 7th period by 0.1804, 0.2061, and 0.1288 units respectively. The changes in the purchasing scheme is due to the selected controlling scheme for the controllable customer demand type 2. Shown in Table 7-9, the selected control scheme defers 24 customers demand type 2 at the 4th period for 1 period, and have these deferred demands paid back at 5th, 6th, 7th, and 8th period. This control scheme, which does not vary with the modification in the controllable demand, results in the change in the purchasing scheme.

Since the rebate system is proportionate to the amount of energy deferred, changes in the controllable demand increases the customer benefits for participating in the DLC program.

Table 7-7. Purchasing market contracts before and after changes in controllable customer demand.

Period	Before changes in market prices					After changes in market prices				
	Demand after scheduling	Contract type A	Contract type B	Contract type C	Contract type D	Demand after scheduling	Contract type A	Contract type B	Contract type C	Contract type D
1	40.0000	0	0	40.4211	0	40.0000	0	0	40.4211	0
2	42.0000	—	—	42.4421	0	42.0000	—	—	42.4421	0
3	66.4640	—	—	67.0989	0	66.4640	—	—	67.0989	0
4	63.9200	—	—	64.4211	0	63.4304	—	—	63.9057	0
5	43.8072	—	—	44.3444	0	43.9786	—	—	44.5248	0
6	41.7712	—	—	42.2855	0	41.9670	—	—	42.4916	0
7	43.4040	0	0	43.9200	0	43.5264	0	0	44.0488	0
8	44.7920	—	—	45.2968	0	44.7920	—	—	45.2968	0
9	67.4720	—	—	68.1600	0	67.4720	—	—	68.1600	0
10	65.8000	—	—	66.3158	0	65.8000	—	—	66.3158	0
11	44.6564	—	—	45.1962	0	44.6564	—	—	45.1962	0
12	43.8960	—	—	44.4379	0	43.8960	—	—	44.4379	0
13	44.9020	0	0	45.4126	0	44.9020	0	0	45.4126	0
14	45.2720	—	—	45.7600	0	45.2720	—	—	45.7600	0
15	70.0000	—	—	70.7368	0	70.0000	—	—	70.7368	0
16	67.9200	—	—	68.4632	0	67.9200	—	—	68.4632	0
17	47.5096	—	—	48.0733	0	47.5096	—	—	48.0733	0
18	45.8768	—	—	46.4387	0	45.8768	—	—	46.4387	0
19	45.6120	0	0	46.1179	0	45.6120	0	0	46.1179	0
20	46.0000	—	—	46.4842	0	46.0000	—	—	46.4842	0
21	72.3200	—	—	73.0105	0	72.3200	—	—	73.0105	0
22	67.6800	—	—	68.2105	0	67.6800	—	—	68.2105	0
23	48.9296	—	—	49.5259	0	48.9296	—	—	49.5259	0
24	45.8888	—	—	46.4514	0	45.8888	—	—	46.4514	0
25	47.5000	0	0	48.0632	0	47.5000	0	0	48.0632	0
26	48.8520	—	—	49.4021	0	48.8520	—	—	49.4021	0
27	74.0000	—	—	74.7789	0	74.0000	—	—	74.7789	0
28	71.6800	—	—	72.2526	0	71.6800	—	—	72.2526	0
29	50.5984	—	—	51.1983	0	50.5984	—	—	51.1983	0
30	51.9872	—	—	52.6181	0	51.9872	—	—	52.6181	0
31	48.6480	0	0	49.1874	0	48.6480	0	0	49.1874	0
32	51.0000	—	—	51.5368	0	51.0000	—	—	51.5368	0
33	74.2640	—	—	74.9305	0	74.2640	—	—	74.9305	0
34	75.1336	—	—	75.8880	0	75.1336	—	—	75.8880	0
35	51.8240	—	—	52.4463	0	51.8240	—	—	52.4463	0
36	48.6872	—	—	49.2707	0	48.6872	—	—	49.2707	0

Table 7-8. Economic implications of the changes in controllable customer demand.

	Before market price changes	After market price changes
Cost of energy	$131,634.42	$ 132,308.08
Revenue	$186,653.73	$ 187,251.88
Profit	$54,946.05	$ 54,948.82
Increased profit	0	$2.77
DLC customer benefits	$73.26	$74.48

Table 7-9. Controllable customer demand control scheme before and after changes in controllable demand.

Controllable customer demand			Number of customers scheduled		
Type	Beginning control at period	Deferment duration	Before changes in market prices	After changes in market prices	Net changes in market prices
1	3	2	24	24	0
1	9	2	8	8	0
1	10	1	16	16	0
1	16	1	24	24	0
1	21	2	24	24	0
1	28	1	24	24	0
1	34	1	24	24	0
2	4	1	24	24	0
2	10	1	24	24	0
2	16	1	24	24	0
2	22	1	24	24	0
2	28	1	24	24	0
2	33	1	24	24	0

7.2.4 Remarks

The scheduling models used in the analyses in section 7.2.1 through 7.2.3 use six months of data. However, the interested issue in section 7.2.1 through 7.2.3 is only the responses of an ESCO in a short period of time (less than a day), given the changes in the operating conditions. The purpose of using six months of data that is to show that purchasing and control schemes in the immediate days may be affected, as section 7.2.1 shows, even when changes in the operating conditions occur only at the reactive scheduling/control level. It is also clear, from these examples, that the impact of changed operating conditions on the purchasing and control schemes in the future declines gradually.

At the reactive scheduling/control level, knowing how to react promptly to the changes in operating conditions is important. In scheduling models, similar to those proposed in this research, the fewer variables there are in the models the faster one will be able to find an optimal decision. This corresponds to reducing the scheduling duration. However, the failure to consider operating conditions in the immediate future can prevent one from making a better decision. Unfortunately, finding an *optimal* scheduling duration can be difficult. For example, in section 7.2.1, the optimal scheduling duration would be 2 months, but, in section 7.2.2 and 7.2.3, the optimal scheduling duration would be only 1 month.

7.3 SCHEDULING

In the long run, an ESCO may not be certain if the DLC program can be profitable, as the market may react to lower the profitability of load management programs. However, the example presented shows that the DLC program is profitable, at least in the near future. In the scheduling level, the ESCO is assumed not to change the variable rebate system. Instead, the ESCO is interested to know how much rebate should be given to the customers to encourage their participation in the DLC program for *only* one month. The general approach used to determine the *optimal* rebate is shown in Figure 7-1.

STEP 1	Determine the marginal benefits of increasing the number of customers participating in the DLC program.
STEP 2	Determine the marginal costs of offering fixed rebates to attract an additional number of customers to participate in the DLC program.
STEP 3	Determine the marginal profits of acquiring additional controllable customer demand into the DLC program at the scheduling level.
STEP 4	Determine the return on investment of acquiring additional controllable customer demand into the DLC program at the scheduling level.
STEP 5	Select an *optimal* fixed rebate that provides the best return on investment or marginal profits to the ESCO.

Figure 7-1. Determining an *optimal* fixed rebate for an ESCO.

In section 7.3.1, the scheduling model is used to trace the marginal benefit of acquiring an additional customer to participate in the DLC program. In section 7.3.2, the ESCO uses the results in section 7.3.1 and studies on how customers respond to a given rebate to select an *optimal* rebate to attract the desired participation. Section 7.3.3 comments on the results.

7.3.1 Tracing the Marginal Benefit of Acquiring Additional Customers

In order to evaluate the optimal rebate to attract the desired customer participation in the DLC program, an ESCO needs to realize the marginal benefit of acquiring additional customers. The ESCO in this example has two types of customers participating in the DLC program. Using the original customer size in the DLC program as the base, Table 7-10 shows the marginal benefits of acquiring additional customers into the DLC program for the 1st month only.

Even though the marginal benefits in Table 7-10 are obtained by solving the linear programming model, similar results can be obtained using parametric analysis. To use parametric analysis, g_1 and g_2 in (3.5), , $\forall\, j = 1{:}6$, are changed to $24+\lambda_1 5$ and $24+\lambda_2 5$ respectively.

Table 7-10. Marginal benefits of acquiring additional customers into the DLC program.

Marginal benefits		Additional number of customers type 2 acquired			
		$0\ (\lambda_2 = 0)$	$5\ (\lambda_2 = 1)$	$10\ (\lambda_2 = 2)$	$15\ (\lambda_2 = 3)$
Additional number of customers type 1 acquired	$0\ (\lambda_1 = 0)$	\$0.00	\$1.50	\$3.01	\$4.51
	$5\ (\lambda_1 = 1)$	\$2.25	\$3.75	\$5.26	\$6.76
	$10\ (\lambda_1 = 2)$	\$4.50	\$6.00	\$7.51	\$9.01
	$15\ (\lambda_1 = 3)$	\$6.75	\$8.25	\$9.76	\$11.26

7.3.2 *Finding an Optimal Rebate at the Scheduling Level*

Suppose that the ESCO has gathered information on the rebates the customers desire in order to participate in the DLC program under the terms described in Appendix A. This information is shown in Table 7-11. Then, Table 7-12 shows the marginal cost of acquiring additional customers for the DLC program. Table 7-13 shows the marginal profit of acquiring additional customers into the DLC program. Table 7-13 is the results of subtracting the marginal costs in Table 7-12 from the marginal benefits in Table 7-10. Table 7-14 shows the return on investment of acquiring additional customers into the DLC program. Table 7-14 is the result of dividing the marginal profits in Table 7-13 by the marginal costs in Table 7-12.

Table 7-11. Rebates desired by customers in order to participate in the DLC program.

Additional customers type 1 desired	Per customer rebate desired by customer type 1	Additional customers type 2 desired	Per customer rebate desired by customer type 2
5	\$0.10	5	\$0.11
10	\$0.12	10	\$0.14
15	\$0.24	15	\$0.25

Table 7-12. Marginal costs of acquiring additional customers into the DLC program.

Marginal costs		Additional number of customers type 2 acquired			
		0	5	10	15
Additional number of customers type 1 acquired	0	\$0.00	\$0.55	\$1.40	\$3.75
	5	\$0.50	\$1.05	\$1.90	\$4.25
	10	\$1.20	\$1.75	\$2.60	\$4.95
	15	\$3.60	\$4.15	\$5.00	\$7.35

Table 7-13. Marginal profits of acquiring additional customers into the DLC program.

Marginal profits		Additional number of customers type 2 acquired			
		0	5	10	15
Additional number of customers type 1 acquired	0	\$0.00	\$0.95	\$1.61	\$0.76
	5	\$1.75	\$2.70	\$3.36	\$2.51
	10	\$3.30	\$4.25	\$4.91	\$4.06
	15	\$3.15	\$4.10	\$4.76	\$3.91

Table 7-14. Return on investment of acquiring additional customers into the DLC program.

Marginal profits		Additional number of customers type 2 acquired			
		0	5	10	15
Additional number of customers type 1 acquired	0	–	173.45%	114.86%	20.32%
	5	350.01%	257.53%	176.74%	59.10%
	10	275.01%	243.09%	188.77%	82.06%
	15	87.50%	98.89%	95.16%	53.23%

From Table 7-13, the maximum profit that the ESCO can gain from acquiring additional customers into the DLC program for 1 month (1st month) is \$4.91. If the ESCO has excess capital and does not have investment opportunities that provide a return on investment greater than 188.77%, to maximize profit at the scheduling level, the ESCO should attract an additional 10 customers type 1 and 10 customers type 2. However, if the ESCO has other investment opportunities or limited capital to invest, it should select one that is within the company budget and yet provides the best return on investment. This is an issue of capital budgeting and has been addressed in various financial management books like [59]. In this example, the main concern is to utilize the presented scheduling models to derive the desired information. Capital budgeting will be introduced in section 7.6.

7.3.3 Remarks

Assuming that the ESCO has decided to maximize marginal profit at the scheduling level, Table 7-15 shows the contract purchasing schemes of the selected strategy. In this example, the market prices do not change when there is a change in the number of contracts purchased, i.e., the market prices do not react to the changes in the market conditions. For example, at the 3rd period, the number of contracts purchased has been reduced from 67.0989 contracts in the base to 65.28 contracts with the new addition of controllable demand. However, the market price for contract type C for the 3rd period remains at \$70.59 per contract.

In reality, changes in the contract purchasing schemes of an ESCO may affect the market prices. This is especially true if more than one ESCO is simultaneously using the same strategy of acquiring additional customers to participate in the DLC program. Thus, to take into account of the possible change in market prices, an ESCO should discount the marginal profit in Table 7-13.

Table 7-15. Contract purchasing schemes for different number of customers participating in the DLC program.

	Purchased contract type C	
Period	Base case (24 customer type 1, 24 customer type 2)	Strategy 1 (34 customer type 1, 34 customer type 2)
1	40.4211	40.4211
2	42.4421	42.4421
3	67.0989	65.2800
4	63.9057	63.8265
5	44.5248	45.5387
6	42.4916	43.3400

7.4 SHORT-RANGE PLANNING

At the short-range planning level, the process of determining an *optimal* rebate scheme to offer the customers participating in the DLC program is similar to the one presented in section 7.3. There are only three differences between the two processes.

First, at the scheduling level, only a temporary rebate is considered; however, at the short-range planning level, the whole rebate scheme needs to be evaluated. For example, the impact of a temporary rebate is considered in section 7.3. However, at the short-range planning level, to determine an *optimal* rebate scheme, an ESCO should consider how the combination of fixed and variable rebates affect customer participation and profits of acquiring these controllable customers demands.

Second, at the scheduling level, the customers who had participated in the DLC program will not receive any temporary rebate. However, at the short-range planning level, unless an ESCO can price discriminate customers offering the same controllable demand, any changes in the fixed and variable rebates will change the offering received by all customers of similar controllable demand pattern and contractual terms.

Finally, at the scheduling level, the contract specifications most likely are not to be evaluated. However, at the short-range planning level, all contract specifications should be evaluated. For example, in the ESCO presented, the deferred duration of per controllable customer type 1 is 200 periods, but the deferred duration of controllable customer type 2 is only 144 periods, far less than the 200 periods agreed upon in the contracts. If the ESCO could have changed the contracted deferred duration of controllable customer type 2 from 200 periods to 144 periods, the ESCO might have been able to lower the offered rebate scheme to the controllable customer type 2. Also, the ESCO may also determine if the contracted deferred duration of controllable customer type 1 should be lengthened. In addition, the ESCO may also consider if the maximum deferred duration of 2 periods can be changed, and evaluate the cost-benefit of such changes.

Since there are many evaluation choices, from the impact of fixed and variable rebate schemes to the impact of contract specifications, the time devoted to the analysis can be lengthy. For this reason, examples are not provided. Instead, Figure 7-2 shows the general approach to determining an *optimal* rebate schedule to attract customer participation in the DLC program.

7.5 MIDDLE-RANGE PLANNING

At the middle-range planning level, one of the ESCO's objectives is to determine an *optimal* tariff to offer customers under its service. The decision includes the determination of the fixed tariff, variable tariff, and offered ancillary services. The approaches shown in section 7.4 may be used to determine the *optimal* tariff to be offered to the customers.

STEP 1	Determine the factors influencing customer participation in the DLC program that an ESCO may decide on. These include (1) fixed rebate (2) variable rebate and (3) contractual terms. Select the potential variations (different rebate schemes or contractual terms) that the ESCO wish to analyze.
STEP 2	For each of these variations, use the scheduling model to determine the benefits of such variations.
STEP 3	Determine the costs of offering the rebate scheme.
STEP 4	Determine the profits for each of these variation.
STEP 5	Determine the return on investment for each of these variations.
STEP 6	Select an *optimal* rebate scheme that provides the best return on investment or profits to the ESCO, depending on the restrictions on investment choices and capital expenditure.

Figure 7-2. Determining an *optimal* rebate scheme for an ESCO.

7.6 LONG-RANGE PLANNING

The ESCO, shown in chapter 6, does not own any energy storage systems. Since the capital requirements for energy storage systems are higher than the capital requirements for the DLC programs, decision-making on the installation of energy storage system is considered as a long-range planning. There are numerous energy storage systems that an ESCO can select to serve its purpose.

To evaluate the benefit of installing an energy storage system, the concepts of capital budgeting are used. Capital budgeting is a process of planning expenditures on assets whose cash flows are expected to extend beyond one year [59]. The cash flows impacts of installing an energy storage system can evaluated using: (1) net present value (NPV), which evaluates the present value of future net cash flows, and (2) internal rate of return (IRR), which evaluates the discount rate that equates the present value of future cash inflows to the project cost. Other evaluation techniques for capital budgeting can be found in [59].

In this research, the full impact (including the cost of installation, cost of interest, salvage value, etc.) of installing ESS is not evaluated. Instead, the scheduling customer demand model is used to evaluate the operating cash flows impact of the pump-hydro storage system (PHSS). Section 7.6.1 shows the impact on the revenue flow and cost of energy flow of installing PHSS. Section 7.6.2 comments on the result.

7.6.1 The Impact on the Revenue and Cost of Energy Flow

Since PHSS does not change the customer demand profile, there is no revenue flow impact from the installation of PHSS. However, the utilization of PHSS changes the contract purchasing scheme. As a result, there is impact on the cost of energy flow. Table 7-16 shows the cost of purchasing energy contracts before and after scheduling the PHSS. The cost of energy impact is the difference between the cost of energy before and after the installation of the PHSS.

7.6.2 Remarks

The scheduling model has been used to estimate the impact on the operating cash flows. However, the impact on the operating cash flows is only one of the few to be considered in capital budgeting. To name a few, the cost of installing PHSS and the interest payments, if capital is raised to install PHSS.

To decide if the ESCO should invest in the PHSS, other long-range investment opportunities should be evaluated as well. These include other energy storage systems such as battery energy storage systems. In addition, the risk of these investments should be considered, including the stand-alone risk and corporate risk. Stand-alone risk is measured by the variability of an investment's expected return. Corporate risk is measured by the investment's effect on uncertainty about the ESCO's future earnings [59].

Table 7-16. The cost of energy flow resulted from installing the PHSS.

Period	Before installing PHSS	After installing PHSS	Impact of PHSS
1	2,222.35	2,280.22	57.87
2	2,425.99	2,449.16	23.17
3	4,736.51	4,587.90	-148.61
4	4,511.74	4,437.43	-74.32
5	2,588.23	2,611.04	22.81
6	2,374.86	2,433.69	58.83
7	2,546.02	2,606.87	60.84
8	2,710.56	2,710.56	0
9	4,814.14	4,739.79	-74.35
10	4,772.08	4,696.34	-75.75
11	2,684.65	2,707.97	23.31
12	2,584.51	2,645.73	61.22
13	2,722.49	2,785.59	63.11
14	2,790.44	2,790.44	0
15	5,095.88	5,020.05	-75.83
16	5,022.46	4,945.24	-77.22
17	2,995.93	2,995.93	0
18	2,802.11	2,865.63	63.52
19	2,835.33	2,900.04	64.72
20	2,887.60	2,903.11	15.51
21	5,445.86	5,367.34	-78.52
22	4,999.83	4,946.36	-53.47
23	3,145.39	3,145.39	0
24	2,809.84	2,873.52	63.67
25	3,016.92	3,083.00	66.07
26	3,183.47	3,183.47	0
27	5,633.10	5,563.26	-69.84
28	5,525.16	5,444.66	-80.49
29	3,360.15	3,360.15	0
30	3,484.90	3,484.90	0
31	3,158.32	3,225.91	67.59
32	3,483.89	3,483.89	0
33	5,815.36	5,746.03	-69.33
34	5,830.48	5,830.48	0
35	3,495.55	3,515.13	19.59
36	3,115.39	3,248.50	133.12

7.7 ADDITIONAL REMARKS

The main purpose of this chapter is to show how the scheduling model can be used in the ESCO operation and management. The examples presented have been simplified to show the focus at each operational level.

There are limitations on using the techniques presented to assist the ESCO decision-making. First, assumptions are needed to simplify the problems so as to make the stated problems solvable. These assumptions may result in decisions that do not optimally achieve the goals of the stated problems. Second, at most planning levels, there are many ways that the ESCO can have think of to maximize its goal. The scheduling model only evaluates the benefits of the given strategies. To maximize its goals, an ESCO would still need to be creative and efficient in bringing in new ideas. Third, the scheduling model presented so far has used linear programming and assumed all information is deterministic. The model is not able to capture the effects of uncertainty.

Nonetheless, the presented technical analyses provide valuable information that an ESCO may use in decision-making.

CHAPTER 8 RISK MANAGEMENT AND ESCO

In Chapter 6 and 7, deterministic information is assumed in the analysis. However, Chapter 2 suggests that factors influencing ESCO operation can be uncertain. To provide a better analysis, the uncertain characteristic should be included in the analyses. Throughout this chapter, the risk management tools presented in Chapter 5 are used to complement the analyses presented so far. Section 8.1 shows the basic scheduling model where risk management tools will be applied. Section 8.2 through section 8.6 applies the risk management tools to analyze the model presented in section 8.1. Section 8.8 concludes this chapter by discussion the results in general.

8.1 BASIC ESCO SCHEDULING MODEL

There are three periods in the scheduling model. The expected values of the information are similar to those shown in Chapters 6 and 7 from the 5th period to the 7th period. There are several exceptions that differentiate this model from those presented in Chapters 6 and 7. First, instead of considering 36 periods as in Chapters 6 and 7, this model only considers 3 periods in the analyses to provide better insight into the differences among the risk management tools. Second, any load management choices that do not defer or pay back demand completely during the three periods are not considered in the analysis. For example, demand deferment choice that is initiated in the 6th period and paid back in the 7th and 8th periods will not be considered. Third, energy contracts that deliver energy for 1 month are not considered in the analysis. Only energy contracts that deliver energy for 1 period will be considered.

The profit-based model, presented using expected value, is shown in (8.1). It is derived using equations in Chapter 3 and 4. The objective function in (8.1) is derived using (4.7). The first 3 constraints are derived using (4.20). The 4th through 6th constraints are derived using (4.23). The 7th through 9th constraints are derived using (4.24). Since the contract duration is only 1 period for all contracts traded, (4.25) is not used in this example. The 10th through 12th constraints are derived using (4.26). Since contract duration is only 1 period for all contracts traded, $EX^{+}_{j,1}$ is set to 0 for all j. The 13th through 15th constraints are derived using (4.26). The 7th through 12th constraints can be simplified with 3 constraints by requiring the right-side equations of the 7th through 9th constraints to be smaller than or equal to 0. These changes are reflected in (8.2). The last constraint is derived using (3.5).

$$max \quad \sum_{j=5}^{7} r_j TE_j + x_{1,11,1} Ed_{1,11}\left(\lambda_{1,5,1,1} r_6 + \lambda_{1,5,1,2} r_7 - r_5 - r_5'\right) - \sum_{j=5}^{7}\sum_{k=1}^{2} pr_j^{1,\alpha_k,\beta_k} P_j^{1,\alpha_k,\beta_k}$$

subject to:

$$TE_5 - x_{1,5,1} Ed_{1,5} \le \sum_{k=1}^{2}\left(1+\beta_k^{5,1}\right) P_5^{1,\alpha_k,\beta_k}$$

$$TE_6 + x_{1,5,1}\lambda_{1,5,1,1} Ed_{1,5} \le \sum_{k=1}^{2}\left(1+\beta_k^{6,1}\right) P_6^{1,\alpha_k,\beta_k}$$

$$TE_7 + x_{1,5,1}\lambda_{1,5,1,2} Ed_{1,5} \le \sum_{k=1}^{2}\left(1+\beta_k^{7,1}\right) P_7^{1,\alpha_k,\beta_k}$$

$$TE_5 - x_{1,5,1} Ed_{1,5} - \sum_{k=1}^{2}\left(1-\beta_k^{5,1}\right) P_5^{1,\alpha_k,\beta_k} = P_5^+ - P_5^-$$

$$TE_6 + x_{1,5,1}\lambda_{1,5,1,1} Ed_{1,5} - \sum_{k=1}^{2}\left(1-\beta_k^{6,1}\right) P_6^{1,\alpha_k,\beta_k} = P_6^+ - P_6^-$$

$$TE_7 + x_{1,5,1}\lambda_{1,5,1,2} Ed_{1,5} - \sum_{k=1}^{2}\left(1+\beta_k^{7,1}\right) P_7^{1,\alpha_k,\beta_k} = P_7^+ - P_7^-$$

$$EX_{5,1}^+ - EX_{5,1}^- = TE_5 - x_{1,5,1} Ed_{1,5} + P_5^- - \sum_{k=1}^{2} P_5^{1,\alpha_k,\beta_k}$$

$$EX_{6,1}^+ - EX_{6,1}^- = TE_6 + x_{1,5,1}\lambda_{1,5,1,1} Ed_{1,5} + P_6^- - \sum_{k=1}^{2} P_6^{1,\alpha_k,\beta_k}$$

$$EX_{7,1}^+ - EX_{7,1}^- = TE_7 + x_{1,5,1}\lambda_{1,5,1,2} Ed_{1,5} + P_7^- - \sum_{k=1}^{2} P_7^{1,\alpha_k,\beta_k}$$

$$EX_{5,1}^+ = 0$$

$$EX_{6,1}^+ = 0$$

$$EX_{7,1}^+ = 0$$

$$TE_5\left(1-\alpha_5^{TE}\right) - x_{1,5,1} Ed_{1,5}\left(1-\alpha_5^{ED}\right) \le \sum_{k=1}^{2}\left(1-\alpha_k^{5,1}\right) P_5^{1,\alpha_k,\beta_k}$$

$$TE_6\left(1-\alpha_6^{TE}\right) + x_{1,5,1}\lambda_{1,5,1,1} Ed_{1,5}\left(1-\alpha_6^{EP}\right) \le \sum_{k=1}^{2}\left(1-\alpha_k^{6,1}\right) P_6^{1,\alpha_k,\beta_k}$$

$$TE_7\left(1-\alpha_7^{TE}\right) + x_{1,5,1}\lambda_{1,5,1,2} Ed_{1,5}\left(1-\alpha_7^{EP}\right) \le \sum_{k=1}^{2}\left(1-\alpha_k^{7,1}\right) P_7^{1,\alpha_k,\beta_k}$$

$$x_{1,5,1} \le 100 \qquad (8.1)$$

$$\max \quad \sum_{j=5}^{7} r_j TE_j + x_{1,11,1} Ed_{1,11}\left(\lambda_{1,5,1,1} r_6 + \lambda_{1,5,1,2} r_7 - r_5 - r_5'\right) - \sum_{j=5}^{7}\sum_{k=1}^{2} pr_j^{1,\alpha_k,\beta_k} P_j^{1,\alpha_k,\beta_k}$$

subject to:

$$TE_5 - x_{1,5,1} Ed_{1,5} \le \sum_{k=1}^{2}\left(1+\beta_k^{5,1}\right) P_5^{1,\alpha_k,\beta_k}$$

$$TE_6 + x_{1,5,1}\lambda_{1,5,1,1} Ed_{1,5} \le \sum_{k=1}^{2}\left(1+\beta_k^{6,1}\right) P_6^{1,\alpha_k,\beta_k}$$

$$TE_7 + x_{1,5,1}\lambda_{1,5,1,2} Ed_{1,5} \le \sum_{k=1}^{2}\left(1+\beta_k^{7,1}\right) P_7^{1,\alpha_k,\beta_k}$$

$$TE_5 - x_{1,5,1} Ed_{1,5} - \sum_{k=1}^{2}\left(1-\beta_k^{5,1}\right) P_5^{1,\alpha_k,\beta_k} = P_5^{+} - P_5^{-}$$

$$TE_6 + x_{1,5,1}\lambda_{1,5,1,1} Ed_{1,5} - \sum_{k=1}^{2}\left(1-\beta_k^{6,1}\right) P_6^{1,\alpha_k,\beta_k} = P_6^{+} - P_6^{-}$$

$$TE_7 + x_{1,5,1}\lambda_{1,5,1,2} Ed_{1,5} - \sum_{k=1}^{2}\left(1+\beta_k^{7,1}\right) P_7^{1,\alpha_k,\beta_k} = P_7^{+} - P_7^{-}$$

$$TE_5 - x_{1,5,1} Ed_{1,5} + P_5^{-} - \sum_{k=1}^{2} P_5^{1,\alpha_k,\beta_k} \le 0$$

$$TE_6 + x_{1,5,1}\lambda_{1,5,1,1} Ed_{1,5} + P_6^{-} - \sum_{k=1}^{2} P_6^{1,\alpha_k,\beta_k} \le 0$$

$$TE_7 + x_{1,5,1}\lambda_{1,5,1,2} Ed_{1,5} + P_7^{-} - \sum_{k=1}^{2} P_7^{1,\alpha_k,\beta_k} \le 0$$

$$TE_5\left(1-\alpha_5^{TE}\right) - x_{1,5,1} Ed_{1,5}\left(1-\alpha_5^{ED}\right) \le \sum_{k=1}^{2}\left(1-\alpha_k^{5,1}\right) P_5^{1,\alpha_k,\beta_k}$$

$$TE_6\left(1-\alpha_6^{TE}\right) + x_{1,5,1}\lambda_{1,5,1,1} Ed_{1,5}\left(1-\alpha_6^{EP}\right) \le \sum_{k=1}^{2}\left(1-\alpha_k^{6,1}\right) P_6^{1,\alpha_k,\beta_k}$$

$$TE_7\left(1-\alpha_7^{TE}\right) + x_{1,5,1}\lambda_{1,5,1,2} Ed_{1,5}\left(1-\alpha_7^{EP}\right) \le \sum_{k=1}^{2}\left(1-\alpha_k^{7,1}\right) P_7^{1,\alpha_k,\beta_k}$$

$$x_{1,5,1} \le 100 \qquad (8.2)$$

Since there is only one control choice in this example, the only control, $x_{1,5,1}$, should be smaller than or equal to the maximum controllable units.

Table 8-1 shows the values of all parameters in (8.2). These values are similar to those in Chapter 6 and Appendix A. They are re-posted here for clarity. The standard deviations and correlation of all uncertain parameters are shown in Appendix B. Section 8.1.1 shows the results of solving (8.2) using the expected values of the uncertain parameters.

Table 8-1. Parameters used in (8.2).

Factor	Description	Variable name	Value	Remark
Customer	variable tariff	$r_j, j=5, 6, 7$	\$90/ MW-period	deterministic
	fixed tariff	–	–	–
	demand	TE_5	42 MW	uncertain
		TE_6	40 MW	uncertain
		TE_7	42 MW	uncertain
	reliability	$\alpha_j^{TE}, j=5, 6, 7$	0.04	deterministic
	decision variables	–	–	–
Market	price of energy	$pr_5^{1,\alpha_1,\beta_1}$	\$59.40/MW-period	uncertain
		$pr_5^{1,\alpha_2,\beta_2}$	\$66.28/MW-period	uncertain
		$pr_6^{1,\alpha_1,\beta_1}$	\$58.16/MW-period	uncertain
		$pr_6^{1,\alpha_2,\beta_2}$	\$64.89/MW-period	uncertain
		$pr_7^{1,\alpha_1,\beta_1}$	\$59.95/MW-period	uncertain
		$pr_7^{1,\alpha_2,\beta_2}$	\$66.89/MW-period	uncertain
	reliability	$\alpha_1,\ \alpha_1^{j,1}, j=5, 6, 7$	0.05	uncertain
		$\alpha_2,\ \alpha_2^{j,1}, j=5, 6, 7$	0.03	uncertain
	variability	$\beta_1,\ \beta_1^{j,1}, j=5, 6, 7$	0.05	deterministic
		$\beta_2,\ \beta_2^{j,1}, j=5, 6, 7$	0.10	deterministic
	contract duration	–	1 period	–
	decision variables	$P_j^{1,\alpha_k,\beta_k}, j=5, 6, 7$ $k=1, 2$	–	to be determined
Supplementary energy	variable rebate	$r'_j, j=5, 6, 7$	\$2.50/MW deferred	deterministic
	fixed rebate	–	0	–
	deferrable demand	$Ed_{1,5}$	0.044 MW/unit	uncertain
	reliability	$\alpha_j^{EP}, j=5, 6, 7$	0.03	deterministic
	decision variable	$x_{1,5,1}$	–	to be determined

8.1.1 Solving (8.2) using the Expected Values

Even though the expected values used in this chapter are similar to those used in the ESCO analysis in Chapter 6 and 7, the size of the problem and the number of decision variables are different. Table 8-2 shows the results of solving (8.2) and compares to the results in section 6.4.

The expected profit of serving customer demand during the 3 periods is \$3,743.65. The cost of purchasing energy contracts is \$7,416.35 and the revenue of serving customer demands is \$11,160.00. Contract type C is purchased to meet customer demand. In both cases, scheduling 3 periods or 36 periods, no contract type D is purchased because it is not cost effective. Even though no demand is deferred at the 5th period in both cases, the contracts purchased during the three periods, from the 5th to the 7th period, are higher in section 6.4. More contracts are purchased in section 6.4 because some controllable customer demands during the 3rd and 4th period have been deferred to the 5th, 6th, and 7th period.

Table 8-2. Results from solving (8.2) using expected values.

Variable	Solving (8.2)	Results from section 6.4
P_5^{1,α_1,β_1}	42.4421	44.3444
P_5^{1,α_2,β_2}	0	0
P_6^{1,α_1,β_1}	40.4211	42.2855
P_6^{1,α_2,β_2}	0	0
P_7^{1,α_1,β_1}	42.4421	43.9200
P_7^{1,α_2,β_2}	0	0
$x_{1,5,1}$	0	0

Before proceeding to analyzing (8.2) using risk management tools presented in Chapter 5, there are two important results that should be emphasized.

- *No* controllable customer demand is deferred during the 5th period.
- *No* contract type D is purchased to serve customer demand.

Controllable customer demand and contract type D are not scheduled in this example because they are not cost effective.

8.1.2 Remarks

The time horizon in (8.2) is approximately 1 month in the future. Based on the discussion in Chapter 2, the analysis can either be considered as a short-range planning level or scheduling level of an ESCO operation. Since I have assumed the rate structure and rebate structure to load management programs to be parametric and deterministic, (8.2) is analyzed as a scheduling level problem to reduce the size of uncertain parameters. Even though only a scheduling level problem is considered in this chapter, the presented examples may be extended to analyze other ESCO operational planning level problems.

The reliability level requested by the customers is 97%. However, the purchased contracts have reliability level of 95%. To provide the desired reliability level to the customers, results recommend additional purchased of energy contracts. However, will purchasing additional contracts of lower reliability level sufficient in compensating contracts of higher reliability level?

For example, assuming that there is a request for 90% reliability for a customer demand of 5 MW. Two contract choices, with X of 90% and Y of 80% reliability, are available. Using (4.26), the minimum contracts to be purchased using contract X is $5\left(=\frac{5(.9)}{.9}\right)$ contracts and using contract Y is $5.625\left(=\frac{5(.9)}{.8}\right)$ contracts. The probabilistic mass functions and cumulative mass functions, determining using convolution technique, of either purchasing contract X or contract Y are shown in Figure 8-1 and Figure 8-2 respectively. Clearly, the probabilistic mass functions or cumulative mass functions of purchasing 5.0 MW of contract X and purchasing 5.625 MW of contract Y are different. However, at 90% confidence level, approximately 4.2 MW of energy will be delivered under contract X or contract Y. Therefore, (4.26) does approximate the required reliability level needed to serve the customer demand.

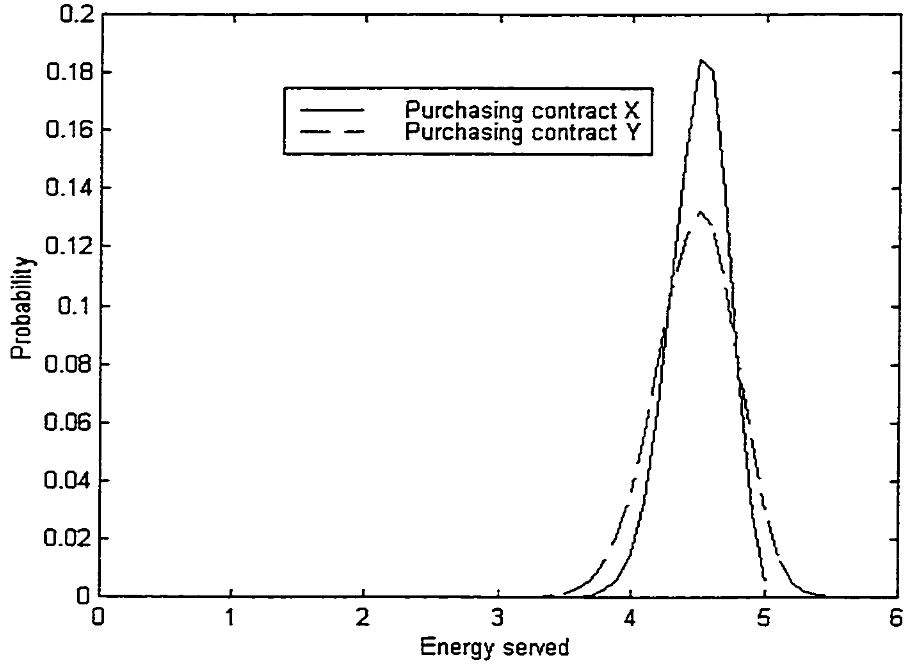

Figure 8-1. Probabilistic mass functions of purchasing contract X and contract Y.

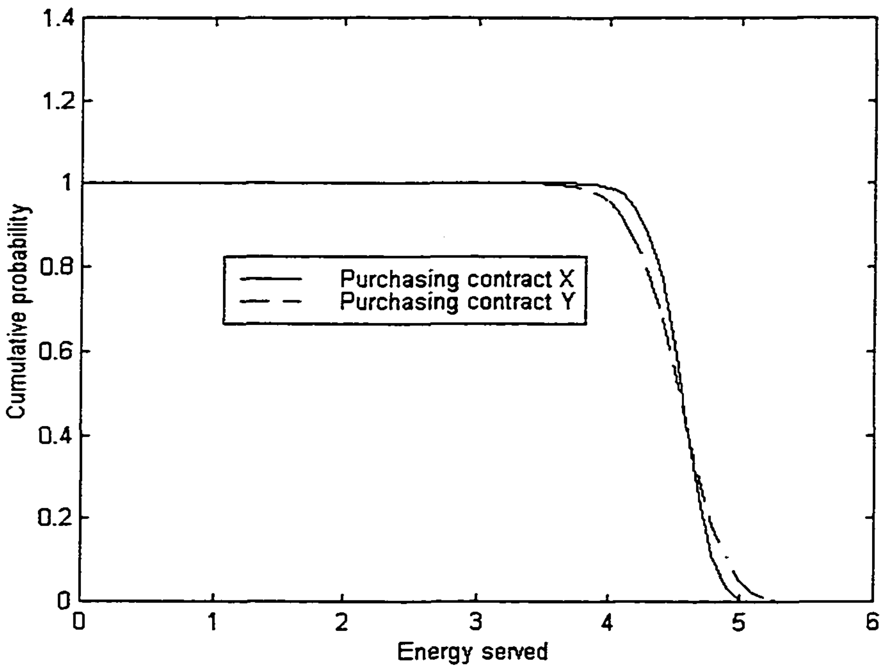

Figure 8-2. Cumulative probabilistic mass functions of purchasing contract X and contract Y.

8.1.3 Prelude to utilizing Risk Management Tools

In section 8.1.1, (8.2) is solved by assuming that the parameters are all deterministic so that the expected value of the uncertain parameters can be used in the analysis. Because all parameters are deterministic, three important costs associated with uncertainty are not considered. First is the cost of not serving the customer demand (ENS). Second is the cost of not purchasing sufficient reliability from the market to meet customer request. Third is the cost of demand exceeding the contract variability level.

The cost of ENS and cost of not purchasing sufficient reliability is shown in (8.3).

$$CNS_j = r_j^{\pi}\left[TE_j\left(1-\alpha_j^{TE}\right)-ED_j\left(1-\alpha_j^{ED}\right)+EP_j\left(1-\alpha_j^{EP}\right)+ES_j\left(1-\alpha_j^{ES}\right)-ER_j\left(1-\alpha_j^{ER}\right)-\sum_{\forall h}\sum_{\forall d^f}\left(1-\alpha_h^{j,d^f}\right)P_a^{d^f,\alpha_h,\beta_h}\right] \tag{8.3}$$

r_j^{π} is the per unit energy penalty cost when the customer demand is not equivalent to the purchased energy. Ideally, r_j^{π} should be a nonlinear function of the difference between the purchased energy and the customer demand. Prior to determining r_j'', there are two two issues that need to be addressed. First, when the purchased energy exceeds the customer demand, what cost does the *ESCO* bear? Second, when the customer demand exceeds the purchased energy, how should the *ESCO* be penalized? To address the two issues, the following assumptions are made.

When there is an excess energy (purchased energy exceeds the customer demand,) the *ESCO* loses the opportunity to sell that energy. [15] When there is a shortage energy (customer demand exceeds the purchased energy), the *ESCO* suffers the opportunity cost to serve customer demand and that the customers may refuse future services from the *ESCO*. The opportunity cost to serve customer demand is the rate that the customers will pay if there is no shortage in energy. [16] The opportunity cost that the customers may refuse future services is the expected cost of customers refusing the *ESCO* services. This opportunity cost will be a monotonically increasing function of the increased shortage in energy served.

To preserve the linearity of the objective function, r_j'' is assumed to be \$30/MW-period, the average profit margin of serving customer demand during off-peak periods. This deterministic and constant r_j'' is used in sensitivity analysis and parametric analysis, mean-variance analysis, fuzzy linear programming, and stochastic linear programming. However, when *VaR* analysis is conducted, the linearity of r_j'' is relaxed because *VaR* analysis provides greater flexibility when the financial risks are evaluated. The relaxation on r_j'' will be presented in section 8.6 when *VaR* analysis is conducted.

Equation (8.4) shows the modified objective function after including (8.3) into the objective function of (8.2). The addition of r_j'' in (8.4) does not affect the solution. Similar results as shown in Table 8-2 are found when (8.4) is used as the objective function.

$$\max \quad \sum_{j=5}^{7}\left(r_j - r_j''\left(1-\alpha_j^{TE}\right)\right)TE_j + x_{1,5,1}Ed_{1,5}\left[\lambda_{1,5,1,1}\left(r_6 - r_6''\left(1-\alpha_6^{Ed}\right)\right) + \lambda_{1,5,1,2}\left(r_7 - r_7''\left(1-\alpha_7^{Ed}\right)\right) - r_5 + r_5''\left(1-\alpha_5^{Ed}\right) - r_5'\right]$$
$$- \sum_{j=5}^{7}\sum_{k=1}^{2}\left(pr_j^{1,\alpha_k,\beta_k} - r_j''\left(1-\alpha_k^{j,1}\right)\right)P_j^{1,\alpha_k,\beta_k} \tag{8.4}$$

---

[15] This opportunity cost can be measured in various ways. First is the average cost of energy when there is an excess energy. Second is the opportunity cost of excess energy, assuming that the *ESCO* could have sold the excess energy at discount. The opportunity cost of excess comes in two forms, one is the average rate that the *ESCO* may receive, the other one is a decreasing function of the excess rate (assuming that the *ESCO* will sell the excess energy first to buyers offering the highest discount rate.)

[16] The rate can come in two forms. First is a monotonically increasing function, assuming that the customers paying higher rate will be served first. Second is an average of what the customer pay for the energy services, assuming that any additional energy will be partitioned equally to serve the customers.

The cost of demand exceeding the contract variability level is not considered in this research except when *VaR* analysis is conducted. Additional comments will be presented in section 8.6 when *VaR* analysis is applied.

When risk management tools are used for analysis, (8.4) is assumed to be the objective function.

8.2 SENSITIVITY ANALYSIS AND PARAMETRIC ANALYSIS

Sensitivity analysis is presented in section 8.2.1. Parametric analysis is presented in section 8.2.2. Section 8.2.3 comments on the applicability of sensitivity analysis and parametric analysis in the stated problem.

8.2.1 Sensitivity Analysis

There are several sensitivity analyses that can be conducted on (8.2). In this section, sensitivity analysis is used to analyze when should the ESCO in this example should purchase contract type D instead of contract type C. Table 8-3 shows how much should the price of contract type D drop before they will be considered. For example, to favor contract type D at the 5th period, the price of contract type D at that period should drop from \$66.28/MW-period to \$60.65/MW-period. Since contract type D has a higher quality, providing higher reliability and allowing higher volatility in demand, there is still a price difference between contract type C and D. For example, the desired price of contract type D at the 5th period is still \$1.25/MW-period higher than that of contract type C.

Table 8-3. Desired price drop in contract type D.

Period	Contract type C		Contract type D		Desired price drop in contract type D before purchase	Desired price of contract type D should be lower than
	Variable name	Original price	Variable name	Original price		
5	P_5^{1,α_1,β_1}	\$59.40/MW-period	P_5^{1,α_2,β_2}	\$66.28/MW-period	\$5.63/MW-period	\$60.65/MW-period
6	P_5^{1,α_1,β_1}	\$58.16/MW-period	P_5^{1,α_2,β_2}	\$64.89/MW-period	\$5.51/MW-period	\$59.38/MW-period
7	P_6^{1,α_1,β_1}	\$59.95/MW-period	P_7^{1,α_2,β_2}	\$66.89/MW-period	\$5.68/MW-period	\$61.21/MW-period

8.2.2 Parametric Analysis

Sensitivity analysis provides only the desired price change in contract type D at a particular period. The effect of a simultaneous change in the market price is not considered. To consider simultaneous change in the market price, parametric analysis is used. To analyze the changes in the market prices, the direction of perturbation needs first to be determined.

In this section, two directions of perturbation are considered. First, the standard deviations of the market prices are used as the direction of perturbation. Equation (8.5) shows the market prices after including the direction of perturbation. Table 8-5 shows the results of using the standard deviations as the direction of perturbation. As λ increases, the purchasing scheme changes. When $\lambda > 3.3565$, DLC program becomes desirable and all controllable customer demand at the 5th period is deferred.

$$\begin{bmatrix} P_5^{1,\alpha_1,\beta_1} \\ P_5^{1,\alpha_2,\beta_2} \\ P_6^{1,\alpha_1,\beta_1} \\ P_6^{1,\alpha_2,\beta_2} \\ P_7^{1,\alpha_1,\beta_1} \\ P_7^{1,\alpha_2,\beta_2} \end{bmatrix} = \begin{bmatrix} 59.40 \\ 66.28 \\ 58.16 \\ 64.89 \\ 59.95 \\ 66.89 \end{bmatrix} + \lambda \begin{bmatrix} 3 \\ 2 \\ 2 \\ 3 \\ 2 \\ 3 \end{bmatrix} \tag{8.5}$$

However, using the standard deviations as the direction of perturbation ignores the effect of correlation between the market prices. To consider the correlation effect, (5.15) is used to derive the uncertain market prices. Equation (8.6) shows the uncertain market prices as a function of a set of uniformly distributed probabilistic numbers using (5.15). n_1 through n_6 are randomly generated numbers from a uniformly distributed probabilistic function with a mean of zero and a standard deviation of one. Replacing these random numbers by λ, the degree of perturbation, (8.7) shows the changes. Table 8-5 shows the results of using (8.7) as the direction of perturbation.

$$\begin{bmatrix} pr_5^{1,\alpha_1,\beta_1} \\ pr_5^{1,\alpha_2,\beta_2} \\ pr_6^{1,\alpha_1,\beta_1} \\ pr_6^{1,\alpha_2,\beta_2} \\ pr_7^{1,\alpha_1,\beta_1} \\ pr_7^{1,\alpha_2,\beta_2} \end{bmatrix} = \begin{bmatrix} 59.40 \\ 66.28 \\ 58.16 \\ 64.89 \\ 59.95 \\ 66.89 \end{bmatrix} + \begin{bmatrix} -0.9314 & 0.1788 & 0.1904 & -0.7329 & -2.1565 & 1.7059 \\ 0.6125 & -0.0265 & -0.1370 & -0.5445 & -1.3510 & 1.2181 \\ -0.1571 & -0.7986 & -0.1462 & 1.2713 & 0.0300 & 1.3035 \\ 0.3257 & 0.8967 & 0.3707 & 1.6712 & 0.5236 & 2.2103 \\ -0.2040 & 0.4974 & -0.2883 & -0.5883 & 1.1385 & 1.4091 \\ 0.1640 & -0.8912 & 0.3531 & -1.7309 & 1.5537 & 1.6261 \end{bmatrix} \begin{bmatrix} n_1 \\ n_2 \\ n_3 \\ n_4 \\ n_5 \\ n_6 \end{bmatrix} \tag{8.6}$$

$$\begin{bmatrix} pr_5^{1,\alpha_1,\beta_1} \\ pr_5^{1,\alpha_2,\beta_2} \\ pr_6^{1,\alpha_1,\beta_1} \\ pr_6^{1,\alpha_2,\beta_2} \\ pr_7^{1,\alpha_1,\beta_1} \\ pr_7^{1,\alpha_2,\beta_2} \end{bmatrix} = \begin{bmatrix} 59.40 \\ 66.28 \\ 58.16 \\ 64.89 \\ 59.95 \\ 66.89 \end{bmatrix} + \begin{bmatrix} -0.9314 & 0.1788 & 0.1904 & -0.7329 & -2.1565 & 1.7059 \\ 0.6125 & -0.0265 & -0.1370 & -0.5445 & -1.3510 & 1.2181 \\ -0.1571 & -0.7986 & -0.1462 & 1.2713 & 0.0300 & 1.3035 \\ 0.3257 & 0.8967 & 0.3707 & 1.6712 & 0.5236 & 2.2103 \\ -0.2040 & 0.4974 & -0.2883 & -0.5883 & 1.1385 & 1.4091 \\ 0.1640 & -0.8912 & 0.3531 & -1.7309 & 1.5537 & 1.6261 \end{bmatrix} \begin{bmatrix} \lambda \\ \lambda \\ \lambda \\ \lambda \\ \lambda \\ \lambda \end{bmatrix}$$

$$= \begin{bmatrix} 59.40 \\ 66.28 \\ 58.16 \\ 64.89 \\ 59.95 \\ 66.89 \end{bmatrix} + \lambda \begin{bmatrix} -1.7277 \\ -0.2283 \\ 1.5030 \\ 5.9982 \\ 1.9643 \\ 1.0748 \end{bmatrix} \tag{8.7}$$

8.2.3 Remarks to Sensitivity Analysis and Parametric Analysis

The uncertain customer demand, controllable customer demand, and delivered reliability level are not considered in sensitivity analysis and parametric analysis. The two approaches do not accommodate these uncertainties well. For example, to consider the uncertain delivered reliability level, simultaneous changes in the objective function and the constraint matrix are required. Parametric analysis is not applicable when changes in the constraint matrix are required. Sensitivity analysis is not effective because the numbers of changes required is considerable high (six in the objective function and six in the constraint matrix).

Table 8-4. Using the standard deviation of market prices as the direction of perturbation.

	λ			
Variable	$0 \le \lambda \le 3.3565$	$3.3565 < \lambda \le 5.295$	$5.295 < \lambda \le 6.28$	$\lambda > 6.28$
p_5^{1,α_1,β_1}	42.4421	41.3639	21.0000	0
p_5^{1,α_2,β_2}	0	0	19.9440	40.9440
p_6^{1,α_1,β_1}	40.4211	40.8523	40.8523	40.8523
p_6^{1,α_2,β_2}	0	0	0	0
p_7^{1,α_1,β_1}	42.4421	43.0351	43.0351	43.0351
p_7^{1,α_2,β_2}	0	0	0	0
$x_{1,5,1}$	0	24.0000	24.0000	24.0000

Table 8-5. Using (8.7) as the direction of perturbation.

Variable	λ: $0 \le \lambda \le 6.1$	$6.1 < \lambda \le 6.9$	$6.9 < \lambda \le 7.1$	$7.1 < \lambda \le 9.5$	$9.5 < \lambda \le 17.9$
p_5^{1,α_1,β_1}	42.4421	42.4421	42.4421	42.4421	42.4421
p_5^{1,α_2,β_2}	0	0	0	0	0
p_6^{1,α_1,β_1}	40.4211	40.4211	40.0000	40.0000	40.4211
p_6^{1,α_2,β_2}	0	0	0.4124	0.4124	0
p_7^{1,α_1,β_1}	42.4421	21.0000	1.0000	0	0
p_7^{1,α_2,β_2}	0	21.0000	40.5876	41.5876	42.0000
$x_{1,5,1}$	0	0	0	0	0

8.3 FUZZY LINEAR PROGRAMMING

Section 8.3.1 applies the approach developed by Zimmerman et al. Section 8.3.2 applies the approach developed by Tanaka et al. Section 8.3.3 comments on the applicability of both approaches in the stated problem.

8.3.1 Approach 1 to Fuzzy Linear Programming [53]

Instead of trying to consider the impact of the uncertain parameters, the ESCO has learnt that buying additional 10% of energy and using only 90% of the controllable demand are the *safest* ways to guard against not buying sufficient energy to serve the customers. However, the word, *safest*, is fuzzy. The fuzziness in the operating conditions can be described using (5.21). The fuzziness changes the 1st through the 3rd constraints and the 7th through the 13th constraints in (8.2). For example, the fuzziness in the 1st constraint is shown in (8.8), the fuzziness in the 7th constraint is shown in (8.9), and the fuzziness in the 13th constraint is shown in (8.10).

The objective function (8.4) is assumed crisp. The fuzzy set of the crisp objective function is determined using (5.26), (5.27), and (5.28). The fuzzy set of the objective function (8.4) is shown in (8.11) using (5.26), where the $\sup_{S(R)} f$ and $\inf_{S(R)} f$ are determined in (8.13) and (8.14) respectively using (5.27) and (5.28). Using (8.13) and (8.14), $\sup_{S(R)} f$ is 3743.65 and $\inf_{S(R)} f$ is 2705.47.

$$\mu_i\left(\begin{bmatrix} x_{1,5,1} & \sum_{k=1}^{2} P_5^{1,\alpha_k,\beta_k} \end{bmatrix}\right)=\begin{cases} 1 & \text{if } TE_5 - x_{1,5,1}Ed_{1,5} - \sum_{k=1}^{2}\left(1+\beta_k^{5,1}\right)P_5^{1,\alpha_k,\beta_k} \le -4.2 \\ 1-\dfrac{TE_5 - x_{1,5,1}Ed_{1,5} - \sum_{k=1}^{2}\left(1+\beta_k^{5,1}\right)P_5^{1,\alpha_k,\beta_k} + 4.2}{4.2} & \text{if } -4.2 \le TE_5 - x_{1,5,1}Ed_{1,5} - \sum_{k=1}^{2}\left(1+\beta_k^{5,1}\right)P_5^{1,\alpha_k,\beta_k} \le 0 \\ 0 & \text{if } TE_5 - x_{1,5,1}Ed_{1,5} - \sum_{k=1}^{2}\left(1+\beta_k^{5,1}\right)P_5^{1,\alpha_k,\beta_k} > 0 \end{cases} \tag{8.8}$$

$$\mu_7\left(\begin{bmatrix} x_{1,5,1} & \sum_{k=1}^{2} P_5^{1,\alpha_k,\beta_k} \end{bmatrix}\right)=\begin{cases} 1 & \text{if } TE_5\left(1-\alpha_5^{TE}\right)-x_{1,5,1}Ed_{1,5}\left(1-\alpha_5^{ED}\right)-\sum_{k=1}^{2}\left(1-\alpha_k^{5,1}\right)P_5^{1,\alpha_k,\beta_k} \le 0 \\ 1-\dfrac{TE_5\left(1-\alpha_5^{TE}\right)-x_{1,5,1}Ed_{1,5}\left(1-\alpha_5^{ED}\right)-\sum_{k=1}^{2}\left(1-\alpha_k^{5,1}\right)P_5^{1,\alpha_k,\beta_k}+4.20}{4.2} & \text{if } 0 \le TE_5\left(1-\alpha_5^{TE}\right)-x_{1,5,1}Ed_{1,5}\left(1-\alpha_5^{ED}\right)-\sum_{k=1}^{2}\left(1-\alpha_k^{5,1}\right)P_5^{1,\alpha_k,\beta_k}+4.2 \le 4.2 \\ 0 & \text{if } TE_5\left(1-\alpha_5^{TE}\right)-x_{1,5,1}Ed_{1,5}\left(1-\alpha_5^{ED}\right)-\sum_{k=1}^{2}\left(1-\alpha_k^{5,1}\right)P_5^{1,\alpha_k,\beta_k} > 4.2 \end{cases} \tag{8.9}$$

$$\mu_{13}\left(x_{1,5,1}\right)=\begin{cases} 1 & \text{if } x_{1,5,1}-90 \le 0 \\ 1-\dfrac{x_{1,5,1}-90}{10} & \text{if } 0 \le x_{1,5,1}-90 \le 10 \\ 0 & \text{if } x_{1,5,1}-90 > 10 \end{cases} \tag{8.10}$$

$$\mu_G(\mathbf{x})=\begin{cases} 0 & \text{if } \mathbf{c}^T\mathbf{x} \ge \sup_{S(R)} f \\ 1-\dfrac{\mathbf{c}^T\mathbf{x}-\inf_{S(R)} f}{\sup_{S(R)} f - \inf_{S(R)} f} & \text{if } \inf_{S(R)} f \le \mathbf{c}^T\mathbf{x} \le \sup_{S(R)} f \\ 1 & \text{if } \mathbf{c}^T\mathbf{x} \le \inf_{S(R)} f \end{cases} \tag{8.11}$$

where

$$\mathbf{c}^T\mathbf{x} \;=\; \sum_{j=5}^{7}\left(r_j - r_j^{*}\left(1-\alpha_j^{TE}\right)\right)TE_j \quad -\sum_{j=5}^{7}\sum_{k=1}^{2}\left(pr_j^{1,\alpha_k,\beta_k} - r_j^{*}\left(1-\alpha_k^{j,1}\right)\right)P_j^{1,\alpha_k,\beta_k}$$

$$+x_{1,5,1}Ed_{1,5}\left[\lambda_{1,5,1,1}\left(r_6-r_6''\left(1-\alpha_6^{Ed}\right)\right)+\lambda_{1,5,1,2}\left(r_7-r_7''\left(1-\alpha_7^{Ed}\right)\right)-r_5+r_5''\left(1-\alpha_5^{Ed}\right)-r_5'\right] \quad (8.12)$$

With the transformed objective function, the fuzzy linear programming model of (8.4) using (5.29) is shown in (8.15). Table 8-6 shows the results of solving (8.15).

$$\begin{aligned}\sup_{S(R)} f \;\equiv\; & \max \sum_{j=5}^{7}\left(r_j-r_j''\left(1-\alpha_j^{TE}\right)\right)TE_j \;-\sum_{j=5}^{7}\sum_{k=1}^{2}\left(pr_j^{1,\alpha_k,\beta_k}-r_j''\left(1-\alpha_k^{j,1}\right)\right)P_j^{1,\alpha_k,\beta_k}\\ & +x_{1,5,1}Ed_{1,5}\left[\lambda_{1,5,1,1}\left(r_6-r_6''\left(1-\alpha_6^{Ed}\right)\right)+\lambda_{1,5,1,2}\left(r_7-r_7''\left(1-\alpha_7^{Ed}\right)\right)-r_5+r_5''\left(1-\alpha_5^{Ed}\right)-r_5'\right]\end{aligned}$$

subject to:

$$TE_5-x_{1,5,1}Ed_{1,5}\le\sum_{k=1}^{2}\left(1+\beta_k^{5,1}\right)P_5^{1,\alpha_k,\beta_k}$$

$$TE_6+x_{1,5,1}\lambda_{1,5,1,1}Ed_{1,5}\le\sum_{k=1}^{2}\left(1+\beta_k^{6,1}\right)P_6^{1,\alpha_k,\beta_k}$$

$$TE_7+x_{1,5,1}\lambda_{1,5,1,2}Ed_{1,5}\le\sum_{k=1}^{2}\left(1+\beta_k^{7,1}\right)P_7^{1,\alpha_k,\beta_k}$$

$$TE_5-x_{1,5,1}Ed_{1,5}-\sum_{k=1}^{2}\left(1-\beta_k^{5,1}\right)P_5^{1,\alpha_k,\beta_k}=P_5^{+}-P_5^{-}$$

$$TE_6+x_{1,5,1}\lambda_{1,5,1,1}Ed_{1,5}-\sum_{k=1}^{2}\left(1-\beta_k^{6,1}\right)P_6^{1,\alpha_k,\beta_k}=P_6^{+}-P_6^{-}$$

$$TE_7+x_{1,5,1}\lambda_{1,5,1,2}Ed_{1,5}-\sum_{k=1}^{2}\left(1+\beta_k^{7,1}\right)P_7^{1,\alpha_k,\beta_k}=P_7^{+}-P_7^{-}$$

$$TE_5-x_{1,5,1}Ed_{1,5}+P_5^{-}-\sum_{k=1}^{2}P_5^{1,\alpha_k,\beta_k}\le 0$$

$$TE_6+x_{1,5,1}\lambda_{1,5,1,1}Ed_{1,5}+P_6^{-}-\sum_{k=1}^{2}P_6^{1,\alpha_k,\beta_k}\le 0$$

$$TE_7+x_{1,5,1}\lambda_{1,5,1,2}Ed_{1,5}+P_7^{-}-\sum_{k=1}^{2}P_7^{1,\alpha_k,\beta_k}\le 0$$

$$TE_5\left(1-\alpha_5^{TE}\right)-x_{1,5,1}Ed_{1,5}\left(1-\alpha_5^{ED}\right)\le\sum_{k=1}^{2}\left(1-\alpha_k^{5,1}\right)P_5^{1,\alpha_k,\beta_k}$$

$$TE_6\left(1-\alpha_6^{TE}\right)+x_{1,5,1}\lambda_{1,5,1,1}Ed_{1,5}\left(1-\alpha_6^{EP}\right)\le\sum_{k=1}^{2}\left(1-\alpha_k^{6,1}\right)P_6^{1,\alpha_k,\beta_k}$$

$$TE_7\left(1-\alpha_7^{TE}\right)+x_{1,5,1}\lambda_{1,5,1,2}Ed_{1,5}\left(1-\alpha_7^{EP}\right)\le\sum_{k=1}^{2}\left(1-\alpha_k^{7,1}\right)P_7^{1,\alpha_k,\beta_k}$$

$$x_{1,5,1}\le 100 \quad (8.13)$$

$$\inf_{S(R)} f \equiv \max \sum_{j=5}^{7}\left(r_j - r_j''\left(1-\alpha_j^{TE}\right)\right)TE_j \quad - \sum_{j=5}^{7}\sum_{k=1}^{2}\left(pr_j^{1,\alpha_k,\beta_k} - r_j''\left(1-\alpha_k^{j,1}\right)\right)P_j^{1,\alpha_k,\beta_k}$$
$$+ x_{1,5,1}Ed_{1,5}\left[\lambda_{1,5,1,1}\left(r_6 - r_6''\left(1-\alpha_6^{Ed}\right)\right) + \lambda_{1,5,1,2}\left(r_7 - r_7''\left(1-\alpha_7^{Ed}\right)\right) - r_5 + r_5''\left(1-\alpha_5^{Ed}\right) - r_5'\right]$$

$$TE_5 - x_{1,5,1}Ed_{1,5} \le \sum_{k=1}^{2}\left(1+\beta_k^{5,1}\right)P_5^{1,\alpha_k,\beta_k} - 4.2$$
$$TE_6 + x_{1,5,1}\lambda_{1,5,1,1}Ed_{1,5} \le \sum_{k=1}^{2}\left(1+\beta_k^{6,1}\right)P_6^{1,\alpha_k,\beta_k} - 4.0$$
$$TE_7 + x_{1,5,1}\lambda_{1,5,1,2}Ed_{1,5} \le \sum_{k=1}^{2}\left(1+\beta_k^{7,1}\right)P_7^{1,\alpha_k,\beta_k} - 4.2$$
$$TE_5 - x_{1,5,1}Ed_{1,5} - \sum_{k=1}^{2}\left(1-\beta_k^{5,1}\right)P_5^{1,\alpha_k,\beta_k} = P_5^{+} - P_5^{-}$$
$$TE_6 + x_{1,5,1}\lambda_{1,5,1,1}Ed_{1,5} - \sum_{k=1}^{2}\left(1-\beta_k^{6,1}\right)P_6^{1,\alpha_k,\beta_k} = P_6^{+} - P_6^{-}$$
$$TE_7 + x_{1,5,1}\lambda_{1,5,1,2}Ed_{1,5} - \sum_{k=1}^{2}\left(1+\beta_k^{7,1}\right)P_7^{1,\alpha_k,\beta_k} = P_7^{+} - P_7^{-}$$
$$TE_5 - x_{1,5,1}Ed_{1,5} + P_5^{-} - \sum_{k=1}^{2}P_5^{1,\alpha_k,\beta_k} \le -4.2$$
$$TE_6 + x_{1,5,1}\lambda_{1,5,1,1}Ed_{1,5} + P_6^{-} - \sum_{k=1}^{2}P_6^{1,\alpha_k,\beta_k} \le -4.0$$
$$TE_7 + x_{1,5,1}\lambda_{1,5,1,2}Ed_{1,5} + P_7^{-} - \sum_{k=1}^{2}P_7^{1,\alpha_k,\beta_k} \le -4.2$$
$$TE_5\left(1-\alpha_5^{TE}\right) - x_{1,5,1}Ed_{1,5}\left(1-\alpha_5^{ED}\right) \le \sum_{k=1}^{2}\left(1-\alpha_k^{5,1}\right)P_5^{1,\alpha_k,\beta_k} - 4.2$$
$$TE_6\left(1-\alpha_6^{TE}\right) + x_{1,5,1}\lambda_{1,5,1,1}Ed_{1,5}\left(1-\alpha_6^{EP}\right) \le \sum_{k=1}^{2}\left(1-\alpha_k^{6,1}\right)P_6^{1,\alpha_k,\beta_k} - 4.0$$
$$TE_7\left(1-\alpha_7^{TE}\right) + x_{1,5,1}\hat{\lambda}_{1,5,1,2}Ed_{1,5}\left(1-\alpha_7^{EP}\right) \le \sum_{k=1}^{2}\left(1-\alpha_k^{7,1}\right)P_7^{1,\alpha_k,\beta_k} - 4.2$$
$$10\lambda + x_{1,5,1} \le 100 \tag{8.14}$$

$$max \quad \lambda$$

subject to:

$$\lambda\left(\sup_{S(R)} f - \inf_{S(R)} f\right) + \mathbf{c}^T\mathbf{x} \le \sup_{S(R)} f$$

$$4.2\lambda + TE_5 - x_{1,5,1}Ed_{1,5} \le \sum_{k=1}^{2}\left(1+\beta_k^{5,1}\right)P_5^{1,\alpha_k,\beta_k}$$

$$4.0\lambda + TE_6 + x_{1,5,1}\lambda_{1,5,1,1}Ed_{1,5} \le \sum_{k=1}^{2}\left(1+\beta_k^{6,1}\right)P_6^{1,\alpha_k,\beta_k}$$

$$4.2\lambda + TE_7 + x_{1,5,1}\lambda_{1,5,1,2}Ed_{1,5} \le \sum_{k=1}^{2}\left(1+\beta_k^{7,1}\right)P_7^{1,\alpha_k,\beta_k}$$

$$TE_5 - x_{1,5,1}Ed_{1,5} - \sum_{k=1}^{2}\left(1-\beta_k^{5,1}\right)P_5^{1,\alpha_k,\beta_k} = P_5^+ - P_5^-$$

$$TE_6 + x_{1,5,1}\lambda_{1,5,1,1}Ed_{1,5} - \sum_{k=1}^{2}\left(1-\beta_k^{6,1}\right)P_6^{1,\alpha_k,\beta_k} = P_6^+ - P_6^-$$

$$TE_7 + x_{1,5,1}\lambda_{1,5,1,2}Ed_{1,5} - \sum_{k=1}^{2}\left(1+\beta_k^{7,1}\right)P_7^{1,\alpha_k,\beta_k} = P_7^+ - P_7^-$$

$$4.2\lambda + TE_5 - x_{1,5,1}Ed_{1,5} + P_5^- - \sum_{k=1}^{2}P_5^{1,\alpha_k,\beta_k} \le 0$$

$$4.0\lambda + TE_6 + x_{1,5,1}\lambda_{1,5,1,1}Ed_{1,5} + P_6^- - \sum_{k=1}^{2}P_6^{1,\alpha_k,\beta_k} \le 0$$

$$4.2\lambda + TE_7 + x_{1,5,1}\lambda_{1,5,1,2}Ed_{1,5} + P_7^- - \sum_{k=1}^{2}P_7^{1,\alpha_k,\beta_k} \le 0$$

$$4.2\lambda + TE_5\left(1-\alpha_5^{TE}\right) - x_{1,5,1}Ed_{1,5}\left(1-\alpha_5^{ED}\right) \le \sum_{k=1}^{2}\left(1-\alpha_k^{5,1}\right)P_5^{1,\alpha_k,\beta_k}$$

$$4.0\lambda + TE_6\left(1-\alpha_6^{TE}\right) + x_{1,5,1}\lambda_{1,5,1,1}Ed_{1,5}\left(1-\alpha_6^{EP}\right) \le \sum_{k=1}^{2}\left(1-\alpha_k^{6,1}\right)P_6^{1,\alpha_k,\beta_k}$$

$$4.2\lambda + TE_7\left(1-\alpha_7^{TE}\right) + x_{1,5,1}\lambda_{1,5,1,2}Ed_{1,5}\left(1-\alpha_7^{EP}\right) \le \sum_{k=1}^{2}\left(1-\alpha_k^{7,1}\right)P_7^{1,\alpha_k,\beta_k}$$

$$x_{1,5,1} \le 100$$

$$0 \le \lambda \le 1 \tag{8.15}$$

Table 8-6. Results after solving (8.15).

Variable	Value
P_5^{1,α_1,β_1}	8.40
P_5^{1,α_2,β_2}	37.80
P_6^{1,α_1,β_1}	8.00
P_6^{1,α_2,β_2}	36.00
P_7^{1,α_1,β_1}	8.40
P_7^{1,α_2,β_2}	37.80
$x_{1,5,1}$	0
λ	1

The contract purchasing scheme in Table 8-6 results in an expected profit of \$2705.47 when evaluated using the objective function of (8.1). Compared to the expected profit resulted from the contract purchasing scheme in Table 8-2, \$3743.65, the profit has dropped 27.73%. The drop in expected profit, however, guarantees the highest satisfaction of criteria, *safest* in this example.

The formulation in (8.15) implicitly accounts for the uncertainties in the customer demand, controllable demand, and contract reliability. The uncertainties in the market prices for energy are not included in the analysis. The trade off between the profit of serving customer demand and risk (the uncertainties in the operating conditions) is formulated in the first constraining equation in (8.15). However, since the objective function of (8.15) is to determine the highest possible satisfaction of criteria, solution reached in this example does not guarantee the desired trade off between profit and risk. The only restriction on λ in (8.15) is the last constraining equation. If the last constraining equation in (8.15) is removed, the solution will be unbounded and suggests unlimited purchase of energy contracts.

8.3.2 Approach 2 to Fuzzy Linear Programming [54]

In the approach by Tanaka et al, the uncertainties in market prices, contract reliability, customer demand and controllable customer demand are described by triangle-shaped fuzzy numbers. The centers of the fuzzy numbers, in this example, are described by the expected values of the uncertain parameters while the widths are described by the standard deviation of the uncertain parameters multiplied by 1.65. The reason for multiplying the standard deviation by 1.65 is that the number provides 95% confidence level when the uncertain parameter is described by a normally distributed probabilistic distribution function. For example, shown in Figure 8-3 is the fuzzy number that describes TE_5 (42, 3.3).

Table 8-7 shows the fuzzy numbers of all uncertain parameters. Equation (8.16) shows the fuzzy linear programming model of (8.4) using (5.35). To solve (8.16), the TOL is set to be 0.01. The scheduling of customer demand and the contracts purchasing scheme under various aspiration levels, z, are evaluated and shown in Table 8-8.

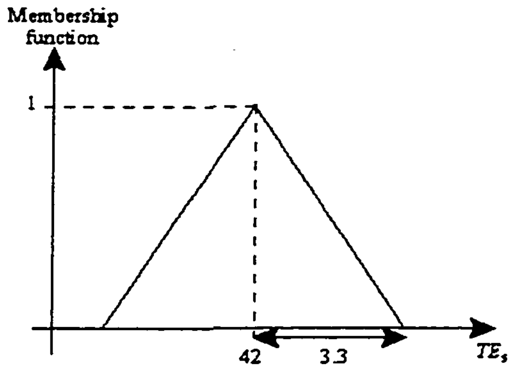

Figure 8-3. Fuzzy number, TE_5.

Table 8-7. The fuzzy numbers of uncertain parameters.

Factors	Parameter	Fuzzy number
Customer	TE_5	(42, 3.30)
	TE_6	(40, 4.95)
	TE_7	(42, 3.30)
Market	$pr_5^{1,\alpha_1,\beta_1}$	(59.40, 4.95)
	$pr_5^{1,\alpha_2,\beta_2}$	(66.28, 3.30)
	$pr_6^{1,\alpha_1,\beta_1}$	(58.16, 3.30)
	$pr_6^{1,\alpha_2,\beta_2}$	(64.89, 4.95)
	$pr_7^{1,\alpha_1,\beta_1}$	(59.95, 3.30)
	$pr_7^{1,\alpha_2,\beta_2}$	(66.89, 4.95)
	$\alpha_1^{5,1}$	(0.05, 0.004125)
	$\alpha_1^{6,1}$	(0.05, 0.004125)
	$\alpha_1^{7,1}$	(0.05, 0.004125)
	$\alpha_2^{5,1}$	(0.03, 0.000165)
	$\alpha_2^{6,1}$	(0.03, 0.000165)
	$\alpha_2^{7,1}$	(0.03, 0.000165)
Supplementary energy	$Ed_{1,5}$	(0.044, 0.000759)
Aspiration level	z	(3000, 500)

$$\max \quad 7466.40 - 30.90P_5^{1,\alpha_1,\beta_1} - 37.18P_5^{1,\alpha_2,\beta_2} - 29.66P_6^{1,\alpha_1,\beta_1} - 35.79P_6^{1,\alpha_2,\beta_2} - 31.45P_7^{1,\alpha_1,\beta_1} - 37.79P_7^{1,\alpha_2,\beta_2} + 1.18096x_{1,5,1}$$

subject to:

$$1.05P_5^{1,\alpha_1,\beta_1} + 1.10P_5^{1,\alpha_2,\beta_2} - (42 + 3.3\lambda) + (0.044 - 0.00759\lambda)x_{1,5,1} \geq 0$$

$$1.05P_6^{1,\alpha_1,\beta_1} + 1.10P_6^{1,\alpha_2,\beta_2} - (40 + 4.95\lambda) - (0.0176 + 0.003036\lambda)x_{1,5,1} \geq 0$$

$$1.05P_7^{1,\alpha_1,\beta_1} + 1.10P_7^{1,\alpha_2,\beta_2} - (42 + 3.3\lambda) - (0.0242 + 0.0041745\lambda)x_{1,5,1} \geq 0$$

$$(42 + 3.3\lambda) - (0.044 + 0.00759\lambda)x_{1,5,1} - 1.05P_5^{1,\alpha_1,\beta_1} - 1.10P_5^{1,\alpha_2,\beta_2} = P_5^+ - P_5^-$$

$$(40 + 4.95\lambda) + (0.0176 - 0.003036\lambda)x_{1,5,1} - 1.05P_6^{1,\alpha_1,\beta_1} - 1.10P_6^{1,\alpha_2,\beta_2} = P_6^+ - P_6^-$$

$$(42 + 3.3\lambda) + (0.00242 - 0.0041745\lambda)x_{1,5,1} - 1.05P_7^{1,\alpha_1,\beta_1} - 1.10P_7^{1,\alpha_2,\beta_2} = P_7^+ - P_7^-$$

$$P_5^{1,\alpha_1,\beta_1} + P_5^{1,\alpha_2,\beta_2} - (42 + 3.3\lambda) + (0.044 - 0.00759\lambda)x_{1,5,1} - P_5^- \geq 0$$

$$P_6^{1,\alpha_1,\beta_1} + P_6^{1,\alpha_2,\beta_2} - (40 + 4.95\lambda) - (0.0176 + 0.003036\lambda)x_{1,5,1} - P_6^- \geq 0$$

$$P_7^{1,\alpha_1,\beta_1} + P_7^{1,\alpha_2,\beta_2} - (42 + 3.3\lambda) - (0.0242 + 0.0041745\lambda)x_{1,5,1} - P_7^- \geq 0$$

$$(0.95 - 0.004125\lambda)P_5^{1,\alpha_1,\beta_1} + (0.97 - 0.000165\lambda)P_5^{1,\alpha_2,\beta_2} - (40.32 + 3.168\lambda) + (0.04268 - 0.0073623\lambda)x_{1,5,1} \geq 0$$

$$(0.95 - 0.004125\lambda)P_6^{1,\alpha_1,\beta_1} + (0.97 - 0.000165\lambda)P_6^{1,\alpha_2,\beta_2} - (38.4 + 4.752\lambda) - (0.017072 + 0.00294492\lambda)x_{1,5,1} \geq 0$$

$$(0.95 - 0.004125\lambda)P_7^{1,\alpha_1,\beta_1} + (0.97 - 0.000165\lambda)P_7^{1,\alpha_2,\beta_2} - (40.32 + 3.168\lambda) - (0.023474 + 0.004049265\lambda)x_{1,5,1} \geq 0$$

$$x_{1,5,1} \leq 100$$

$$(4896 - 605.88\lambda) + (2570.4 - 201.96\lambda) - (30.9 + 4.82625)P_5^{1,\alpha_1,\beta_1} - (37.18 + 3.29505\lambda)P_5^{1,\alpha_2,\beta_2} - (29.66 + 3.17625\lambda)P_6^{1,\alpha_1,\beta_1} - (35.79 + 4.94505\lambda)P_6^{1,\alpha_2,\beta_2} - (31.45 + 3.17625\lambda)P_7^{1,\alpha_1,\beta_1} - (37.79 + 4.82625\lambda)P_7^{1,\alpha_2,\beta_2} + (1.18096 - 0.2037156\lambda)x_{1,5,1} - z \geq 0 \tag{8.16}$$

Table 8-8. Solving (8.16) at various aspiration levels.

Variable	Aspiration level, z			
	2000	2500	3000	3500
λ	0.9531	0.6719	0.3906	0.0781
p_5^{1,α_1,β_1}	45.8101	44.4559	42.6464	42.4301
p_5^{1,α_2,β_2}	0	0	0	0
p_6^{1,α_1,β_1}	45.3765	44.0904	42.9081	40.9437
p_6^{1,α_2,β_2}	0	0	0	0
p_7^{1,α_1,β_1}	45.8101	45.0615	44.4531	42.8793
p_7^{1,α_2,β_2}	0	0	0	0
$x_{1,5,1}$	0	8.9744	24.0000	6.4746

The aspiration levels are the expected profits that the objective function of (8.16) must meet. When the desired aspiration level, z, is highest, the *satisfaction of criteria*, λ, is the lowest, and vice-versa. When the desired aspiration level is high, the controllable customer demand, $x_{1,5,1}$, is scheduled to improve λ. However, when the desired aspiration level is low, additional contracts can be purchased to improve λ. The controllable customer demand $x_{1,5,1}$ is not scheduled because the additional contracts purchased are more effective in improving λ.

8.3.3 Remarks to Fuzzy Linear Programming

The two approaches to fuzzy linear programming consider the uncertain customer demand, controllable customer demand, and delivered reliability level at different degree. In the presented examples, the second approach, Tanaka's approach, to fuzzy linear programming is significantly better than first approach. By evaluating the scheduling of customer demand and contract purchasing scheme at various aspiration levels, the second approach provides alternatives to the decision-maker.

As a final remark, to adopt either one of the two fuzzy linear programming approaches, interpreting uncertainty in terms of fuzziness is required. Unfortunately, the interpretation of fuzziness is still not well recognized. For instance, in the presented examples, the standard deviations of the uncertain parameters are used as the basis of fuzziness. However, whether the standard deviation may be used as the basis to interpret fuzziness is debatable. In section 8.6, VaR is used to compare the financial risks of the decisions reached under various risk management tools.

8.4 MEAN-VARIANCE ANALYSIS

In this section, mean-variance analytical model described in (5.6) is used to evaluate the scheduling of customer demand and contract purchasing scheme shown in (8.4). In section 8.4.1, the variance of (8.4) is modeled. In section 8.4.2, mean-variance analysis is used to evaluate (8.4). Section 8.4.3 comments on the applicability of mean-variance analysis in the stated problem.

8.4.1 Modeling the Variance of (8.4)

The uncertain parameters include the market prices, the customer demand, the controllable customer demand, and the delivered reliability level. To facilitate the modeling process, the following vectors, (8.17) through (8.30), are introduced.

$$\mathbf{P} = \begin{bmatrix} P_5^{1,\alpha_1,\beta_1} & P_5^{1,\alpha_2,\beta_2} & P_6^{1,\alpha_1,\beta_1} & P_6^{1,\alpha_2,\beta_2} & P_7^{1,\alpha_1,\beta_1} & P_7^{1,\alpha_2,\beta_2} \end{bmatrix} \tag{8.17}$$

$$\mathbf{b}_1 = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 \end{bmatrix} \tag{8.18}$$

$$\begin{aligned} \mathbf{a}_1 &= \begin{bmatrix} -P_5^{1,\alpha_1,\beta_1} & -P_5^{1,\alpha_2,\beta_2} & -P_6^{1,\alpha_1,\beta_1} & -P_6^{1,\alpha_2,\beta_2} & -P_7^{1,\alpha_1,\beta_1} & -P_7^{1,\alpha_2,\beta_2} \end{bmatrix} \\ &= -\mathbf{b}_1 \bullet \mathbf{P} \end{aligned} \tag{8.19}$$

$$\mathbf{b}_2 = \begin{bmatrix} -r_5'' & -r_5'' & -r_6'' & -r_6'' & -r_7'' & -r_7'' \end{bmatrix} \tag{8.20}$$

$$\begin{aligned} \mathbf{a}_2 &= \begin{bmatrix} -r_5''P_5^{1,\alpha_1,\beta_1} & -r_5''P_5^{1,\alpha_2,\beta_2} & -r_6''P_6^{1,\alpha_1,\beta_1} & -r_6''P_6^{1,\alpha_1,\beta_1} & -r_7''P_7^{1,\alpha_1,\beta_1} & -r_7''P_7^{1,\alpha_1,\beta_1} \end{bmatrix} \\ &= \mathbf{b}_2 \bullet \mathbf{P} \end{aligned} \tag{8.21}$$

$$\mathbf{b}_3 = \begin{bmatrix} 1 & 1 & 1 \end{bmatrix} \tag{8.22}$$

$$\mathbf{a}_3 = \begin{bmatrix} \left(r_5 - r_5''\left(1 - \alpha_5^{TE}\right)\right) & \left(r_6 - r_6''\left(1 - \alpha_6^{TE}\right)\right) & \left(r_6 - r_6''\left(1 - \alpha_6^{TE}\right)\right) \end{bmatrix} \tag{8.23}$$

$$\mathbf{x} = x_{1,5,1} \tag{8.24}$$

$$\mathbf{b}_4 = \left(\lambda_{1,5,1,1}\left(r_6 - r_6''\left(1 - \alpha_6^{TE}\right)\right) + \lambda_{1,5,1,2}\left(r_7 - r_7''\left(1 - \alpha_7^{TE}\right)\right) - r_5 + r_5''\left(1 - \alpha_5^{Ed}\right) - r_5'\right) \tag{8.25}$$

$$\mathbf{a}_4 = \left(\lambda_{1,5,1,1}\left(r_6 - r_6''\left(1-\alpha_6^{TE}\right)\right) + \lambda_{1,5,1,2}\left(r_7 - r_7''\left(1-\alpha_7^{TE}\right)\right) - r_5 + r_5''\left(1-\alpha_5^{Ed}\right) - r_5'\right)x_{1,5,1}$$
$$= \mathbf{b}_4 \bullet \mathbf{x} \tag{8.26}$$

$$\mathbf{a}_5 = \begin{bmatrix} r_5'' & r_5'' & r_6'' & r_6'' & r_7'' & r_7'' \end{bmatrix} \tag{8.27}$$

$$\mathbf{pr} = \begin{bmatrix} pr_5^{1,\alpha_1,\beta_1} \\ pr_5^{1,\alpha_2,\beta_2} \\ pr_6^{1,\alpha_1,\beta_1} \\ pr_6^{1,\alpha_2,\beta_2} \\ pr_7^{1,\alpha_1,\beta_1} \\ pr_7^{1,\alpha_2,\beta_2} \end{bmatrix} \tag{8.28}$$

$$\alpha = \begin{bmatrix} \alpha_1^{5,1} \\ \alpha_2^{5,1} \\ \alpha_1^{6,1} \\ \alpha_2^{6,1} \\ \alpha_1^{7,1} \\ \alpha_2^{7,1} \end{bmatrix} \tag{8.29}$$

$$\mathbf{TE} = \begin{bmatrix} TE_5 \\ TE_6 \\ TE_7 \end{bmatrix} \tag{8.30}$$

$$\mathbf{ED} = Ed_{1,5} \tag{8.31}$$

The variance of (8.4) is shown in (8.32). Equation (8.33) shows the variance of (8.4) after substituting (8.17) through (8.31) into (8.32).

$$VAR(Equation\,(8.4)) = VAR(\mathbf{a}_1\mathbf{pr} + \mathbf{a}_2\alpha + \mathbf{a}_3\mathbf{TE} + \mathbf{a}_4\mathbf{ED} + \mathbf{a}_5\mathbf{pr})$$
$$= VAR(\mathbf{a}_1\mathbf{pr} + \mathbf{a}_2\alpha + \mathbf{a}_3\mathbf{TE} + \mathbf{a}_4\mathbf{ED}) \tag{8.32}$$

$$VAR(Equation\,(8.4)) = \begin{bmatrix} \mathbf{a}_1 & \mathbf{a}_2 & \mathbf{a}_3 & \mathbf{a}_4 \end{bmatrix} \begin{bmatrix} cov(\mathbf{pr},\mathbf{pr}) & cov(\mathbf{pr},\alpha) & cov(\mathbf{pr},\mathbf{TE}) & cov(\mathbf{pr},\mathbf{ED}) \\ cov(\alpha,\mathbf{pr}) & cov(\alpha,\alpha) & cov(\alpha,\mathbf{TE}) & cov(\alpha,\mathbf{ED}) \\ cov(\mathbf{TE},\mathbf{pr}) & cov(\mathbf{TE},\alpha) & cov(\mathbf{TE},\mathbf{TE}) & cov(\mathbf{TE},\mathbf{ED}) \\ cov(\mathbf{ED},\mathbf{pr}) & cov(\mathbf{ED},\alpha) & cov(\mathbf{ED},\mathbf{TE}) & cov(\mathbf{ED},\mathbf{ED}) \end{bmatrix} \begin{bmatrix} \mathbf{a}_1^T \\ \mathbf{a}_2^T \\ \mathbf{a}_3^T \\ \mathbf{a}_4^T \end{bmatrix}$$

$$=\left[(-\mathbf{b}_1 \bullet \mathbf{P}) \quad (\mathbf{b}_2 \bullet P) \quad (\mathbf{a}_3 \bullet \mathbf{b}_3) \quad (\mathbf{b}_4\mathbf{x})\right]\begin{bmatrix} cov(\mathbf{pr},\mathbf{pr}) & cov(\mathbf{pr},\alpha) & cov(\mathbf{pr},\mathbf{TE}) & cov(\mathbf{pr},\mathbf{ED}) \\ cov(\alpha,\mathbf{pr}) & cov(\alpha,\alpha) & cov(\alpha,\mathbf{TE}) & cov(\alpha,\mathbf{ED}) \\ cov(\mathbf{TE},\mathbf{pr}) & cov(\mathbf{TE},\alpha) & cov(\mathbf{TE},\mathbf{TE}) & cov(\mathbf{TE},\mathbf{ED}) \\ cov(\mathbf{ED},\mathbf{pr}) & cov(\mathbf{ED},\alpha) & cov(\mathbf{ED},\mathbf{TE}) & cov(\mathbf{ED},\mathbf{ED}) \end{bmatrix}\begin{bmatrix} (-\mathbf{b}_1 \bullet \mathbf{P})^T \\ (\mathbf{b}_2 \bullet P)^T \\ (\mathbf{a}_3 \bullet \mathbf{b}_3)^T \\ (\mathbf{b}_4\mathbf{x})^T \end{bmatrix}$$

$$=\left[\mathbf{P} \quad \mathbf{b}_3 \quad \mathbf{x}\right]\begin{bmatrix} cov_{1,1} & cov_{1,2} & cov_{1,3} \\ cov_{2,1} & cov_{2,2} & cov_{2,3} \\ cov_{3,1} & cov_{3,2} & cov_{3,3} \end{bmatrix}\begin{bmatrix} \mathbf{P}^T \\ \mathbf{b}_3^T \\ \mathbf{x}^T \end{bmatrix}$$

$$=\left[\mathbf{P} \quad \mathbf{x}\right]\begin{bmatrix} cov_{1,1} & cov_{1,3} \\ cov_{3,1} & cov_{3,3} \end{bmatrix}\begin{bmatrix} \mathbf{P}^T \\ \mathbf{x}^T \end{bmatrix} + (\mathbf{b}_3)cov_{2,2}(\mathbf{b}_3)^T + 2\mathbf{P}\,cov_{1,2}(\mathbf{b}_3)^T + 2\mathbf{b}_3\,cov_{2,3}\,\mathbf{x}^T \tag{8.33}$$

where

$$cov_{11} = cov(\mathbf{pr},\mathbf{pr}) + 2\left(-\mathbf{b}_1^T\mathbf{b}_2\right)\bullet cov(\mathbf{pr},\alpha) + \left(\mathbf{b}_2^T\mathbf{b}_2\right)cov(\alpha,\alpha) \tag{8.34}$$

$$cov_{1,2} = cov_{2,1}^T = \left(-\mathbf{b}_1^T\mathbf{a}_3\right)\bullet cov(\mathbf{pr},\mathbf{TE}) + \left(\mathbf{b}_2^T\mathbf{a}_3\right)\bullet cov(\alpha,\mathbf{TE}) \tag{8.35}$$

$$cov_{1,3} = cov_{3,1}^T = \left(-\mathbf{b}_1^T\mathbf{b}_4\right)\bullet cov(\mathbf{pr},\mathbf{ED}) + \left(\mathbf{b}_2^T\mathbf{b}_4\right)\bullet cov(\alpha,\mathbf{ED}) \tag{8.36}$$

$$cov_{2,2} = \left(\mathbf{a}_3^T\mathbf{a}_3\right)\bullet cov(\mathbf{TE},\mathbf{TE}) \tag{8.37}$$

$$cov_{2,3} = cov_{3,2}^T = \left(\mathbf{a}_3^T\mathbf{b}_4\right)\bullet cov(\mathbf{TE},\mathbf{ED}) \tag{8.38}$$

$$cov_{3,3} = \left(\mathbf{b}_4^T\mathbf{b}_4\right)\bullet ov(\mathbf{ED},\mathbf{ED}) \tag{8.39}$$

8.4.2 Solving the uncertain model using mean-variance analysis

Equation (8.40) shows the mean-variance analytical mode of (8.4) using (5.6). The scheduling of customer demand and the contracts purchasing scheme under various expected profit levels, λ, are evaluated and shown in Table 8-9.

$$min \quad \begin{bmatrix}\mathbf{P} & \mathbf{x}\end{bmatrix}\begin{bmatrix} cov_{1,1} & cov_{1,3} \\ cov_{3,1} & cov_{3,3}\end{bmatrix}\begin{bmatrix}\mathbf{P}^T \\ \mathbf{x}^T\end{bmatrix} + \mathbf{b}_1\, cov_{2,2}\, \mathbf{b}_1^T + 2\mathbf{P}\, cov_{1,2}\, \mathbf{b}_1^T + 2\mathbf{x}\, cov_{2,3}\, \mathbf{b}_3^T$$

subject to:

$$\sum_{j=5}^{7}\left(r_j - r_j^{\prime\prime}\left(1-\alpha_j^{TE}\right)\right)TE_j + x_{1,5,1}Ed_{1,5}\left[\lambda_{1,5,1,1}\left(r_6 - r_6^{\prime\prime}\left(1-\alpha_6^{Ed}\right)\right) + \lambda_{1,5,1,2}\left(r_7 - r_7^{\prime\prime}\left(1-\alpha_7^{Ed}\right)\right) - r_5 + r_5^{\prime\prime}\left(1-\alpha_5^{Ed}\right) - r_5^{t}\right]$$

$$-\sum_{j=5}^{7}\sum_{k=1}^{2}\left(pr_j^{1,\alpha_k,\beta_k} - r_j^{\prime\prime}\left(1-\alpha_k^{j,1}\right)\right)P_j^{1,\alpha_k,\beta_k} \geq \lambda$$

$$TE_5 - x_{1,5,1}Ed_{1,5} \leq \sum_{k=1}^{2}\left(1+\beta_k^{5,1}\right)P_5^{1,\alpha_k,\beta_k}$$

$$TE_6 + x_{1,5,1}\lambda_{1,5,1,1}Ed_{1,5} \leq \sum_{k=1}^{2}\left(1+\beta_k^{6,1}\right)P_6^{1,\alpha_k,\beta_k}$$

$$TE_7 + x_{1,5,1}\lambda_{1,5,1,2}Ed_{1,5} \leq \sum_{k=1}^{2}\left(1+\beta_k^{7,1}\right)P_7^{1,\alpha_k,\beta_k}$$

$$TE_5 - x_{1,5,1}Ed_{1,5} - \sum_{k=1}^{2}\left(1-\beta_k^{5,1}\right)P_5^{1,\alpha_k,\beta_k} = P_5^{+} - P_5^{-}$$

$$TE_6 + x_{1,5,1}\lambda_{1,5,1,1}Ed_{1,5} - \sum_{k=1}^{2}\left(1-\beta_k^{6,1}\right)P_6^{1,\alpha_k,\beta_k} = P_6^{+} - P_6^{-}$$

$$TE_7 + x_{1,5,1}\lambda_{1,5,1,2}Ed_{1,5} - \sum_{k=1}^{2}\left(1+\beta_k^{7,1}\right)P_7^{1,\alpha_k,\beta_k} = P_7^{+} - P_7^{-}$$

$$TE_5 - x_{1,5,1}Ed_{1,5} + P_5^{-} - \sum_{k=1}^{2}P_5^{1,\alpha_k,\beta_k} \leq 0$$

$$TE_6 + x_{1,5,1}\lambda_{1,5,1,1}Ed_{1,5} + P_6^{-} - \sum_{k=1}^{2}P_6^{1,\alpha_k,\beta_k} \leq 0$$

$$TE_7 + x_{1,5,1}\lambda_{1,5,1,2}Ed_{1,5} + P_7^{-} - \sum_{k=1}^{2}P_7^{1,\alpha_k,\beta_k} \leq 0$$

$$TE_5\left(1-\alpha_5^{TE}\right) - x_{1,5,1}Ed_{1,5}\left(1-\alpha_5^{ED}\right) \leq \sum_{k=1}^{2}\left(1-\alpha_k^{5,1}\right)P_5^{1,\alpha_k,\beta_k}$$

$$TE_6\left(1-\alpha_6^{TE}\right) + x_{1,5,1}\lambda_{1,5,1,1}Ed_{1,5}\left(1-\alpha_6^{EP}\right) \leq \sum_{k=1}^{2}\left(1-\alpha_k^{6,1}\right)P_6^{1,\alpha_k,\beta_k}$$

$$TE_7\left(1-\alpha_7^{TE}\right) + x_{1,5,1}\lambda_{1,5,1,2}Ed_{1,5}\left(1-\alpha_7^{EP}\right) \leq \sum_{k=1}^{2}\left(1-\alpha_k^{7,1}\right)P_7^{1,\alpha_k,\beta_k}$$

$$x_{1,5,1} \leq 100 \qquad (8.40)$$

Table 8-9. Solving (8.40) at various aspiration levels.

Variable	Minimum expected profit level, λ			
	2000	2400	2800	3200
Actual expected profit	\$3225.19	\$3225.19	\$3225.19	\$3225.19
var	85,088	85,088	85,088	85,088
$\sqrt{var}$	\$291.70	\$291.70	\$291.70	\$291.70
P_5^{1,α_1,β_1}	0.0000	0.0000	0.0000	0.0000
P_5^{1,α_2,β_2}	42.0000	42.0000	42.0000	42.0000
P_6^{1,α_1,β_1}	35.4647	35.4647	35.4647	35.4647
P_6^{1,α_2,β_2}	4.8541	4.8541	4.8541	4.8541
P_7^{1,α_1,β_1}	21.0005	21.0005	21.0005	21.0005
P_7^{1,α_2,β_2}	20.9995	20.9995	20.9995	20.9995
$x_{1,5,1}$	0.0000	0.0000	0.0000	0.0000

In this example, even though the minimum requirement on the expected profit, λ, is lowered, the variance can never be lower than 85,088. The contract purchasing scheme and scheduling customer demand scheme does not change with the changes in λ. The expected profit from solving (8.40) is \$3225.19 with the lowest standard deviation of \$291.19. The result shows a diversified pattern in the purchased contracts. Some contracts of each contract type are purchasing to diversify away the risk, with the exception that contract type 1 at the 5$^{\text{th}}$ period, P_5^{1,α_1,β_1}, and controllable customer demand, $x_{1,5,1}$, not being utilized to minimize the risk.

8.4.3 Remarks to Mean-variance Analysis

In the example presented, the simultaneous impact of uncertain customer demands, controllable customer demands, market prices, and delivered contract reliabilities is considered. The recommendations using mean-variance analysis are different from the recommendations using other approaches, fuzzy linear programming in particular. For example, mean-variance analysis has recommended the ESCO not to purchase additional energy contracts from the auction market or not to utilize any controllable customer demand. Instead, using mean-variance analysis, the ESCO is recommended to purchase a mix of contracts providing different reliability levels and volatility levels. Other approaches, fuzzy linear programming for instance, have recommended different strategies to lower the impact of uncertain customer demand and controllable demand. Aside from purchasing a mixture of contracts providing different reliability levels and volatility levels, fuzzy linear programming has recommended the purchase of additional energy contracts. Second, mean-variance analysis has recommended that the ESCO's financial risk can not be reduced at the expense of lower expected profit through additional purchase of energy contracts. Fuzzy linear programming (Tanaka's approach in particular) has shown that by purchasing additional energy contracts, the risk is lowered.

Even though mean-variance analysis has recommended no additional purchase of energy contracts in this example, the recommendation is specific only to the given example. In previous research [60], it is shown that, at the presence of uncertain market price, customer demand, and controllable demand, mean-variance analysis may also recommend the purchase of additional energy contracts.

8.5 STOCHASTIC LINEAR PROGRAMMING

To apply the two-stage stochastic linear programming approach, there should be some decisions that need to be determined *now* while some decisions to be determined in the *future*. In the presented example, the combination of contract purchasing scheme and scheduling customer demand scheme is to be determined *now*. Thus, the example should be considered as a single-stage model and is not appropriate not be modeled as a two-stage stochastic linear programming model described in (5.3) and (5.4).

8.6 PRIOR TO VaR ANALYSIS

In section 8.2, the impacts of uncertain customer demand and market price are analyzed using sensitivity analysis and parametric analysis. In section 8.3, the impacts of uncertain customer demand, controllable customer demand, market price, and delivered contract reliability are analyzed using fuzzy linear programming. In section 8.4, the impacts of all uncertain parameters are analyzed using mean-variance analysis. Since the presented example is not suitable for stochastic linear programming analysis, no result is presented in section 8.6. The recommended scheduling customer demand scheme and contract purchasing scheme under the various approaches vary. Two factors contribute toward the differences. First, the number of uncertain parameters considered varies from one approach to another. For instance, in parametric analysis, only the impact of uncertain market prices is considered while, in fuzzy linear programming, the impact of all uncertain parameters is considered. Second and most importantly, how the uncertainty is modeled under the various approaches. On one hand, in fuzzy linear programming for instance, the uncertain parameters embedded in the constraining equations are reflected in the constraining equations by using the lower estimates. On the other hand, in mean-variance analysis for instance, the uncertain parameters embedded in the constraining equations are reflected through the objective function, i.e., lower estimates are *not* used in the constraining equations.

In addition to recommending different responses, there are limitations that the approaches presented. First, the mathematical model prior to risk management analysis using the approaches presented so far has to be linear. Any nonlinearity in the original mathematical model may results in the inapplicability of the risk management tools. A non-linear market price, for instance, results in a nonlinear objective function. This nonlinearity renders the sensitivity analysis and parametric analysis inapplicable. Second, there are limitations on the number of uncertain parameters that can be considered using the approaches presented so far. For example, when the controllable customer demand, Ed_j, and the variable tariff, r_j, are uncertain, the resulting variance can no longer be expressed as a quadratic function and complicates the applicability of mean-variance analysis using quadratic programming. Third, in some approaches, the uncertain parameters need to be symmetric. For instance, the uncertain parameters in fuzzy linear programming (Tanaka's appraoch) are described as symmetrical triangle fuzzy numbers while the uncertain parameters in mean-variance analysis are described as normally distributed probabilistic functions.

To provide a useful comparison to the recommendations offered by these various approaches and to improve the limitations of the approaches, VaR analysis is presented in the following section.

8.7 VaR ANALYSIS

VaR analysis, presented in section 5.6, analyzes the financial risks of carrying out a particular scheduling customer demand scheme and contract purchasing scheme, assuming that the decision has been made. In this section, various decisions made under the risk management tools will be evaluated using VaR analysis. Table 8-10 shows the list of scheduling customer demand schemes and contract purchasing schemes to be evaluated using VaR analysis. Section 8.7.1 shows how the VaR analysis is used to compare the various decisions. Section 8.7.2 shows the results of using the VaR analysis. Section 8.7.3 comments on the applicability of VaR analysis in this example. To provide comparable analysis, the ESCO will not receive any compensation for any contract reliability not delivered, i.e, pm_k in (5.37) is assumed to be 0.

8.7.1 Comparing the decisions using the VaR Analysis

To provide a meaningful comparison among various decision choices presented in Table 8-10, VaR of these decision choices are first evaluated. Then, the combinations of expected profit and VaR of these decision choices are compared. To compute the expected profits of the decision choices in Table 8-10, (8.4) is used. The expected profits of these decision choices are computed and presented in Table 8-11. To compute the cost of risk, VaR at 95% confidence level is used.

Table 8-10. Decisions to be evaluated using VaR analysis.

Selection	Source		Decision variables						
	Approach	Table	P_5^{1,α_1,β_1}	P_5^{1,α_2,β_2}	P_6^{1,α_1,β_1}	P_6^{1,α_2,β_2}	P_7^{1,α_1,β_1}	P_7^{1,α_2,β_2}	$x_{1,5,1}$
1	linear programming	8.1	42.4	0	40.4	0	42.4	0	0
2	parametric analysis	8.4	41.4	0	40.8	0	43.0	0	24
3	parametric analysis	8.4	21.0	19.94	40.9	0	43.0	0	24
4	parametric analysis	8.5	42.4	0	40.4	0	21.0	21.0	0
5	fuzzy LP	8.6	8.4	37.8	8	36.0	8.4	37.8	0
6	fuzzy LP	8.8	45.8	0	45.4	0	45.8	0	0
7	fuzzy LP	8.8	44.5	0	44.1	0	45.1	0	9.0
8	fuzzy LP	8.8	42.6	0	42.9	0	44.5	0	24.0
9	fuzzy LP	8.8	42.4	0	40.9	0	42.9	0	6.5
10	mean-variance analysis	8.9	0	42.0	35.5	4.9	21.0	21.0	0

Table 8-11. Calculating the expected profit of the decision choices in Table 8-10 using (8.4).

Selection	Expected profit
1	\$3,746.90
2	\$3,741.21
3	\$3,627.23
4	\$3,626.34
5	\$2,705.47
6	\$3,386.61
7	\$3,485.15
8	\$3,594.67
9	\$3,714.76
10	\$3,344.90

Section 8.2 through section 8.4 assume r_j^{*} to be \$30/MW-period to preserve the linearity of the objective function. However, as pointed out, a more realistic r_j^{*} should be a nonlinear function of the difference between the purchased energy and the customer demand. To evaluate the financial risk using VaR analysis, two set of r_j^{*} is used. The first, with results presented in section 8.7.2.1, assumes r_j^{*} to be \$30/MW-period. The results will be used primarily to compare the various approaches. The second, with results

presented in section 8.7.2.2, assumes r_j^{π} to be a nonlinear function shown in Table 8-12. The results will be used primarily to compare the impacts of linearizing r_j^{π}.

Table 8-12. The nonlinear r_j^{π}, used in section 8.7.2.2.

Condition	r_j^{π}
$TE_j - ED_j + EP_j + ES_j - ER_j > \sum_{\forall h} \sum_{\forall d^f} P_a^{d^f, \alpha_h, \beta_h}$	\$30.00/MW-period
$TE_j - ED_j + EP_j + ES_j - ER_j < \sum_{\forall h} \sum_{\forall d^f} P_a^{d^f, \alpha_h, \beta_h}$	-\$30/MW-period

8.7.2 Results

Section 8.7.2.1 shows the VaR of the decision choices in Table 8-10 using the linear r_j^{π}. Section 87.2.2 shows the VaR of the decision choices in Table 8-10 using the nonlinaer r_j^{π} presented in Table 8-12.

8.7.2.1 Linear r_j^{π}

Table 8-13 shows the VaR of the decisions shown in Table 8-10. The last column in Table 8-13 shows the expected profit of the various decision choices and is duplicated from Table 8-11. 2500 randomly generated data for each uncertain parameter are collected for the analysis using MATLAB. Figure 8-4 shows the plot of the expected profit versus the total VaR of each decision in Table 8-11. Of all, the decision, selection 10, under mean-variance analysis results in the lowest VaR in market price fluctuation due to the diversification of the purchased energy contracts. However, since no additional energy contracts are purchased to guard against potential increase in the customer demand, mean-variance analysis results in one of the highest VaR of ENS. Fuzzy linear programming (Zimmerman's approach) recommends the highest increase in the energy contracts. Thus, the decision, selection 5, results in the highest VaR in market price fluctuation, but the lowest VaR in ENS. In this example, VaR of contract violation is insignificant compared to the other components of the ESCO VaR. From Figure 8-4, the decisions that provide the best combination of risk, VaR, and expected profit include selections 1,2, 5, 6, 7, 8, and 9.

8.7.2.2 Nonlinear r_j^{π} as Shown in Table 8-12

In this section, the impact of nonlinear r_j^{π} is considered. Table 8-14 shows the VaR of the decisions shown in Table 8-10. The last column in Table 8-14 shows the expected profit of the various decision choices and is duplicated from Table 8-11. 2500 randomly generated data for each uncertain parameter are collected for the analysis using MATLAB. Figure 8-5 shows the plot of the expected profit versus the total VaR of each decision in Table 8-11.

When r_j^r is nonlinear and the decisions in Table 8-11 are evaluated, it is obvious that the VaR of ENS does not decrease because of the additional purchase of energy contracts. Instead, because of the additional purchase, the potential of buying too much energy cost the ESCO. In Table 8-14, selection 5 under fuzzy linear programming (Zimmermann's approach) results in the highest VaR because of the additional purchase. Selection 10, under mean-variance analysis, that does not encourage additional purchase of energy contracts does not result in a lower VaR either. The potential of energy not delivered according to contract specifications can cost the ESCO as well. From Figure 8-5, selections 1, 2, 8, and 9 prevail in providing the best combinations of risk, VaR, and return, expected profit.

8.7.3 Remarks to VaR Analysis

The results in sections 8.7.2.1 suggest that, when r_j^r is linear, additional purchase of energy contracts increases the VaR of market price fluctuations, but lowers the VaR of ENS. The results in section 8.7.2.2 suggest that, when r_j^r is dependent on the absolute difference between the delivered energy and the customer demand (Table 8-12 for example), additional purchase of energy contracts increases the VaR of market price fluctuation and ENS, but lowers the VaR of contract violation.

Table 8-13. VaR analysis using a linear r_j^r.

	VaR				
Selection	Market price fluctuation	ENS	Contract violation	Total	Expected profit
1	$325.47	$480.00	$6.00	$811.47	$3,746.90
2	$323.66	$477.00	$6.00	$806.66	$3,741.21
3	$293.39	$475.80	$7.20	$776.39	$3,627.23
4	$333.15	$477.00	$3.00	$813.15	$3,626.34
5	$377.69	$ 93.00	-$6.00	$464.69	$2,705.47
6	$355.22	$144.00	$3.00	$502.22	$3,386.61
7	$346.26	$237.00	$6.00	$589.26	$3,485.15
8	$335.45	$342.00	$3.00	$680.45	$3,594.67
9	$327.45	$453.00	$3.00	$783.45	$3,714.76
10	$293.03	$462.00	$12.00	$767.03	$3,344.90

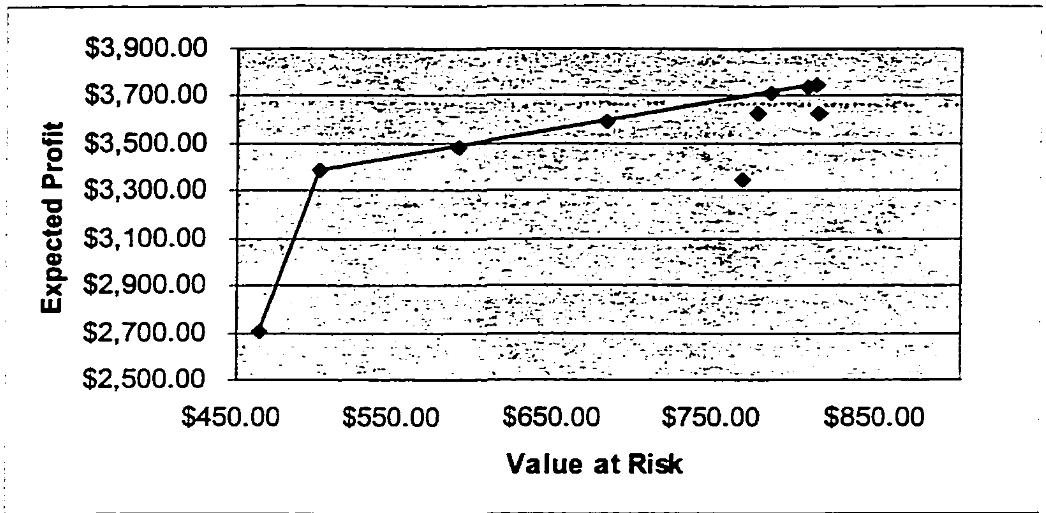

Figure 8-4. Expected profit versus value at risk when $r_j^{"}$ is linear.

Table 8-14. VaR analysis using a nonlinear $r_j^{"}$ as shown in Table 8-12.

	VaR				
Selection	Market price fluctuation	ENS	Contract violation	Total	Expected profit
1	$325.47	$495.00	$90.00	$910.47	$3,746.90
2	$323.66	$492.00	$93.00	$908.66	$3,741.21
3	$293.39	$490.80	$94.20	$878.39	$3,627.23
4	$333.15	$495.00	$99.00	$927.15	$3,626.34
5	$377.69	$555.00	$75.00	$1007.69	$2,705.47
6	$355.22	$513.00	$132.00	$1000.22	$3,386.61
7	$346.26	$441.00	$120.00	$907.26	$3,485.15
8	$335.45	$411.00	$102.00	$848.45	$3,594.67
9	$327.45	$468.00	$90.00	$885.45	$3,714.76
10	$293.03	$480.00	$111.00	$884.03	$3,344.90

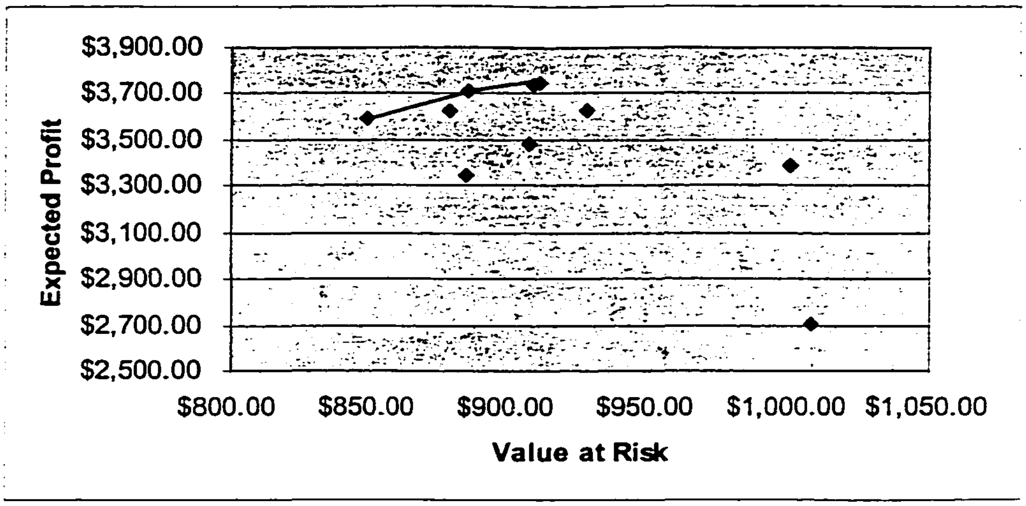

Figure 8-5. Expected profit versus value at risk when r_j^* is nonlinear.

8.8 REMARKS TO RISK MANAGEMENT AND ASSESSMENT TOOLS

Section 8.2 through section 8.7 provides risk analysis to the scheduling customer demand model using various risk management tools. First, linear programming, parametric analysis, mean-variance analysis and fuzzy linear programming are used to derive recommendations. Then, VaR analyses are used to evaluate the cost of risks of the recommendations proposed by the various tools. The combinations of expected profit, return of investment, and cost of risk, VaR, are then used to evaluate the effectiveness of each approach.

In this example, the simplest approach, a deterministic model solved using linear programming, provides among the best combination of risk and return that the ESCO can choose (Figure 8-4 and Figure 8-5). However, it is important to recognize that, by ignoring the impact of uncertainties, the deterministic model may not always results in the best recommendation. More importantly, by using the risk management tools, options that also provide the best combinations of risk and return can be found.

8.8.1 Choosing the Right Risk Management and Assessment Tool for Analytical Purpose

From sensitivity analysis to mean-variance analysis, each of the presented risk management tools has recommended different scheduling customer demand scheme and contract purchasing scheme. So, when decision-making is needed, what tool should a decision-maker adopt?

Prior to answering that, it should be noted that most of the decision choices recommended by the various risk management tools result in efficient combinations of expected profit and VaR, as shown in Figure 8-4 (r_j^* is linear). More decision choices do not result in efficient combinations of expected profit and VaR in

Figure 8-5 because r_j^e is assumed nonlinear in evaluating the VaR while the models recommending the decision choices use linear r_j^e in the analytical process. When decision choices result in efficient combinations of expected profit and VaR, the selection process depends on the cost of risk, VaR in this instance, that an ESCO is willing to assume. When the ESCO is willing to assume a higher VaR, it can expect a higher expect profit, and vice versa. However, when decision choices do not result in efficient combinations of expected profit and VaR, an ESCO should adopt one that provides the best combination of expected profit and VaR.

To decide if one risk management tool should prevail over another, there are various factors that should be considered. In section, the risk management tools are compared on their applicability, computational time requirement, and technical requirement. These factors influence when and why a particular tool should be adopted. For instance, when decision is to be made in a short time period, sensitivity analysis and parametric analysis can be more handful than VaR analysis or stochastic linear programming. Also, when a developed ESCO model is nonlinear, there could be a problem of utilizing mean-variance analysis to address uncertainties in the ESCO model.

In addition to the time requirement, technical requirement and applicability described in section 5.7, the data available to analyze the uncertainty is also an important factor to decide if one risk management tool should prevail in the decision-making process. Depending on the data available to characterize the uncertain parameters, one risk management tool can provide better recommendation than another tool. In general, sensitivity analysis and parametric analysis require the least information on the uncertainty; mean-variance analysis, stochastic linear programming and VaR require the most information on the uncertainty; while fuzzy linear programming falls in between. When insufficient data is available to describe the uncertainties, some risk management tools are not applicable, mean-variance analysis, stochastic linear programming, and VaR analysis in particular. When sufficient data is available, depending on the applicability, time requirement, and technical requirement described in section 5.7, the decision-maker may select the risk management tool that best fit his/her profile. For example, when ample time is provided, VaR analysis results in the most thorough analysis on the decision choices. However, when time is restricted but data is ample, mean-variance analysis may be adopted.

CHAPTER 9 CONCLUSIONS AND FUTURE WORK

This chapter summarizes this research; presents major conclusions reached in Chapter 6 through Chapter 8; and proposes extensions to this research.

9.1 RESEARCH SUMMARY

This research is an extension to my thesis work for Master of Science in Electrical Engineering. The load management models developed during my Master's program, presented in Chapter 3, are enhanced and used to develop the scheduling customer demand model in this research. To extend this research, a heterogeneous auction market, presented in Chapter 4, for electric energy is assumed. The assumed auction market trades energy contracts characterized by: (1) delivery duration, (2) delivered reliability, and (3) allowed variability. The scheduling customer demand model, presented in Chapter 4, is then developed for an energy service company (ESCO), assuming that all energy contracts are purchased from the auction market. The ESCO model, presented in Chapter 2, uses the scheduling customer demand model to decide an optimal contract purchasing scheme and scheduling customer demand scheme at various operational planning levels. Finally, risk management and assessment tools, presented in Chapter 5, are reviewed and adopted to consider uncertainties in the ESCO model.

Three chapters of results are presented for an assumed ESCO model. Chapter 6 evaluates the scheduling customer demand model under various economics objectives, and presents the interaction between scheduling customer demand scheme and contract purchasing scheme. Chapter 7 analyzes the ESCO operation at various operational planning levels and discusses the limitations of the scheduling customer demand model. Finally, Chapter 8 applies the risk management and assessment tools to complement the shortfall of the scheduling customer demand model. The tools used in Chapter 8 include sensitivity analysis, parametric analysis, fuzzy linear programming, mean-variance analysis, and VaR analysis. The example presented in Chapter 8 is not suitable for stochastic linear programming analysis because the example is a one-stage problem.

9.2 CONCLUSIONS

This research primarily provides technical development on how an ESCO may utilize load management programs and energy contracts optimally to provide customers energy services and earn profit. In this section, the benefits of load management programs, economics of an ESCO operation and management; and the role of risk management and assessment tools in an ESCO operation are presented to emphasize the key findings in this research.

In this research, the load management programs have assisted an ESCO to improve the profitability of serving customer energy, lower the cost of energy, and enhance the cash flow of the company. In addition, the load management programs have also improved the flexibility of customer demand. A more flexible customer demand has allowed the ESCO more flexibility on how energy contracts may be purchased to serve customer demand and on the services it can provide the customer. The load management programs have also lowered the ESCO reliance on purchasing energy contracts to meet the contractual requirements with the customers. Finally, this research has also shown that the load management programs can be used as an asset to diversify the risks of ESCO operation.

With the load management programs, all four economic objectives (load-based, cost-based, profit-based, and cash management-based) evaluated in the ESCO scheduling customer demand model show lowered cost of energy, increased profit, enhanced cash flow, and improved reliability of serving customer energy. However, due to the differences in their emphases, the four economic objectives vary on how much they can lower the cost of energy, increase the profit, enhance the cash flow, and improve the reliability. In a re-regulated power industry, the profit-based objective and the cash management-based objective have shown to better serve an ESCO – profiting from the business. However, this research has emphasized that the cost-based objective can be used to evaluate the ESCO's performance in the long run. Finally, this research has shown that the cost-based objective and the profit-based objective differ only on how the changes in the revenue are reflected in the economic objectives. Two ways that the revenue could change are identified. First, when DLC energy is deferred to a low-rate period from a high-rate period (or vice-versa,) the ESCO experiences a reduction (increase) in the revenue due to a difference in the rate over time. Second, when paid back DLC energy is lower (higher) than the deferred energy, the ESCO experiences a reduction (increase) in the revenue due to changes in the customer demand or energy loss.

Various risk management and assessment tools are reviewed in this research to assist an ESCO operation and management. Even though differing on their recommendations on how an ESCO should respond to uncertainty, these tools have recommended decisions that are mostly efficient. The efficiencies are evaluated based on the combination of expected profit and VaR that these decisions have resulted. This research suggests that each of these risk management tools has pros and cons. To decide if one risk management tool should prevail over another, this research has recommended four factors consideration. The four factors to be considered in selecting an appropriate tool include: the applicability, how easy the uncertainty may be addressed by these tools; the technical requirement, the degree of knowledge needed in analyzing the uncertainty using the different tools; the time requirement, the time available to analyze an operational problem using these tools; and the data, the availability of information to describe the uncertainty. In addition, this research indicates that when decision choices result in efficient combinations of expected profit and VaR, the selection process depends on the cost of risk, VaR in this instance, that an ESCO is willing to assume. When the ESCO is willing to assume a higher VaR, it can expect a higher expect profit, and vice versa. However, when decision choices do not result in efficient combinations of expected profit and VaR, an ESCO should adopt one that provides the best combination of expected profit and VaR.

Finally, this research cautions the limitations of using the technical analysis in the business operation, particularly the models presented in this dissertation. First, certain assumptions are needed to simplify an ESCO operational problem in order to make the stated problem solvable using existing operations research techniques. These assumptions may result in decisions that do not optimally achieve the goals of the stated problems. Second, at most operational planning levels, there are many ways that an ESCO can think of to maximize its goal. The developed mathematical models can only evaluate what has been included in the analysis. Thus, in business practice, creativity and efficiency shown by decision-makers are as well important. Furthermore, creativity and efficiency, often than not, bring in new ideas to assist an ESCO operation.

Despite the limitations, the technical development presented in this research has no doubt provided valuable information that an ESCO may use in decision-making.

9.3 FUTURE WORK

In this research, energy contracts traded in an auction market are tied to the scheduling of customer demand. In addition to economic analysis, the uncertainties in an ESCO operation have also been considered. However, there are still more that can be extended to complement this research. They include:

- Present scheduling customer demand model considers only the real power. In a re-regulated business environment, the reactive power will probably be priced and traded. To account for the cost of reactive power, the customer demand for reactive power should also be modeled.
- The scheduling customer demand scheme and contract purchasing scheme only provide one-side story of energy trading in the auction market. In an auction market where market participants have to submit bids and offers for the energy traded, the ability to bid and offer the *right* price and *right* amount is important. Thus, strategies to bid and offer in an auction market should be researched.
- In this research, the options contracts are not included. With options contracts prospering in other industries, there is little doubt about the future of options contracts for electric energy. Thus, option theory should be investigated on its applicability in the energy market.

- The risk management tools developed in this research evaluate the cost of risks of holding a combination of scheduling customer demand scheme and contract purchasing scheme. These tools, however, are different from the options theories that have been developed in the financial industry. To justify the merits of the risk management and assessment tools, they should be compared to the options theories. In addition, in this research, example using stochastic linear programming is not presented. Additional examples may be developed to compare and contrast the impact of various risk management tools.

APPENDIX A. INFORMATION AND RESULT PERTINENT TO CHAPTER 6 AND CHAPTER 7

This appendix contains information, data used in Chapter 6 and Chapter 7 and detailed results from solving various models in chapter 6. Appendix A.1 provides the data on the customer factors. Appendix A.2 provides the information on the supplementary energy factors. Appendix A.3 provides the information on the market factors. Appendix A.4 shows the marginal cost functions of the generation units and how graphical techniques can be used to determine the marginal cost of producing an additional unit of electric energy. Appendix A.5 shows the iterative procedure to solve a nonlinear objective function containing monotonically increasing nonlinear cost functions. Appendix A.6 provides detailed results for section 6.2.

A.1 CUSTOMER FACTORS

Appendix A.1.1 shows the details about the customer demand factors in a regulated power industry. Appendix A.1.2 shows the detailed customer demand factors in a re-regulated power industry.

A.1.1 Customer Demand in Regulated Power Industry

Table A-1 shows the customer demand and the corresponding variable tariff (dollar per MW period) for a six months duration, assuming six periods in each day, and one day in each month. In addition, the corresponding customer demand is rated 'on-peak' or 'off-peak' to be used for generation scheduling in Appendix A.4 and A.5. There is no fixed tariff charged to the customers.

A.1.2 Customer Demand of an ESCO in a Re-regulated Power Industry

Table A-2 shows the customer demand and the corresponding variable tariff (dollar per MW period) for a six months duration, assuming six periods in each day, and one day in each month. There is no fixed tariff charged to the ESCO customers. In addition, the reliability requirement is 96% at all time, i.e., $\alpha_j^{TE} = 0.04, \quad \forall j$.

Table A-1. Customer demand and corresponding tariff in a regulated power industry.

Month	Day	Period	variable tariff ($/MW period)	Customer Demand (MW)	On-peak/Off-peak
1	1	1	90	200	Off-peak
		2	90	210	Off-peak
		3	100	340	On-peak
		4	100	340	On-peak
		5	90	210	Off-peak
		6	90	200	Off-peak
2	1	1	90	210	Off-peak
		2	90	220	Off-peak
		3	100	340	On-peak
		4	100	350	On-peak
		5	90	215	Off-peak
		6	90	210	Off-peak
3	1	1	90	220	Off-peak
		2	90	225	Off-peak
		3	100	350	On-peak
		4	100	360	On-peak
		5	90	230	Off-peak
		6	90	220	Off-peak
4	1	1	90	225	Off-peak
		2	90	230	Off-peak
		3	100	370	On-peak
		4	100	360	On-peak
		5	90	235	Off-peak
		6	90	220	Off-peak
5	1	1	90	230	Off-peak
		2	90	240	Off-peak
		3	100	370	On-peak
		4	100	380	On-peak
		5	90	245	Off-peak
		6	90	250	Off-peak
6	1	1	90	240	Off-peak
		2	90	255	Off-peak
		3	100	385	On-peak
		4	100	380	On-peak
		5	90	250	Off-peak
		6	90	235	Off-peak

Table A-2. Customer demand and corresponding tariff of an ESCO.

Month	Day	Period	variable tariff ($/MW period)	Customer Demand (MW)
1	1	1	90	40
		2	90	42
		3	100	68
		4	100	68
		5	90	42
		6	90	40
2	1	1	90	42
		2	90	44
		3	100	68
		4	100	70
		5	90	43
		6	90	42
3	1	1	90	44
		2	90	45
		3	100	70
		4	100	72
		5	90	46
		6	90	44
4	1	1	90	45
		2	90	46
		3	100	74
		4	100	72
		5	90	47
		6	90	44
5	1	1	90	46
		2	90	48
		3	100	74
		4	100	76
		5	90	49
		6	90	50
6	1	1	90	48
		2	90	51
		3	100	77
		4	100	76
		5	90	50
		6	90	47

A.2 SUPPLEMENTARY ENERGY FACTORS

In this section, the information regarding the supplementary energy factors used in Chapter 6 and Chapter 7 are presented. Appendix A.2.1 provides detailed information about the DLC program. Appendix A.2.2 provides detailed information about the ESS type I system, which is a battery system. Appendix A.2.3 provides detailed information about the ESS type II system, which is a pump-hydro system.

A.2.1 DLC Program

There are two types of customers participating in the DLC program. Appendix A.2.2.1 provides the information needed in solving a cost-based customer demand scheduling in a regulated power industry. Appendix A.2.2.2 provides the detailed information about the DLC program owned by an ESCO in a re-regulated power industry.

A.2.2.1 DLC Program in a Regulated Power Industry

Table A-3 shows the details about the controllability of the customer demand in a regulated power industry. Table A-4 shows the per customer deferrable demand in the DLC program. When solving for a cost-based demand scheduling in section 6.2, the incentives offered to the customers are ignored and not shown in here.

A.2.2.2 DLC Program of an ESCO in a Re-regulated Power Industry

In this section, the data used in analyzing the problem in section 6.Table A-5 shows the deferrable customer demand and the variable tariff (per kW period) of an ESCO for a six-month duration. Table A-6 shows the contract specifications with the customers in the DLC program and the pay back ratio at the end of controlled duration.

Table A-3. Controllability of the customer demand in a regulated power industry.

Item		Customer type	
		1	2
Size of customers participating in DLC program		100	100
Minimum/Maximum control duration		1/2	1/2
Pay back ratio for 1 period of control after energy deferment	1st period	40% of total deferred	35% of total deferred
	2nd period	55% of total deferred	40% of total deferred
	3rd period	0% of total deferred	25% of total deferred
Pay back ratio for 2 periods of control after energy deferment	1st period	30% of total deferred	25% of total deferred
	2nd period	25% of total deferred	25% of total deferred
	3rd period	25% of total deferred	25% of total deferred
	4th period	25% of total deferred	20% of total deferred

Table A-4. Per customer deferrable demand in a regulated power industry.

Month	Day	Period	Controllable demand type (kW)	
			1	2
1	1	1	40	60
		2	44	66
		3	64	96
		4	68	102
		5	44	66
		6	42	63
2	1	1	40	60
		2	44	66
		3	66	99
		4	70	105
		5	46	69
		6	44	66
3	1	1	44	66
		2	46	69
		3	70	105
		4	68	102
		5	48	72
		6	46	69
4	1	1	44	66
		2	48	72
		3	70	105
		4	72	108
		5	48	72
		6	46	69
5	1	1	46	69
		2	48	72
		3	74	111
		4	72	108
		5	48	72
		6	46	69
6	1	1	46	69
		2	48	72
		3	76	114
		4	76	114
		5	50	75
		6	48	72

Table A-5. Per customer deferrable demand and corresponding tariff offered by an ESCO.

Month	Day	Period	*DLC* program			
			Customer type I		Customer type II	
			deferrable demand (kW)	Rate ($/kW)	deferrable demand (kW)	Rate ($/kW)
1	1	1	40	0.09	60	0.09
		2	44	0.09	66	0.09
		3	64	0.10	96	0.10
		4	68	0.09	102	0.09
		5	44	0.09	66	0.09
		6	42	0.09	63	0.09
2	1	1	40	0.09	60	0.09
		2	44	0.09	66	0.09
		3	66	0.10	99	0.10
		4	70	0.09	105	0.09
		5	46	0.09	69	0.09
		6	44	0.09	66	0.09
3	1	1	44	0.09	66	0.09
		2	46	0.09	69	0.09
		3	70	0.10	105	0.10
		4	68	0.09	102	0.09
		5	48	0.09	72	0.09
		6	46	0.09	69	0.09
4	1	1	44	0.09	66	0.09
		2	48	0.09	72	0.09
		3	70	0.10	105	0.10
		4	72	0.09	108	0.09
		5	48	0.09	72	0.09
		6	46	0.09	69	0.09
5	1	1	46	0.09	69	0.09
		2	48	0.09	72	0.09
		3	74	0.10	111	0.10
		4	72	0.09	108	0.09
		5	48	0.09	72	0.09
		6	46	0.09	69	0.09
6	1	1	46	0.09	69	0.09
		2	48	0.09	72	0.09
		3	76	0.10	114	0.10
		4	76	0.09	114	0.09
		5	50	0.09	75	0.09
		6	48	0.09	72	0.09

Table A-6. Contract with the customers participating in the DLC program.

Item		Customer type 1	Customer type 2
Size of customers participating in DLC program		24	24
Minimum/Maximum control duration		1/2	1/2
Maximum control during six month duration (periods)		8 1/3	8 1/3
Reliability of the controlling devices,	α_j^{ED}, $\forall j$	0.03	0.03
	α_j^{EP}, $\forall j$	0.03	0.03
Rebate scheme	fixed part	$0.00/month	$0.00/month
	variable part	$2.50/MW deferred	$2.50/MW deferred
Pay back ratio for 1 period of control after energy deferment	1st period	40% of total deferred	35% of total deferred
	2nd period	55% of total deferred	40% of total deferred
	3rd period	0% of total deferred	25% of total deferred
Pay back ratio for 2 periods of control after energy deferment	1st period	30% of total deferred	25% of total deferred
	2nd period	25% of total deferred	25% of total deferred
	3rd period	25% of total deferred	25% of total deferred
	4th period	25% of total deferred	20% of total deferred

A.2.3 ESS Program

Only the utility in a re-regulated power industry owns the ESS programs. Appendix A.2.3.1 shows the ESS type I system, a battery energy storage system, and Appendix A.2.3.2 shows the ESS type II system, a pump-hydro storage system. In Chapter 7, the ESS programs are evaluated to determine if such programs can benefit the ESCO operation and management.

A.2.3.1 ESS Type I

There is one ESS type I systems capable of consuming a maximum of 4.5 MW period of electric energy during storage stage and releasing a maximum of 3.5 MW period of electric energy during release stage. Table A-7 describes the physical constraints of the storage system.

A.2.3.1 ESS Type II

There is one energy-storing unit and one energy-releasing unit for the ESS type II system, with the ability to release a maximum of 2 MW of energy per period, with a storage capacity of 5000 units of potential energy. Table A-8 provides information on the storing and releasing characteristics of the system.

Table A-7. Physical constraints on the ESS type I system (battery energy storage system).

Descriptions		ESS type I unit
Number of units available		100
Minimum/maximum storage duration (periods)		1/2
Required energy to charge 1 unit in (kW)	1 period	45 kW
	2 periods	22 kW in the 1st period 22 kW in the 2nd period
Minimum/maximum releasing duration (periods)		½
Released energy from 1 unit in (kW)	1 period	35 kW
	2 periods	19 kW in the 1st period 18 kW in the 2nd period
Leakage		None

Table A-8. Physical constraint on ESS type II system (Pumped hydro storage).

k	Energy losses during storage		When releasing energy		When storing energy	
	$\overline{V}_k$	sd_k	$\overline{Pr}_k$	θ_k	$\overline{Ps}_k$	ω_k
1	1500	0.005	1000 kW	0.90	1000 kW	1.10
2	1500	0.01	1000 kW	0.85	1500 kW	1.05
3	2000	0.015				

A.3 MARKET FACTORS

Appendix A.3.1 shows the market factors in a regulated power industry. Appendix A.3.2 shows the market factors in a re-regulated power industry.

A.3.1 Market Factors in a Regulated Power Industry

During off-peak periods (Table A-1), there are two generation units operating with the production cost functions as shown in Table A-9. During on-peak periods (Table A-1), a third generation unit is added, operating with the production cost function as shown in Table A-9. *P* denotes the MW generated by the units. Since the allocation of generation units during on-peak and off-peak periods has been determined, the fixed production cost of the three generating units will not affect the outcome of scheduling the units' generation levels. Thus, the fixed costs of the generating units are assumed to be zero in this research.

Table A-9. Production cost functions of the generating units.

Operating condition	Generation unit	Minimum generation	Maximum generation	Production cost function ($)
During off-peak	1	50	150	$30P + 0.075P^2$
During off-peak	2	50	150	$45.5P + 0.12P^2$
During on-peak	3	50	100	$55P + 0.175P^2$

A.3.2 Market Factors in a Re-regulated Power Industry

In this section, the information regarding various market factors is presented. Appendix A.3.2.1 shows the market prices of energy in an auction market in a re-regulated power industry when the energy is priced according to the marginal cost of production. Appendix A.3.2.2 shows the market factors of an auction market in a re-regulated power industry when the energy contract entails reliability and volatility requirements. Appendix A.3.2.3 shows the capital market factors of an ESCO.

A.3.2.1 Market Prices of Energy Based on Marginal Cost of Production

In this section, the information regarding the market prices for energy is provided. Table A-10 shows the market prices for a six-month duration. The marginal costs are similar to those found in Table 6-1 after load management scheduling.

A.3.2.2 Market Prices of Energy when Reliability and Volatility Requirements are Entailed

In this section, the information regarding the market prices of heterogeneous energy contracts is provided. Table A-11 shows the market prices of these contracts for different delivery periods. Table A-12 shows the various contracts that an ESCO may purchase and their corresponding contract specifications.

A.3.2.3 Capital Market Factors of an ESCO

In this section, the information regarding the capital market factors is provided. Table A-13 shows the annual percentage rate of borrowing at various periods when an ESCO needs to fund its operation. Table A-14 shows the annual percentage rate of investment at various periods when an ESCO has excess capital to invest.

Table A-10. Market prices according to marginal cost of production.

Month	Day	Period	Market prices ($/MW period)
1	1	1	57.77
		2	60.17
		3	73.28
		4	73.20
		5	62.28
		6	59.75
2	1	1	61.65
		2	63.78
		3	73.98
		4	74.55
		5	63.27
		6	62.21
3	1	1	63.48
		2	64.44
		3	75.40
		4	76.26
		5	66.47
		6	64.15
4	1	1	64.82
		2	65.77
		3	77.86
		4	76.16
		5	67.86
		6	64.19
5	1	1	66.36
		2	68.50
		3	78.55
		4	78.98
		5	70.05
		6	71.27
6	1	1	68.15
		2	71.49
		3	80.39
		4	80.89
		5	71.06
		6	67.33

Table A-11. Market prices for contracts in Table A-8.

Periods	Contracts type			
	A ($/MW)	B ($/MW)	C ($/MW)[17]	D ($/MW)
1 (1st period of 1st month)	62.93	70.21	54.98	61.34
2	–	–	57.16	63.78
3	–	–	70.59	78.77
4	–	–	70.60	78.78
5	–	–	58.13	64.86
6	–	–	55.89	62.36
7 (1st period of 2nd month)	64.39	71.85	57.80	64.49
8	–	–	59.84	66.77
9	–	–	70.63	78.81
10	–	–	71.96	80.30
11	–	–	59.40	66.28
12	–	–	58.16	64.89
13 (1st period of 3rd month)	66.13	73.79	59.95	66.89
14	–	–	60.98	68.04
15	–	–	72.04	80.38
16	–	–	73.36	81.85
17	–	–	62.32	69.54
18	–	–	60.34	67.33
19 (1st period of 4th month)	67.28	75.07	61.48	68.60
20	–	–	62.12	69.31
21	–	–	74.59	83.23
22	–	–	73.30	81.79
23	–	–	63.51	70.86
24	–	–	60.49	67.49
25 (1st period of 5th month)	69.66	77.73	62.77	70.03
26	–	–	64.44	71.90
27	–	–	75.33	84.06
28	–	–	76.47	85.32
29	–	–	65.63	73.22
30	–	–	66.23	73.90
31 (1st period of 6th month)	70.63	78.81	64.21	71.65
32	–	–	67.60	75.43
33	–	–	77.61	86.60
34	–	–	76.83	85.72
35	–	–	66.65	74.37
36	–	–	63.23	70.55

[17] Market prices for contract type C are approximately 95% of the market prices in Table A.7. Market prices for contract type D are approximately 106% of the market prices in Table A.7. Market prices for contract type A and B are weighted average of the contract type C and D respectively.

Table A-12. Specifications of contracts traded in an auction market.

Descriptions	Contract A	Contract B	Contract C	Contract D
energy per contract	1 MW/period	1 MW/period	1 MW/period	1 MW/period
reliability level, $(1-\alpha)$	95%	97%	95%	97%
accepted volatility level, β	5%	10%	5%	10%
delivery duration	1 month	1 month	1 period	1 period
beginning period	beginning of each month	beginning of each month	beginning of each period	beginning of each period

Table A-13. Interest for borrowing

Borrow duration	APR for borrowing at the beginning of					
	1st month	2nd month	3rd month	4th month	5th month	6th month
1 month	7.00%	7.20%	7.40%	7.60%	7.80%	8.00%
2 months	7.10%	7.30%	7.50%	7.70%	7.90%	—
3 months	7.20%	7.40%	7.60%	7.80%	—	—
4 months	7.40%	7.60%	7.80%	—	—	—
5 months	7.60%	7.80%	—	—	—	—
6 months	7.80%	—	—	—	—	—

Table A-14. Interest for investment.

Investment duration	APR for investing at the beginning of the					
	1st month	2nd month	3rd month	4th month	5th month	6th month
1 month	5.00%	5.20%	5.40%	5.60%	5.80%	6.00%
2 months	5.10%	5.30%	5.50%	5.70%	5.90%	—
3 months	5.20%	5.40%	5.60%	5.80%	—	—
4 months	5.40%	5.60%	5.80%	—	—	—
5 months	5.60%	5.80%	—	—	—	—
6 months	5.70%	—	—	—	—	—

A.4 SYSTEM MARGINAL COST FUNCTION USING GRAPHICAL TECHNIQUES

The system marginal cost function is determined using graphical techniques for both off-peak and on-peak periods. Table A-15 shows the marginal cost function of the three generating units. Figure A-1 and Table A-16 show the system marginal cost functions during off-peak periods. Figure A-2 and Table A-17 show the system marginal cost functions during on-peak periods.

Table A-15. Marginal cost functions of the generating units.

Operating condition	Generation unit	Minimum generation	Maximum generation	Marginal cost function ($/MW)
During off-peak	1	50	150	$30+0.15P$
During off-peak	2	50	150	$45.5+0.24P$
During on-peak	3	50	100	$55+0.35P$

Table A-16. System marginal cost functions during off-peak periods (demand must at least 100 MW).

Minimum generation	Maximum generation	Marginal cost function ($/MW)
100	200	$22.5+0.15P$
200	300	$9+0.24P$

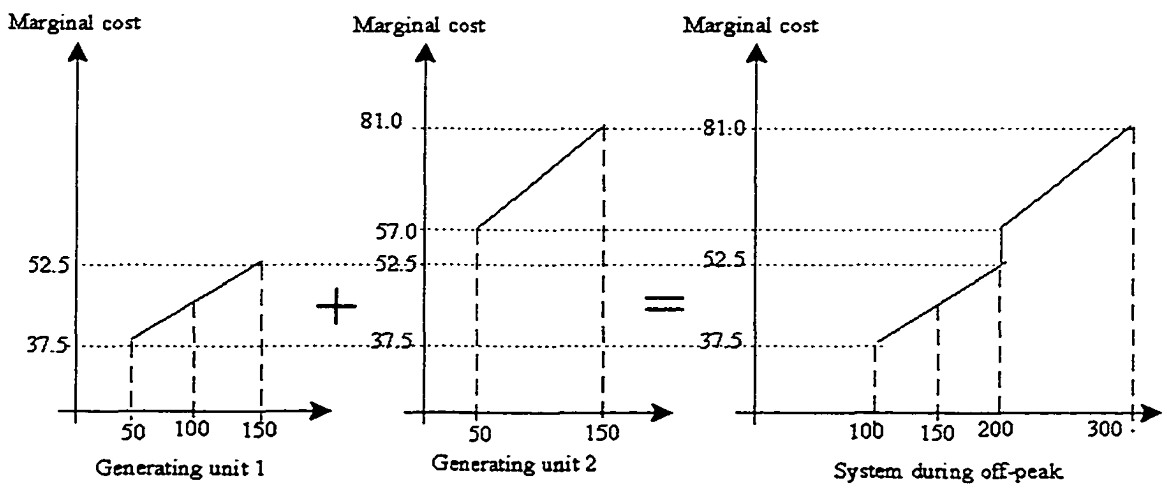

Figure A-1. System marginal cost during off-peak periods.

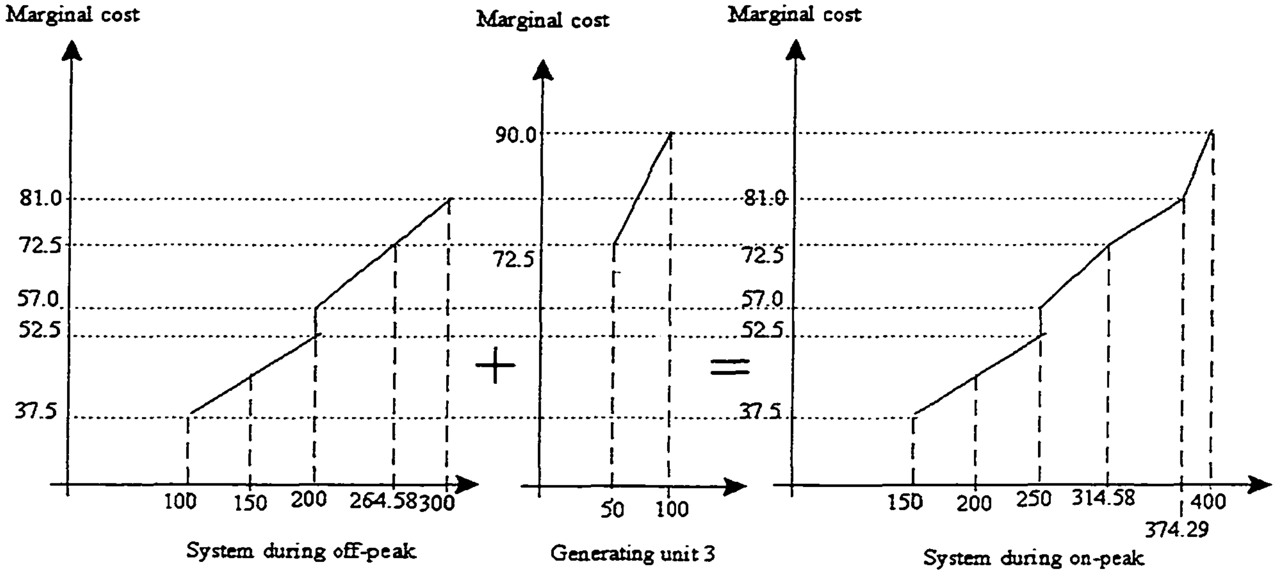

Figure A-2. System marginal cost during on-peak periods.

Table A-17. System marginal cost functions during off-peak periods (demand must exceed 150 MW).

Minimum generation	Maximum generation	Marginal cost function ($/MW)
150	250	$15 + 0.15P$
250	314.58	$-3 + 0.24P$
314.58	374.29	$27.70 + 0.1424P$
374.29	400	$-50.01 + 0.35P$

A.5 ITERATIVE PROCEDURE TO SOLVE MONOTONICALLY INCREASING MARGINAL COST FUNCTIONS

A generic iterative procedure is presented here. In this section, the average marginal cost of energy is determined from the marginal cost functions. An alternative approach that uses the cost functions to derive the average marginal costs is presented in [12]. The marginal cost functions are used in this section because there are several generation units that are available for scheduling at each period, where each unit has a different cost function. Instead of using different variables to represent the generation level of the different units at different periods, by adopting the graphical technique outlined in A.4, the aggregated generation level may be used to reduce the number of variables needed in the scheduling model.

Defining ΔP_j^{iter} to be the increased generation level at period j, iteration *iter*, then, the relationship between the value of *iter* iteration increased generation level and the previous iteration increased generation level is described in Equation (A.1). ΔP_j^+ is the increased generation level at period j determined at iteration *iter*, and ΔP_j^- is the decreased generation level at period j determined at iteration *iter*.

$$\Delta P_j^{iter} = \Delta P_j^{iter-1} + \Delta P_j^+ - \Delta P_j^- \tag{A.1}$$

Define one variable to represent the integer part of ΔP_j^{iter} divided by $\overline{\Delta P_j}$. $\overline{\Delta P_j}$ is the maximum decreaseable or increaseable generation level at period j at each iteration:

$$Q_j = quotient\left(\frac{\Delta P_j^{iter}}{\overline{\Delta P_j}}\right) \tag{A.2}$$

and another variable for the remainder of ΔP_j^{iter} divided by $\overline{\Delta P_j}$:

$$r_j = remainder\left(\frac{\Delta P_j^{iter}}{\overline{\Delta P_j}}\right) \tag{A.3}$$

With the given Q_j, the average marginal cost per unit cost for Q_j-th increase in generation level is shown in Equation (A.4). $MC_j(*)$ is the marginal cost of generation level * at period j. The piecewise-linearized marginal cost function is determined in A.4

$$pr_j(Q_j) = \frac{MC_j\left(P_j + (Q_j + 1)\overline{\Delta P_j}\right) + MC_j\left(P_j + Q_j\overline{\Delta P_j}\right)}{2} \tag{A.4}$$

When the objective is to minimize the cost of generation with constraints shown in Chapter 3, the problem of nonlinearity is linearizable with added constraints to restrict maximum increaseable or decreaseable generation level. Let the function $g(x)$ represent the constraints of load management demand. (A.5) shows the linearized linear programming model. m_j^+ and m_j^-, respectively, represent the average marginal cost for an increase and decrease in generation level at period j.

$$\min_{x, \Delta P_j^+, \Delta P_j^-} \quad m_j^+ \Delta P_j^+ - m_j^- \Delta P_j^-$$

subject to:

$$g(x) \le b \tag{A.5}$$

An iterative procedure can then be carried out to achieve the final optimum objective function.

STEP 0

Initialize all variables, where

$$iter = 1$$
$$\Delta P_j^0 = 0$$

STEP 1

Determine the values of Q_j and r_j as defined in Equations (A.2) and (A.3).

STEP 2

Find/update the values for m_j^+ and m_j^-

if $r_j = 0$

$$m_j^+ = pr_j(Q_j)$$
$$m_j^- = pr_j(Q_j - 1)$$
$$0 \le \Delta P_j^+ \le \overline{\Delta P_j}$$
$$0 \le \Delta P_j^- \le \overline{\Delta P_j}$$

else if $Q_j > 0$

$$m_j^+ = pr_j(Q_j - 1)$$
$$m_j^- = pr_j(Q_j - 1)$$
$$0 \le \Delta P_j^+ \le -r_j$$
$$0 \le \Delta P_j^- \le \overline{\Delta P_j} + r_j$$

else if $r_j > 0$

$$m_j^+ = pr_j(Q_j + 1)$$
$$m_j^- = pr_j(Q_j + 1)$$
$$0 \le \Delta P_j^+ \le \overline{\Delta P_j} - r_j$$
$$0 \le \Delta P_j^- \le r_j$$

else

$$m_j^{+} = pr_j(Q_j - 1)$$

$$m_j^{-} = pr_j(Q_j - 1)$$

$$0 \le \Delta P_j^{+} \le -r_j$$

$$0 \le \Delta P_j^{-} \le \overline{\Delta P_j} + r_j$$

STEP 3

Solve for linear program as defined in (A.5).

STEP 4

Update increased and decreased generation level as defined in (A.1).

STEP 5

Check for optimality.

if $\left(\Delta P_j^{+} - \Delta P_j^{-}\right)$ is not equal to 0

iter = iter + 1

GO TO **STEP 1**

else

Optimal solutions are found

A.6 DETAILED LOAD MANAGEMENT SCHEDULING FOR SECTION 6.2

Table A-18 shows the scheduled controllable customer demand in the DLC program. Table A-19 shows the scheduled ESS type I unit and Table A-20 shows the scheduled ESS type II unit

Table A-18. Scheduled controllable customer demand in the DLC program.

Controllable customer demand			Number of customer
Type	Beginning control at period	Deferment duration	scheduled
1	3	2	100.00
1	9	2	56.45
1	10	1	43.54
1	15	2	77.79
1	16	1	22.21
1	21	2	75.34
1	22	1	24.66
1	27	1	5.076
1	28	1	94.92
1	30	1	5.08
1	34	1	100.00
2	3	2	100.0000
2	9	2	100.0000
2	15	2	100.0000
2	21	2	100.0000
2	27	2	100.0000
2	33	1	100.0000

Table A-19. Scheduled ESS type I unit.

Storing energy			Releasing energy		
Beginning period	Storing duration	Number of units	Beginning period	Storing duration	Number of units
1	2	100.0000	2	2	0
2	2	0	3	2	100.0000
5	2	72.8584	6	2	0
6	2	27.1416	7	2	0
8	2	0	9	2	19.6842
11	2	19.6842	12	2	0
32	2	0	33	2	100.0000

Table A-20. Scheduled ESS type II unit.

Period	Energy used to store at	Energy released at	Stored amount at the end of
1	1.00	0	2.90
2	0.40	0	3.25
3	0	1.00	2.17
4	0	1.00	1.11
5	0	0	1.11
6	1.00	0	2.00
7	0.15	0	2.13
8	0	0	2.12
9	0	1.00	1.06
10	0	1.00	0
11	0.2295	0	0.21
12	1.0000	0	1.11
13	1.0000	0	2.00
14	0	0	1.99
15	0	0.88	1.06
16	0	1.00	0
17	0	0	0
18	1.0000	0	0.90
19	0.1834	0	1.06
20	0	0	1.06
21	0	1.00	0
22	0	0	0
23	0	0	0
24	1.0000	0	0.90
25	1.0000	0	1.80
26	0	0	1.79
27	0	0.52	1.23
28	0	0.52	0.68
29	0	0	0.68
30	0	0	0.67
31	1.0000	0	1.57
32	0	0	1.56
33	0	0	1.55
34	0	0.41	1.11
35	0	0	1.11
36	1.0000	0	2.00

APPENDIX B. INFORMATION PERTINENT TO CHAPTER 8

This appendix contains information and data used in Chapter 8. Appendix B.1 provides the standard deviation of all uncertain parameters in Chapter 8. Appendix B.2 provides the information on the correlation among all uncertain parameters in Chapter 8.

B.1 STANDARD DEVIATION OF THE UNCERTAIN FACTORS

Table B-1 shows the standard deviations of all uncertain parameters used in the analysis in Chapter 8.

Table B-1. The standard deviations of all uncertain parameters.

Factors	Parameter	Standard deviation
Customer	TE_5 (I)	2
	TE_6 (II)	3
	TE_7 (III)	2
Market	$pr_5^{1,\alpha_1,\beta_1}$ (IV)	3
	$pr_5^{1,\alpha_2,\beta_2}$ (V)	2
	$pr_6^{1,\alpha_1,\beta_1}$ (VI)	2
	$pr_6^{1,\alpha_2,\beta_2}$ (VII)	3
	$pr_7^{1,\alpha_1,\beta_1}$ (VIII)	2
	$pr_7^{1,\alpha_2,\beta_2}$ (IX)	3
	$\alpha_1^{5,1}$ (X)	0.0025
	$\alpha_1^{6,1}$ (XI)	0.0025
	$\alpha_1^{7,1}$ (XII)	0.0025
	$\alpha_2^{5,1}$ (XIII)	0.0001
	$\alpha_2^{6,1}$ (XIV)	0.0001
	$\alpha_2^{7,1}$ (XV)	0.0001
Supplementary energy	$Ed_{1,5}$ (XVI)	0.00046

B.2 CORRELATION AMONG UNCERTAIN FACTORS

Table B-2 through Table B-4 shows the correlation among all uncertain parameters used in the analysis in Chapter 8. The following assumptions are made in generating the numbers for the correlation.

- A higher/lower energy demand at a period will result in a higher/lower price at that period, i.e., TE_j is positively correlated to $pr_j^{1,\alpha_k,\beta_k}$.
- The total demands at different periods are positively correlated, but not as much as the correlation between the total demand and deferrable demand at a particular period. For example, TE_5 has a 0.6 correlation with $Ed_{1,5}$, but a 0.2 correlation with TE_6.
- Since load management programs are assumed insignificant in the industry at the beginning of Chapter 6, deferrable demand does not affect the price of energy much, i.e., the deferrable demand has an insignificant correlation with the price of energy and market contract reliability.
- The power system is assumed not congested. Therefore, the correlation between the market contract reliability of any given period and the price of energy (or the ESCO total customer demand at the given period) is insignificant. For the similar reason, the correlation among the differently traded contract reliability is not highly correlated.
- The correlation matrix is positive definite. The eigenvalues of the correlation matrix are positive.

Table B-2. The correlation among market factors.

	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)	(XI)	(XII)	(XIII)	(XIV)	(XV)
(IV)	1	0.80	0.20	0.15	0.10	0.05	0.05	0.02	0.01	0.05	0.02	0.01
(V)	0.80	1	0.20	0.20	0.10	0.15	0.05	0.03	0.00	0.05	0.03	0.00
(VI)	0.20	0.20	1	0.70	0.20	0.10	0.02	0.05	0.02	0.02	0.05	0.02
(VII)	0.15	0.20	0.70	1	0.50	0.10	0.00	0.04	0.03	0.00	0.04	0.01
(VIII)	0.10	0.10	0.20	0.50	1	0.75	0.02	0.02	0.03	0.02	0.02	0.03
(IX)	0.05	0.15	0.10	0.10	0.75	1	0.01	0.01	0.04	0.01	0.01	0.04
(X)	0.05	0.05	0.02	0.00	0.02	0.01	1	0.50	0.40	0.70	0.40	0.30
(XI)	0.02	0.03	0.05	0.04	0.02	0.01	0.50	1	0.30	0.30	0.80	0.30
(XII)	0.01	0.00	0.02	0.03	0.03	0.04	0.40	0.30	1	0.20	0.40	0.50
(XIII)	0.05	0.05	0.02	0.00	0.02	0.01	0.70	0.30	0.20	1	0.30	0.70
(XIV)	0.02	0.03	0.05	0.04	0.02	0.01	0.40	0.80	0.40	0.30	1	0.30
(XV)	0.01	0.00	0.02	0.01	0.04	0.05	0.30	0.30	0.50	0.70	0.30	1

Table B-3. The correlation between customer and supplementary energy factors.

	(I)	(II)	(III)	(XVI)
(I)	1.0000	0.2000	0.3000	0.6000
(II)	0.2000	1.0000	0.4000	0.1000
(III)	0.3000	0.4000	1.0000	0.0500
(XVI)	0.6000	0.1000	0.0500	1.0000

Table B-4. The correlation among market factors, customer factors and supplementary energy factors.

	(I)	(II)	(III)	(XVI)
(IV)	0.40	0.07	0.05	0.02
(V)	0.50	0.07	0.08	0.01
(VI)	0.10	0.30	0.02	0.01
(VII)	0.05	0.35	0.07	0.00
(VIII)	0.06	0.06	0.45	0.01
(IX)	0.07	0.08	0.50	0.01
(X)	0.01	0.00	0.01	0.01
(XI)	0.00	0.01	0.00	0.01
(XII)	0.01	0.01	0.00	0.01
(XIII)	0.01	0.02	0.01	0.00
(XIV)	0.01	0.00	0.01	0.01
(XV)	0.00	0.00	0.01	0.00

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