MADM Framework for Strategic Resource Planning of Electric Utilities

Jiuping Pan

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Saifur Rahman, Chair
Yilu Liu
Robert P. Broadwater
Hugh F. VanLandingham
Hanif D. Sherali
Arnulfo de Castro

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(ABSTRACT)

This study presents a multi-attribute decision making (MADM) framework in support of strategic resource planning of electric utilities. Study efforts have focused on four technical issues identified to be essentially important to the process of strategic resource development, i.e., decision data expansion, MADM analysis with imprecise information, MADM analysis under uncertainty and screening applications. Main contributions from this study are summarized as follows. *First*, an automatic learning method is introduced for decision data expansion aiming at reducing the amount of computations involved in the creation of decision database. Test results have shown that the proposed method is feasible, easy to implement, and more accurate than the techniques available in the existing literature. *Second*, an interval-based MADM methodology is developed, which extends the traditional utility function model with the measure of composite utility variance, accounting for individual errors from inaccurate attribute measurements and inconsistent priority judgments. This enhanced decision approach would help the decision-maker (DM) gain insight into how the imprecise data may affect the choice toward the best solution and how a range of acceptable alternatives may be identified with certain confidence. *Third*, an integrated MADM framework is developed for multi-attribute planning under uncertainty which combines attractive features of utility function, tradeoff/risk analysis and analytical hierarchy process and thus provides a structured decision analysis platform accommodating both probabilistic evaluation approach and risk evaluation approach. *Fourth*, the application of screening models is investigated in the context of integrated resource planning of electric utilities as to identify cost effective demand-side options and robust generation expansion planning schemes.

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1 Introduction

1.1 Problem Statement

The nature of electric utility resource planning has changed dramatically within the past two decades. Increased concerns for environmental quality and efficient resource utilization have resulted in wide range of resource options, both supply-side and demand-side, that need to be evaluated integrally and comprehensively. At the same time, the consequences of alternative resource development strategies must be examined with the consideration of multiple criteria, both economic and non-economic, addressing various concerns from different players involved in the planning process. Moreover, the planning process is further complicated by the need to account for the influence from a variety of uncertainty factors regarding future demand, resource availability and economy situations. Additionally, the power industry in the United States and worldwide is currently in a transition period, moving toward a competitive, market-based economy for the generation, transmission, and distribution of electricity. Industry deregulation has, and will continue to have, significant implications for the strategies of electric utilities in their resource development.

In the following, we will briefly discuss some key issues that need to be addressed in electric utility resource planning process and their significant influences on the performance of future utility systems.

Efficient Resource Utilization

Since late 1980s, electric utilities in the United States have been required to practice integrated resource planning process (IRP) such that all cost-effective resource options would be consistently assessed and implemented [17]. The primary objective of IRP is to develop a least-cost plan that can meet customer energy-service needs and environmental improvements. Strategic resource options considered in this planning process include both conventional and advanced generation technologies, demand-side management programs (DSM), various renewable energy sources, as well as utility and non-utility generation contracts through interconnected transmission grid. New generation facilities are needed to meet demand growth and to replace those less economic, emissions constrained generating units. On the other hand, energy efficiency and peak-demand shaving programs have been encouraged as an efficient and flexible planning strategy in reducing utility-capacity needs, improving system-load factor and environmental quality [10]. Renewable energy sources, especially wind and solar technologies, are likely to play an increasingly important role in the electric utility generation mix and daily operation to reduce the environmental impact from thermal generation. As for the utility and non-utility generation contracts, electric utilities have been required to purchase power from non-utility generators, such as co-generations and independent power producers based on the avoided costs [63]. In recent years, bulk transactions are common among utilities in different regions seeking to maintain reliability and adequacy of supply while at the same time reducing the prices of electric energy [93].

Environmental Concerns

Electricity generation from fossil fuel is responsible for a major share of emissions of sulfur dioxide (SO_2), nitrogen oxides (NO_x), carbon dioxide (CO_2) and particulate (mainly in the form of fly ash). While the impacts of fly ash is limited to local areas, that of CO_2 is of a global concern, and SO_2 and NO_x have both local and regional impacts. It has been estimated that carbon dioxide constitutes one-half of greenhouse gas emissions from human activities, and of this, up to 30% comes from the power generation. In other words, use of fossil fuels for power generation is estimated to amount to 15% of all greenhouse gases. As public concerns about environmental quality, health and safety problems grow, many governments are responding to the call for more stringent environmental regulations and specific pollution standards for power industry. In the United States, for instance, the Clean Air Act Amendments of 1990 (CAAA 1990) requires widespread and comprehensive control of SO_2 emissions from power generation, with the overall goal for nationwide SO_2 emissions set at 8.9 million tons per year. Cooperative actions have been taken by other developed counties and will be in effective in many developing counties. Apparently, environmental regulations and standards will govern the sitting, design and operation of virtually all resources and will significantly raise the costs of capacity addition and system O&M expanses. Therefore, electric utilities are faced with the requirements of allocating their available capital investments and energy resources for the development of power system in a manner that is less harmful to global and regional environments [1,81].

Uncertainty and Risk Management

Uncertainty is a major challenge in electric utility long-range resource planning [18,19]. Some of the primary data in resource planning, such as load growth, fuel price, capital cost, outage cost, emission control cost and allowance, may have a profound influence on the course and outcomes of utility resource development. For instance, the uncertainties associated with future demand forecasts could make the utility resources inadequate or excessive, both cases being unacceptable. If the load level is higher than the forecast demand, there will exist a lack of available capacity in generation and transmission systems that could result in insufficient supply of power to customers. On the other hand, if the load level is lower than the forecast demand, there will be an excess of peak generation capacity and idle status of transmission network that could result in under-utilization of installed utility facilities. Stringent environmental regulations and unexpected variations of fuel prices may make a feasible and economical resource investment a poor decision. Risk management is now an essential part of the planning process in electric utility industry, and flexibility and robustness are two major classes of strategies for managing the risk posed by uncertainties [6,8]. As defined in [13], a robust resource plan would perform well across a variety of possible future conditions while a flexible resource plan would response quickly at reasonable costs to various unexpected events in the future.

Multiple Criteria

In many planning studies, the concept of revenue minimization requirements has been supplemented by a number of other important, but often conflicting criteria, such as system reliability, environmental impacts, electricity prices, financial constraints and social-political preferences, reflecting various concerns from different players involved in the planning process. Most often, there is no single plan that is optimal with respect to all concerned criteria, that is, a plan resulting in favorable outcomes in some criteria may much more often result in poor outcomes in some others. Multi-criteria decision making (MCDM) models thus become more and more popular in utility strategic resource planning leading to a compromise solution that represents a reasonable balance among the chosen criteria [7,44,53,76]. A useful MCDM model should be able to display tradeoffs among the chosen criteria, both quantitative and qualitative, economic as well as non-economic, and quantify the values and the preferences held by different interests with respect to different criteria.

Deregulation and Competition

In recent years, the market and regulatory conditions that were fundamental to IRP by regulated utilities are undergoing dramatic changes. The movement toward a less regulated and more competitive electric industry has, and will continue to have, significant implications for the resource planning process [56,93]. These changes have resulted in a significant decline in utility avoided costs and a market reduction in cost-effective utility- sponsored DSM programs, and in the short run, emerging competitive bulk power market has been assumed by many utilities as the source for additional capacity and energy requirements. Deregulation and competition are also adding new level to the uncertainty that makes responsible decision-making for generation and transmission expansion projects much more difficult. For instance, uncertainties in competitive generation capacity additions in terms of the siting, timing and operating parameters are much greater than before due to the deregulated power supply markets and the increased number of independent power producers. As such, new planning objectives need to be defined and new analytical tools need to be developed in support of market-based resource planning process as to identify potential generation and transmission expansion opportunities and reduce the risks associated with competition.

In summary, the nature of electric utility resource planning may be described as a multi-criteria decision making process in the presence of uncertainties. The main goal of this planning process is thus to identify a desired resource development strategy that could ensure reliable, economical, environmental benign electric services to the customers while at the same time guarantee a sustained competitive advantage of the utility systems in deregulated or re-regulated power markets.

1.2 About This Work

The primary objective of this dissertation work is to develop an enhanced multi-attribute decision making (MADM) framework in support of strategic resource planning of electric utilities. Main features of the developed MADM framework may be described as follows.

It is a strategic planning approach where by extensive use of available and newly developed planning tools a great range of resource strategies can be examined with the chosen attributes. This comprehensive scenario analysis will generate a reliable decision database from which a set of acceptable planning strategies can then be identified according to well-defined decision criteria.

It is an enhanced MADM methodology capable of incorporating the impact of imprecise information into the decision making process. This will yield an interval-based decision approach, providing insight into how the imprecise data may affect the choice toward the best solution and how a set of acceptable alternatives may be identified with certain confidence.

It is an integrated MADM framework for multi-attribute planning under uncertainty, which provides a structured decision analysis platform accommodating both probabilistic evaluation approach and risk evaluation approach and thus allowing the application of hybrid decision methodology.

Specifically, the following study tasks have been successfully completed during the course of this dissertation work.

- Identified four major study topics that are essentially important to the success of strategic resource planning.
- Introduced an efficient automatic learning method for decision data expansion to reduce the amount of computations involved in the creation of decision database.
- Established a structured procedure to facilitate the assessment of preference functions associated with individual attributes and the tradeoffs among conflicting attributes.
- Developed an approximate model to estimate the variance of composite utility, accounting for individual errors from inaccurate attribute measurements and inconsistent priority judgments.
- Developed an interval-based MADM methodology for the identification of acceptable plans or candidate design alternatives;
- Developed an integrated MADM framework for multi-attribute planning under uncertainty supporting both probabilistic evaluation approach and risk evaluation approach.
- Investigated the application of screening models for identifying cost-effective DSM options and optimal generation expansion planning schemes.

1.3 About This Document

This document presents the study results obtained from this dissertation work and the presentation is organized by the following eight chapters.

1. Chapter 1 (this chapter) gives an overview of this dissertation work, including problem statement, major contributions from this work and organization of this document.
2. Chapter 2 presents a literature review of previous research efforts in the field of electric utility resource planning with focus on the application of mathematical programming models, production costing simulation programs, and decision making techniques.
3. Chapter 3 outlines the conceptual procedures of strategic resource planning and highlights four major technical issues identified to be essentially important to the success of strategic planning.
4. Chapter 4 concerns with the feasibility of using ANN-based approach for decision data expansion. The approximate performance of proposed method will be demonstrated through three illustrative examples. Comparison between the ANN-based approach and the techniques available in the existing literature is provided.
5. Chapter 5 concerns with the decision making process with imprecise information. An interval-based MADM methodology is developed which is based on the model of linear additive utility function but extends the problem formulation with the measure of composite utility variance. Sample case study is provided showing how the enhanced MADM methodology can be used for the evaluation of long-range utility generation expansion strategies with increased level of confidence toward the final decision.
6. Chapter 6 concerns with the decision making process under uncertainty. An integrated MADM framework is developed which combines attractive features of utility function, tradeoff/risk analysis and analytical hierarchy process and supports uncertainty analysis using both probabilistic evaluation approach and risk evaluation approach. A novel numerical knee-set searching algorithm will be introduced with meaningful statistical interpretations. Sample case study is provided which involves the optimal design of grid-linked renewable energy systems with the consideration of uncertain future conditions.
7. Chapter 7 concerns with the application of screening models at the preliminary study stage of strategic planning. Two screening models will be discussed in the context of integrated resource planning as to identify cost-effective demand-side resource options and robust generation expansion planning schemes.
8. Chapter 8 gives concluding remarks of this study and some future research efforts in the direction of strategic resource planning are recommended.

2 Review of Literature

The content of electric utility resource planning is broad and may cover all studies related to the development of utility generation, transmission, and distribution systems. In the following, our discussion will focus on the applications of mathematical programming models, production costing simulation programs, and decision making techniques, in particular, as proposed and applied for the studies related to generation expansion planning (GEP) and integrated resource planning (IRP) of electric utilities.

2.1 Introduction

The aim of electric utility generation expansion planning is to seek an optimal generation capacity expansion scheme to meet the forecast demand as economical as possible, subject to reliability and environmental constraints [37,98]. Basically, the following questions are to be answered by the GEP process: i) Where and when to invest in new generating facilities (location and time)? ii) What type and what capacity of generating units to install (fuel and size)?

The aim of electric utility integrated resource planning is to strategically integrate supply-side and demand-side options to meet customer energy-service needs and environmental improvements in a least-cost strategy [4,25]. One major task in electric utility IRP process is to identify and implement cost-effective DSM programs, including load management, energy conservation, and promotion of off-peak uses of electricity. Risk management is another challenging task involved in the process of electric utility IRP for reducing the negative influence associated with uncertainties.

Over many years, a wide range of planning tools have been developed to deal with various aspects of electric utility resource planning. These analytical tools may be broadly categorized as capacity expansion optimization models, production costing simulation programs and decision-making analysis techniques. Generally speaking, capacity expansion models are used to optimize the rate of progress of resource investment going into operation and production costing simulation programs are used to analyze the feasibility and behavior of the utility systems in terms of O&M costs, reliability indices, environmental impacts, etc. Application of advanced decision making techniques are very helpful which allows the introduction of uncertainty and multi-criteria concepts into the strategic resource development of electric utilities.

This chapter presents a literature review of previous research efforts in the field of electric utility resource planning. Section 2.2 attempts to give an overview of mathematical programming models as applied in generation expansion planning. Section 2.3 discusses the role of production costing simulation programs in electric utility planning studies. Section 2.4 discusses decision analysis techniques that are commonly used in the power industry for multi-criteria planning under uncertainty.

2.2 Mathematical Programming Models

Mathematical programming models have long been used as important analytical tools for electric utility resource planning. In general, the optimization problem involved in generation capacity expansion and integrated resource planning is a non-linear, integer, stochastic, and multi-objective optimization process. However, the planning problem is usually solved with certain assumptions and simplifications [42]. A good review of the earlier work could be found in [11], which presents a survey of models for determining least-cost investments in generation planning and possible extensions to basic linear programming. An updated survey of mathematical programming models in electric power capacity planning could be found in [78], which focuses on recent modeling approaches, including nonlinear programming, stochastic programming and multi-objective programming, to address the issues of reliability of supply, uncertainty in demand and environmental consequences. Emerging optimization techniques in electric utility generation planning are discussed in [52], which involves several new techniques for solving large-scale optimization problems, such as expert systems, fuzzy set theory, artificial neural networks, genetic algorithm, etc. Optimization models for generation expansion planning has been an active topic in the literature of Operation Research and Management Science for many years, providing sound theoretical background and insight to the development and implementation of advanced modeling approaches [13,33,34,36,48]. This section will discuss some fundamental problems and modeling techniques concerning optimal resource development of electric utilities. Comprehensive survey and comments on various optimization models are out of the scope of this discussion.

2.2.1 Linear Programming

Linear programming (LP) modeling approach deals with the problem of minimizing or maximizing a linear objective function with a set of linear equality and inequality constraints. In electric utility planning problems, the objective function usually is the sum of discounted investment and operational costs; the constraints may represent the equilibrium between capacity and demand, capacity reserve requirement, environmental limitations, etc. The popularity of using LP can be attributed to many factors including its ability to model large and complex planning problems and the availability of effective algorithms. LP models have experienced extensive and successful applications in utility resource planning for more than thirty years.

When using LP models, generation technologies are categorized by the fuel types such that the decision variables will refer to the total capacity required of each generation technology rather than the size or number of a particular project. In practice, however, the investment in a power plant is greatly influenced by the environment in which the power plant is located even when the generating units are the same category [98]. Furthermore, the generation technologies are commercially available only in certain sizes and the approximation of aggregate capacity requirement by a set of commercially available units may sacrifice the optimization benefits. Thus, the LP formulation could be an appropriate model to determine the optimal generation mix or energy resource mix, but not a very useful approach for the planning problems where actual project selection needs to be considered [78].

2.2.2 Alternative Optimization Models

Since the LP models cannot incorporate many important aspects of utility resource planning, a large number of alternative optimization models have been proposed in the literature and some of them have been widely used in the power industry, including mixed-integer programming, non-linear programming, stochastic programming and multi-objective programming [42]. These optimization models can be used respectively to deal with discrete decision variables, non-linear objective functions, random parameters and multiple objectives. Some of them may retain a linear programming framework like linear multi-objective programming while others can allow for explicit inclusion of non-linearity in capital costs and engineering constraints. In mixed-integer programming models, the project-specific capacities can be assigned to some investment variables while the remainders are still continuous variables. More often, a binary variable is associated with each candidate project to simplify the optimization process. That is, a value one is assigned if the project is to be built in a given time period and zero if it is not. Stochastic programming with recourse is a very promising technique to solve a multistage decision problem when some parameters are known through probability distributions [12]. This modeling approach allows finding the optimal course of resource development and minimizing the total expected discounted costs. In some versions of stochastic programming methods the stochastic problems are transferred into a deterministic equivalent problem. Multi-objective programming is introduced to make decision at the presence of multiple conflicting objectives. Usually, the multi-objective optimization process is converted into a single objective problem either by assigning weighting parameters to each individual objectives or providing proper constraints on all objectives except the most essential one [30,50].

2.2.3 Dynamic Programming

Among available mathematical programming models, dynamic programming (DP) has been proved to be especially useful for utility resource planning, which convert a multistage optimization problem into a series of simple problems. DP problems can be solved very easily because of the recursive application of the principle of optimality on the objective. This modeling approach is flexible in using discrete variables, non-linear objective functions and constraints. DP modeling approach can also be used in conjunction with probabilistic production costing simulation programs, and Electric Generation Expansion Analysis System (EGEAS) and Wien Automatic System Planning Package (WASP) are two representative commercial generation expansion packages widely used around the world [43,88]. The major drawback of DP models is the curse of dimensionality since all possible solutions will be searched in order to find the optimal sequence of decisions that lead from the initial state to the least-cost state in the final stage. This may involve excessive computational requirements in terms of computing time and data storage space. However, by applying insight into the nature of the problem, it is possible for the planner to reduce the state space considerably by using some simple screen techniques. For instance, reserve margin can be used to eliminate system configurations which are either well below or well above a preferred level of system capacity. The number of units of each candidate generation type that may be selected each year can be specified based on the resource availability and other limitations. Further enhancement may be achieved by introducing multiple objectives and random parameters into the DP models, resulting in multi-objective dynamic programming or stochastic dynamic programming models [95,99].

2.3 Production Costing Simulation Programs

Production costing studies have found extensive applications in electric utility capacity expansion planning, including long-range generation expansion, fuel scheduling, purchase and sales analysis, cost-of-service studies, load management studies, and system operation policy analysis. The costs being calculated in production costing simulation are fuel costs, generation operation and maintenance (O&M) charges, and generation startup costs. The ability to accurately evaluate production expanses is of considerable importance to electric utilities because these costs constitute a significant percentage (40-60%) of the total annual costs of power systems [37].

2.3.1 Classification

Various production simulation programs have been discussed in the literature and applied in the power industry. These models have similar basic functions but differ with each other considerably in the model structure and the simulation algorithm. A general classification of production costing simulation models may be as follows.

The first classification is based on whether or not the random nature of demands and generation capacities being taken into account in the simulation. We distinguish between two types of simulation models: deterministic production costing models vs. probabilistic production costing models. The probabilistic models are more widely used than the deterministic models throughout the electric utility industry as an aid in intermediate- and long-range capacity expansion planning. Not only is the production cost estimation more reasonable and more accurate but also the system reliability indices can be evaluated.

The second classification is based on the choice of system load representation. We distinguish between two types of simulation approaches: equivalent load duration curve approaches vs. chronological simulation approaches. For less detailed studies, as for long-range capacity expansion planning, it is convenient to use the concept of equivalent load duration curve (ELDC) as the basis of production costing analysis. For more detailed studies, chronological production costing simulation programs are required. Theoretically, these chronological simulation models are off-line applications of generation economic dispatch and unit commitment techniques. That is, production costs and fuel consumption is computed repetitively, assuming that the load patterns or load cycles are known for an extended period into the future.

2.3.2 Probabilistic Simulation Approach

The ELDC based simulation technology has dominated electric utility planning for nearly thirty years [98]. It is based on the inverted load duration curve (ILDC) and ingeniously integrates the random outage of each generating unit with the probability density function of system load by a recursive procedure. The resulting ELDC serves as the base for calculating production costs and reliability indices. In the original ELDC methods, the equivalent load duration curve is represented by function values at discrete points and the amount of computation is rather great since the function values on these points must be recalculated with each convolution and de-convolution computation. Research efforts have been carried out to improve the computation efficiency of ELDC based production simulation, and two major contributions are Fourier Series method and cumulant method. In Fourier Series method, the original LDC is converted into ILDC by 50 to 100 terms of Fourier series such that the convolution computation can be performed in the Fourier frequency domain [43]. However, this method does not show significant savings in the amount of computation and poor curve fitting has been found when the actual ILDC has a flat tail. In cumulant method, the system load duration curve and the random outage of generating units are described with random distribution numerical characteristic cumulant [88]. This method has demonstrated substantial savings in computation because the convolution and de-convolution process are simplified to addition and subtraction of several cumulants. However, it may suffer from considerable errors when the system scale is relative small or the system load duration curve exhibits multi-mode distribution.

Chronological simulation approach is increasingly being recommended to accurately consider the time-dependent nature of system operation constraints. The production simulation on the hourly framework is especially necessary for studying the system values of energy storage technologies, load management, and renewable energy sources with time varying nature. The chronological simulation models explicitly trace the system states over time by using Monte Carlo technique to capture the random variation of generation capacities and demand levels [60]. Apparently, the results of Monte Carlo chronological simulation are more detailed than the results of ELDC-based analysis, but this is achieved at much higher computation requirements.

A comparison of different probabilistic production costing simulation methods could be found in [58], where the test results of an investigation are reported in term of the relative computational speed and solution quality. These include piece-wise linear approximation method, segmentation method, equivalent energy function method, cumulant method, mixture of normal approximation method, and fast Fourier transform method. From the test results, the equivalent energy function method was shown to be preferred, considering both computation efficiency and accuracy. More recently, a multi-parameter Bata distribution function method was introduced, which was shown to be more accurate than the cumulant method with little addition of computation time.

2.3.3 Intermittent Generation Technologies

In recent years, there has been increased interest in the possibility of obtaining power from locally available renewable energy sources, especially solar photovoltaic power systems (PV) and wind turbine generators (WTG). Since these renewable energy sources are now regarded as capable to supplying a significant proportion of electrical energy in the long-term future, it is thus necessary to analyze the economics of these resources in the process of utility integrated resource planning. The common characteristic of renewable energy sources is that these have generally high capital investments and low operating costs. Moreover, because of the fluctuations in solar radiation and wind speed occurring in the minute-to-minute time frame, the power output of these non-conventional generation technologies are intermittent and thus may cause severe operational problems to utility systems, such as excessive deviations of system frequency and spinning reserve margin. For this reason, it is usual for electric utilities to integrate intermittent generation technologies with adequate storage facilities (battery) or other power sources (fuel cell) to achieve the best value of energy available.

Two commonly used modeling approaches for incorporating intermittent generation technologies into production costing simulation programs are negative load method and equivalent multi-state unit method.

The simplest and traditional method in utility industry is to treat the output of intermittent generation sources as a negative load with the expectation that the electric utility has sufficient on-line capacities to ensure a reliable electricity supply to customers. By this method, the expected energy production from each individual technology is estimated and then the system load is modified to simulate the aggregate impacts of combined intermittent generation sources. Once the modified load duration curve is obtained, probabilistic production costing models can be used to compare alternative expansion strategies, for example, with and without intermittent generation technologies. It should be indicated that this method is acceptable only when the penetration of intermittent generation is insignificant. With the expected increase of intermittent generations into the grid, this method may not be adequate.

In the equivalent multi-state unit method, the probability density functions of PV and WTG power generation need to be calculated based on long-term historical data on solar radiation and wind speed [57]. Once the probability density functions are determined, probabilistic production costing simulation programs can be used in which the intermittent generation will be modeled approximately by equivalent multi-state units. With this method, intermittent generation sources can compete directly with conventional generation technologies as candidate capacity expansion alternatives.

Accurate evaluation of the economics of intermittent generation sources requires the use of chronological hourly production simulation approach, assuming historical data are available for hourly wind speed, solar insolation and system load over a certain time interval. Chronological simulation models have been developed for the optimal design of renewable energy systems and used to investigate the potential value of combined PV and storage systems when they are dispatched as utility peak shaving strategies.

2.4 Multi-Criteria Decision Making under Uncertainty

Multi-criteria decision making and decision analysis under uncertainty are two challenging issues in electric utility resource planning. Over many years, a larger number of decision making techniques have been proposed and applied to address these two issues for selecting a desired resource planning or design strategy which would be acceptable for the given criteria and perform well under various future conditions.

2.4.1 Decision Making under Uncertainty

For many years, uncertainty has been a major issue faced by electric power industry in their generation and transmission planning. Some of the primary data in utility planning, such as load growth, fuel prices, capital costs and regulatory standards, may have a profound influence on the course and outcomes of electric utility resource development. However, it is difficult to provide definite data as these parameters themselves are influenced by many uncertain conditions associated with the changes in public perceptions, government regulations, energy policies and economic situations. Recently, competitive markets are adding new uncertainties that make responsible decision-making for major expansion investment even more difficult.

The common methods used in utility industry for evaluating the influence of uncertainties include scenario analysis, sensitivity analysis and probabilistic analysis [1,19].

In scenario analysis, various scenarios are constructed, each containing internally consistent combination of uncertain parameters. Strategic resource options are then identified and analyzed during the planning horizon with respect to each individual scenario. This method allows the DM to anticipate a broad range of plausible futures and resource options. Resource options that are appropriate under majority futures or easy to adjust their implementation when very different futures occur are more promising. This method appears to be attractive at a glance. However, the required volume of simulations is quite considerable, and there is a need for more precise discriminations among competing alternatives.

The goal of sensitivity studies is to discover the impacts of data perturbations on the model's recommendations. In sensitivity analysis, several least-cost plans are developed according to some base assumptions and resource strategies. The performance of each of these plans is then examined in the fact of changed conditions. This procedure allows the DM to see how each of these plans responds to possible variations of primary assumptions. For systems that can be sufficiently represented using linear or non-linear models, such sensitivity analysis can be readily obtained from shadow prices of gradients of the objective function. However, for systems that are as complex as the resource planning of electric utilities, this method would require conducting the repetitive calculations for all adjusted conditions.

Probabilistic analysis may be more useful than scenario analysis and sensitivity analysis. The key limitation of both scenario analysis and sensitivity analysis is that neither method provides an analytical structure of incorporating the effects of uncertainties and a measure of selecting which plan is optimal with the consideration of various future conditions. Probabilistic analysis includes a variety of approaches, such as deterministic equivalent, Monte Carlo simulation, and stochastic programming. Depending on the models used, uncertainties could be addressed either by assigning probabilities to discrete points or by providing a continuous probability distribution for each uncertainty factor. The simplest approach is to calculate the outcomes associated with various combinations of the key variables and use the expected values as the basis for the evaluation of alternative planning strategies. A more sophisticated approach involves attaching probabilistic weights to different scenarios and performing stochastic programming to determine the optimal resource plan. Decision tree or influence diagram models are often used in probabilistic analysis to graphically represent a complex multistage decision problem [75].

2.4.2 Multi-Criteria Decision Making

Multi-criteria decision making (MCDM) methods may be broadly classified into two categories: multi-objective decision making (MODM) approach and multi-attribute decision making

(MADM) approach. These two decision methodologies share the common characteristics of MCDM problems, such as conflicting criteria, incommensurable units, and difficulties in design/selection of alternatives. The difference between these two approaches is located in the decision space [14,51]. In MODM approach, the decision space is continuous and alternatives are not pre-determined. The decision problem is solved using multi-objective linear or nonlinear mathematical programming models in which several objective functions are integrated and optimized subject to a set of constraints. For the MADM approach, the decision space is discrete and each candidate alternative can be evaluated using a combination of analytical tools. This process will associate each planning or design strategy with a set of attributes, thus yielding an attribute database with which various planning or design strategies can be compared.

MODM problems can be defined and solved by several alternative optimization models: compromising programming, constraint method, goal programming, and fuzzy multi-objective programming.

Compromising Programming methods may be further classified into weighted sum method and composite distance method [14,29,51,79]. With the first method, the multi-objective programming problems are converted into a single-objective optimization formulation by assigning a set of weights to individual objectives. The second method is based on the concept of ideal solution and measures the composite distance from an ideal point on the direction preferred by the DM. In either case, the optimization problem can be solved by existing planning packages for various combinations of weights or directions to create a set of efficient solutions. An efficient solution is defined as a feasible solution and there exists no other feasible solution performing equally or better on all the criteria. From this set of efficient solutions, the best compromise solution can be found or a set of desired compromise solutions can be identified. In *Constraint Method*, the most essential objective is taken as the most essential performance index while others are treated as constraints by providing a proper tolerance level to each of them. Similar to the compromising method, a set of efficient solutions can be identified by varying the tolerance levels. An efficient solution here is a feasible solution under the condition that all constraints on the objectives are binding at the optimal solution. *Goal Programming* method employs a minimum distance concept, which is defined with respect to goals specified by the DM for each objective. In order to have a linear programming problem, additional unknown variables are defined which represent positive and negative deviations from goals.

In real-world decision problems, objectives and constraints are seldom rigid or crisp but rather vague in the degree of attainment. *Fuzzy Mathematical Programming* has been developed significantly in recent years to solve a class of multi-objective optimization problems with fuzzy objectives and constraints [52]. It is an effective method of making coordination among conflicting objectives. The coordination can be done through the shape of membership functions assigned to objectives and also to constraints. It is advantageous to treat future demand and other primary parameters as fuzzy numbers such that the influences of uncertainties can be included in the optimization process. The application of fuzzy set theory may significantly reduce the decision space as compared with traditional multi-objective programming models.

The most commonly used MADM methods in electric utility planning studies include utility function method, tradeoff analysis method and analytical hierarchy process method.

Utility Function method selects an optimal planning or design strategy based on a formulated function known as multi-attribute utility function, which is comprised of the preference functions for individual attributes and the weights that reflect the relative importance of these attributes [27,72,73]. If the condition of additive utility independence of attributes holds, then the linear additive utility model can be used which simplifies the assessment procedure. Less formally, this means that the contributions of an individual attribute to the composite utility is independent of other attribute values. By this method, the alternatives to be evaluated are ranked according to their expected utility values, which are computed as a probability-weighted mean of all possible future conditions [16,81].

Tradeoff Analysis method has been developed to support the identification of robust plans under uncertainty [23,32,64,96]. It can plot a tradeoff curve in a two-dimensional space, and the plans on and near the knee of the tradeoff curve constitute the decision set conditional on the specified future. For multi-dimensional tradeoff analysis, some numerical knee-set searching algorithms are needed to identify the plans not dominated by any other plans. In tradeoff analysis, tolerance levels or significant parameters are specified by the DM for each individual attribute which define the relative importance of attributes or indicate how far the DM is willing to trade off one attribute with respect to another. The process is then repeated for all futures and the global decision set is finally determined by the conditional decision sets. The ranking of alternatives are based on the measure of robustness, i.e., the number of futures supporting the plan.

Analytical Hierarchy Process (AHP) method has been used as a structured approach for dealing with multi-attribute decision problems, especially when the decision process are defined hierarchically [69,85,91,92]. The AHP technique may de described as three-step procedure. *First*, create judgment matrix by pairwisely comparing all the factors at one level of the hierarchy with respect to each factor in the immediately proceeding level. *Then*, compute the eigenvector of judgment matrix corresponding to the largest eigenvalue. *Finally*, calculate the composite priority vector from the local priorities associated with each judgment matrix.

3 Strategic Resource Planning

3.1 Introduction

While traditional optimization and simulation models have been experienced successfully applications for a variety of generation expansion planning and integrated resource planning studies, it is now gradually recognized that identifying a minimum-cost plan under a particular series of constraints is not sufficient. Many other aspects, such as environmental impact and social-political concerns, may be of equally importance as the cost minimization objective. Furthermore, the influence of various uncertainty factors on the outcomes of different planning strategies must be carefully examined because these may significantly affect the system performance if the plans are not designed with adequate level of flexibility or robustness to the possible changes from the base assumptions. It has also been realized that the planning process is only partially done with mathematical models, and human judgment is an integral part of the overall decision making process.

As indicated in Chapter 1, there are four key issues that should be addressed in the process of electric utility resource planning. These include:

- The need for strategically integrating various resource options
- The need for achieving a compromise among conflicting decision criteria
- The need for evaluating the influence of uncertainty factors
- The need for satisfying financial, reliability and environment constraints

Under such complicated planning environments, strategic planning approach, in contrast to traditional tactical planning approach, has become more and more popular in electric utility resource planning [13]. Strategic planning is a structured process of multi-attribute decision making under uncertainty, which is not concerned with finding optimum solutions based on a particular set of constraints and assumptions, but rather with exploring the ranges of resource options and uncertainties as well as the tradeoffs among conflicting attributes [38]. Strategic planning involves the use of extensive analytical tools, such as investment optimization and production costing simulation modes, and needs the support of advanced decision analysis techniques. Instead of determining a single optimal solution, strategic planning approach will yield a range of acceptable plans or efficient decisions. The final resource strategy can then be chosen from among the acceptable plans or efficient decisions based on certain well-defined decision criteria.

Basic definitions and conceptual procedures of strategic planning will be discussed in succeeding sections. Some key technical issues involved in strategic planning process will be emphasized and the proposed solutions or research efforts will be outlined.

3.2 Basic Definitions

The following technical terms and corresponding definitions have been commonly used in electric utility strategic planning studies [41,96].

Options and Plans

Options are potential decisions over which an electric utility has a reasonable degree of control. For example, options for generation expansion planning or integrated resource planning may include supply-side capacity additions, demand-side peak shaving and energy efficiency programs, long-term non-utility and utility contracts, and short-term transactions through the emerging competitive power markets. Options for transmission network planning may include building new interconnection links with neighboring systems and upgrading the transfer limits for some existing lines. Each option has one or more values that are to be specified. A specified option is an option with specified values, such as the type, capacity, location and the timing of a new power plant. A plan is a set of specified options, for example, building a 500 MW gas-fired plant at one specified location together with increasing the transfer capability of one specified 230 kV critical line in the year 2003.

Uncertainties and Futures

Uncertainties are factors over which the utility has little or no foreknowledge. These include load growth, fuel prices and regulatory changes and will have significant influences on the performance of utility systems under different planning strategies. Uncertainties can be modeled either with assumed probability distributions or described as “unknown but bounded” variables without assuming a probabilistic structure. A specified uncertainty is a specific value taken on by a variable associated with the uncertainty, such as 2.5% per year for load growth. A future is a combination of specified uncertainties, for example, “2.5% per year load growth, 2% per year gas and oil price escalation”.

Scenarios and Simulation Studies

A scenario is a combination of a single plan and a single future. Simulation studies related to utility resource planning are essentially production cost, system reliability, environmental impact, revenue requirement and financial studies. These studies are usually conducted using a combination of appropriate analytical models and tools depending on the attributes of interest for decision making.

Attributes

Attributes are the outcomes by which the relative “goodness” of a particular plan is measured. These may include financial attributes, economic attributes, performance attributes, environmental attributes, as well as social-economic attributes, to reflect various concerns of the electric utilities on their strategic resource development. Attributes are functions of options and uncertainties and determined through simulation studies. The objectives of strategic planning process are to minimize or maximize each attribute as appropriate.

3.3 Conceptual Procedures

The conceptual procedures for strategic resource planning of electric utilities may be graphically illustrated by the following flow chart, Fig 3-1, which basically consists of four major function blocks.

- Problem Formulation
- Creation of Decision Database
- Identification of Acceptable Alternatives
- Determination of Final Resource Strategy

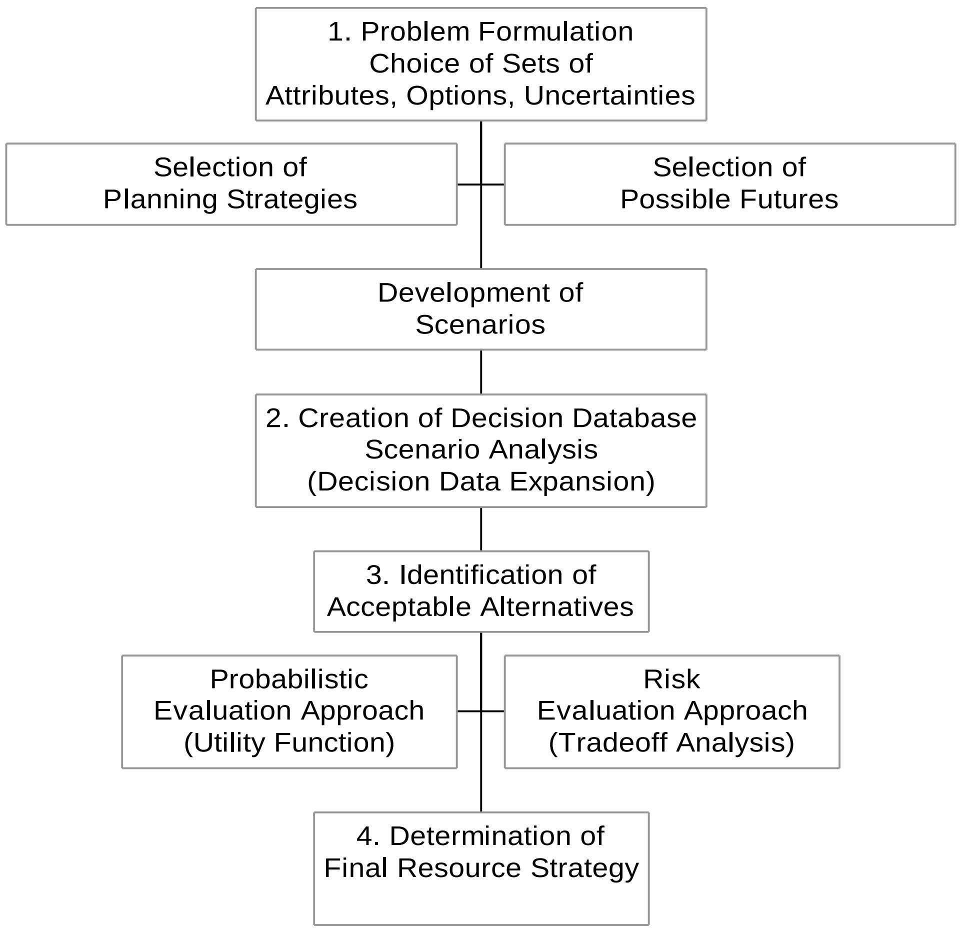

Figure 3-1 Conceptual Procedures of Strategic Planning

<u>Problem Statement</u>

The decision process begins with the choice of sets of attributes, options, and uncertainties. Each alternative planning strategy is a set of scheduled resource options over the planning horizon; and each possible future is a set of selected uncertainty factors. The combination of a specific planning strategy and a specific future constitutes a particular scenario.

Creation of Decision Database

In this stage, each scenario defined in first stage will be evaluated with the use of a combination of utility planning tools, such as investment optimization models, production costing simulation and reliability assessment programs, environmental impact analysis and financing analysis models. This comprehensive scenario analysis will establish an attribute database or decision database with which alternative planning strategies can be compared based on certain well-defined decision criteria.

Identification of Acceptable Alternatives

A key procedure in strategic planning is to identify acceptable alternatives with respect to the given attributes and future conditions. Most frequently used decision analysis techniques in the electric utility industry are multiple utility function method and tradeoff/risk analysis method. Multiple utility function method ranks alternative planning strategies based on the measure of expected performance (i.e., probabilistic evaluation approach) while tradeoff/risk analysis method ranks alternative planning strategies based on the measure of robustness (i.e., risk evaluation approach).

Determination of Desired Resource Strategy

From among the acceptable plans, either based on rules of probability or the measure of robustness, the DM may choose one specific plan as the optimal solution if he/she is satisfied with the performance of that plan. In some cases, the DM may need to identify a better combination of options so as to invent a more robust or flexible planning strategy, or the DM may need to reformulate/restructure the decision problems by adding additional or deleting trivial attributes, options, and uncertainties.

3.4 Proposed Study Topics

The primary objective of this dissertation is to develop an enhanced MADM framework in support of strategic resource planning of electric utilities. Study efforts will focus on the following four major technical tasks which are identified to be significant important to the success of strategic planning approach.

Decision Data Expansion

The creation of decision database is an extremely time-consuming process in performing strategic planning since it involves the evaluation of a larger number of scenarios using a combination of analytical tools. Database expansion is an efficient approach to reduce the amount of computations by developing an approximate model to represent the inherent functional relationship between attribute values and decision variables based on a limited number of detailed case studies. The extracted knowledge then can be used to estimate the attribute values of a considerable number of scenarios that are not directly calculated.

Due to the various limitations of available methods in the existing literature, one major study task of this dissertation is to develop a more accurate, easy-to-use approach for decision data expansion. The study will investigate the potential application of artificial neural networks (ANN) in view of its flexibility in nonlinear input-output vector mapping and the general procedures that can be followed in the approximation model development and verification. Three illustrative examples will be used to support the proposed method where the approximation performance of ANN-based method will be evaluated and compared with the results reported using the techniques available in the existing literature.

MADM Analysis with Imprecise Information

Multi-attribute decision making (MADM) methods have been widely used in strategic planning of electric utilities which provides an efficient decision analysis framework to help the decision maker (DM) in selecting the best resource strategy with regard to the chosen attributes. The information available to the DM, however, is often imprecise due to inaccurate attribute values and inconsistent expert judgments. Thus, it may not be totally satisfactory to use the point estimate as the sole criterion to make a decision, and it appears necessary to include the measure of variance into the decision analysis.

One significant contribution of this dissertation is to introduce a confidence interval-based MADM methodology for strategic planning with imprecise information, which involves the development of an approximate model to estimate the variance of composite utility, accounting for individual errors from inaccurate attribute measurements and inconsistent priority judgments. This would allow the DM gain insights into how the imprecise data may affect the choice toward the best solution and how a range of acceptable alternatives may be identified with certain confidence.

MADM Analysis under Uncertainty

For many years, uncertainty has been a major issue faced by electric power industry in their strategic planning. Some of the primary data, such as demand growth, fuel prices, capital costs, and regulatory standards, may have a profound influence on the course and outcomes of utility resource development, and it is very difficult to provide definite data as these parameters themselves are influenced by many uncertain conditions.

An integrated MADM framework for multi-attribute planning under uncertainty will be introduced in this dissertation, which combines the attractive features of utility function model and tradeoff/risk analysis and thus offers a structured and enhanced decision approach for handling such complicated decision problems. The proposed decision methodology is conceptually within the framework of tradeoff/risk analysis but introduces a novel multi-dimensional numerical knee-set searching algorithm based on the measure of composite distance, a special form of utility function model. This study also propose a hybrid decision approach by which the competing alternatives can be evaluated not only based on the rule of probability (i.e., probabilistic evaluation approach or expected performance) and from a risk aversion perspective (i.e., risk evaluation approach or robustness performance).

Prescreening Tools

Preliminary studies are very helpful in strategic planning of electric utilities as to identify cost-effective resource options and appropriate project configuration schedules. For example, screening tools are needed in utility integrated resource planning to evaluate a large number of DSM options for their potential capacity and operational benefits. This should be done with very limited DSM data, such as peak reduction capability and total energy savings, as calculated using engineering estimate methods. A few cost-effective DSM programs and portfolios can then be selected and compete with supply-side options in the least-cost resource planning process. Screening tools are needed to determine an optimal generation mix over the planning horizon or a reference resource plan from which appropriate project configurations can be scheduled, i.e., the number of units for each candidate generation type that may be selected each year or during a certain time interval. This information is especially useful to the generation expansion planning models with dynamic programming methodology, such as WASP and EGEAS. Screening tools are also needed in a market-based planning environment as to efficiently identify potential merchandise generation plant and transmission expansion opportunities. These screening applications will be discussed in this dissertation with varying details.

Each of the above identified study topics, i.e., decision data expansion, MADM with imprecise information, MADM under uncertainty and screening applications, will be discussed in the follow-up four major chapters of this document (i.e., Chapter 4 through Chapter 7).

4 Decision Data Expansion

This chapter presents an automatic learning method which takes advantage of the flexibility of artificial neural networks (ANN) in nonlinear input-output vector mapping and offers an efficient approach to reduce the amount of computations involved in the creation of decision database in strategic resource planning. The performance of ANN-based method for decision data expansion is demonstrated through three illustrative examples involving renewable energy system design, third party generation evaluation and strategic energy planning. Test results have shown that the ANN-based method is feasible, easy to implement, and more accurate than the techniques available from the literature.

4.1 Introduction

As discussed in Chapter 3, the creation of decision database is a major challenging task in strategic planning, which requires the evaluation of a large number of alternative resource strategies under various future conditions. This comprehensive evaluation process is often termed as Scenario Analysis and needs the support from a combination of utility planning tools, especially, the models for production costing simulation, investment optimization, system reliability assessment and environmental impact analysis. Study results using detailed models associate each scenario with a set of quantified attributes, thus yielding the decision database with which alternative resource strategies can be compared with advanced decision analysis techniques and the best solution or the most desired resource development strategy can then be determined.

The quality of decision database is critical importance in strategic resource planning of electric utilities. If the database is unrepresentative or too small, the conclusion reached using whatever decision analysis techniques will be probably less useful. In order to create a reliable decision database, however, hundreds or thousands of scenarios often need to be evaluated using detailed planning models for examining the circumstances of alternative resource strategies under various future conditions. This will be an extremely time-consuming process, if not impossible, for some complicated electric utility planning problems.

Techniques for decision data expansion have been proposed in the literature aiming to reduce the amount of computations. The basic idea of decision data expansion is to develop an approximate model to represent the inherent functional relationship between attribute values and decision variables (i.e., resource options and uncertainty factors) involved in the decision problem based on a limited number of detailed case studies. The extracted knowledge then can be used to estimate the attribute values of a considerable number of scenarios that are not directly calculated with adequate accuracy.

Three methods have been discussed in the literature, which can be used for the purpose of decision data expansion. These include:

- Describing Function (DF) method [39,40]

- High Order Linear Interpolation (HOLI) method [74]
- Interdependent Data Analysis (IDA) method [84]

Describing function method consists of a set of algebraic equations of the form: $a_i = k_0 + k_1t_1 + k_2t_2 +\ldots$, where a_i is the ith attribute, t_1, t_2, … are some hypothesized nonlinear functions of decision variables, and k_0, k_1, … are coefficients determined by the regression program. This method has been used in some utility planning studies and desired approximation performance has been reported. The main concern of using this method is the choice of proper describing functions which seems to be an art and involves an iterative process with considerable manpower and investigator's experiences.

HOLI method uses the simplex method of linear programming to identify the knots (a knot is a simulated scenario) which surround the target scenario and define the hyperplanes which interpolate between adjacent knots. This method has been proved to be reliable for data interpolation and usually the accuracy of estimation can be improved by performing several interpolations for the same target scenario and averaging the results. However, this method is inherently not applicable for data extrapolation, and as a result, detailed simulation studies are still needed for a large number of scenarios being detected not in the interpolation region.

In IDA method, a number of comparable scenarios are selected from the case library based on the similarity to the target scenario. The relative dependency of attribute values on the level of decision variables are then calculated by comparing each pair of these selected scenarios. Least-square analysis is used to determine the approximate linear relationship between the attribute values and the dependency factors. This method has been shown equally accurate, but more robust, as compared to DF and HOLI methods. The main concern with the use of IDA method is the similarity measure in selecting relevant scenarios that define the boundary conditions for the target scenario.

Considering the various limitations of these methods, one major study task of this dissertation is to seek an accurate, easy-to-use approach for decision data expansion. The study will investigate the potential application of artificial neural network (ANN) in view of its flexibility in nonlinear input-output vector mapping and the general procedure that can be followed in the approximation model development and verification.

Section 4.2 presents the proposed ANN-based method for decision data expansion, including multi-layer perceptron network, back-propagation algorithm, the Universal Approximation Theorem and the general application procedures. Three illustrative examples are presented in Section 4.3 where the approximation performance of ANN-based method is evaluated and compared with the results from the techniques from the literature. Concluding remarks are given in Section 4.4.

4.2 ANN-Based Method

The proposed ANN method is based on the multi-layer perceptron network (MLP) and back-propagation algorithm (BP) [89]. The MLP network is characterized by having a set of sensory units (source nodes) that constitute the input layer, one or more hidden layers of computation nodes, and an output layer of computation nodes. The connections of nodes and inter-influence among input, hidden, and output layers are represented by synaptic weights which are determined during the training process by back-propagation algorithm. Back-propagation is the most popular technique used for training MLP network, which basically consists of two passes through the different layers of the network, on a layer by layer basis. In the forward pass, the input signal is applied to the sensory nodes of the network and its effect then propagates through the network in a forward direction. The output nodes of the network will produce the actual response of the network. During the backward pass, on the other hand, the error information is computed based on the network actual response and the desired response, and then propagates in a backward direction. The synaptic weights are updated so as to make the actual response of the network close to the desired response.

One main characteristics of MLP network is its flexibility in approximating nonlinear functions in a multidimensional space. According to the *Universal Approximation Theorem,* any arbitrary continuous function may be approximated by multilayer perceptron as opposed to exact representation. It also states that a single hidden layer is sufficient for a MLP network to approximate a set of given training data within certain error limit. The approximation process includes learning process and generalization process. In the sense of input-output vector mapping, the learning process may be viewed as a curve fitting problem and the generalization process is similar to the interpolation of data points. The *Universal Approximation Theorem* is an existence theorem only, and therefore does not indicate the best approach regarding to how to achieve a good generalization.

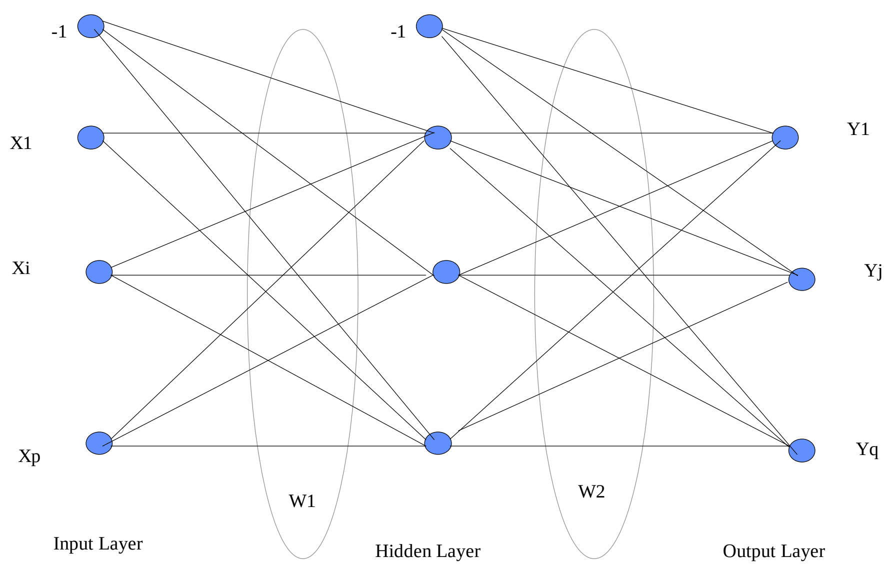

Figure 4-1 Typical MLP Network Structure

The architectural graph of the MLP network depicted in Fig 4-1 has been used in this study. It can be noticed that the network is fully connected and therefore has totally $(p+1)\times h+(h+1)$ ´q weights to be determined by back-propagation training process. Here, p denotes the number of input nodes or decision variables, q represents the number of output nodes or attributes, and h refers to the number of hidden nodes. Each hidden node or output node has an input/output relationship of the form as follows

Hidden Node (j = 1,…,h):

$$Output_j = \tanh\left(\sum_{i=1}^{p} w_{ij} \cdot Input_{ij} - q_j\right) \tag{4-1}$$

Output Node (k = 1,…,q):

$$Output_k = \tanh\left(\sum_{j=1}^{h} w_{jk} \cdot Input_{jk} - q_k\right) \tag{4-2}$$

The convergence criterion used in BP algorithm is the total sum of square errors (TSE) with respect to the training data set (TDS) as given below:

$$TSE = \sum_{state \in TDS} \left(Output_{ref} - Output_{MLP}\right)^2 \tag{4-3}$$

Now, the general procedure of using ANN-based method for decision data expansion may be described as follows.

1. Reference Data Set: A set of representative scenarios are selected and analyzed using detailed planning models, resulting in the reference data set in which each individual scenario is characterized by a set of quantified attributes corresponding the specified decision variables. The reference data set is then divided into two subsets, i.e., the training data subset and the testing data subset, as to be used for MLP network training process and ANN model testing process.

2. Training Process: The constructed MLP network is trained with the training data obtained from the reference data set to extract the inherent functional relationship between attribute values and decision variables. During the training process, the error between the actual network output and the required output is calculated and used to modify the weights related to the network links. The training process will be terminated when an error function as defined in (4-3) becomes smaller than the pre-determined convergence tolerance.

3. Testing Process: The trained MLP network needs to be verified by the testing data obtained from the reference data set. A trained MLP network is said to generalize well when the input-output relationship computed is correct or nearly so for the testing data that are not used in the training process. Otherwise, proper refinements are required to improve the approximation performance of ANN model.

4. Model Refinement: The performance of generalization process may be influenced by many factors, such as the selection of training data, proper data scaling or

preprocessing, the architecture of MLP network, and more importantly, the physical complexity of the problem at hand. User experience is significant important and a trail and error mechanism is often involved in this model refinement process.

5. Model Application: After careful model refinement (if necessary), the trained MLP network is ready to be used for decision data expansion. In general, for a well-defined problem with adequate training data, desired accuracy of the expanded decision database can be expected as will be shown in the follow-up illustrative examples.

The application of ANN techniques involves several practical issues, such as how to choose an optimal network structure and training parameters, as well as how to generate proper training and test cases. Presently, searching for an optimal network structure is still a trial-and-error process, a very time consuming process, as many different ANNs have to be trained and tested in order to find the best one. Preparing and generating proper training and test cases is another challenge. The cases must be selected to encompass all possible patterns to ensure that the trained ANN model will be reliable and perform well for the designated functions.

4.3 Illustrative Examples

In this section, the performance of ANN-based method for decision data expansion will be demonstrated through three illustrative examples. These examples are developed based on the published data from the following resource planning studies.

- Design of hybrid solar-wind power systems [70]
- The evaluation of third party generation [84]
- Strategic planning for electric energy [74,83]

The test results will be presented both in tables and in graphs, and the overall approximation performance will be measured by the average and the median of estimation errors in percentage of the variation range of respective attribute values.

4.3.1 Design of Hybrid Solar-Wind Power Systems

This sample study is based on the decision problem discussed in [70], which introduced a decision support technique for the design of hybrid solar-wind power systems (HSWPS). The proposed HSWPS is composed of four design variables: wind turbine generators, PV arrays, batteries and a grid-linked substation. The candidate site under consideration is the American University of Beirut (AUB) campus where time series data are available for hourly wind speed, solar insolation and load demand. The main goal behind proposing the HSWPS is to increase the penetration level of wind and solar energy technologies in the total generation mix.

Given the range and variation step of the design variables and possible futures, several thousands scenarios have been studied using detailed energy production simulation model. For each scenario, the output of simulation model includes cost of energy production ($/kWh), expected energy unserved (%) and SO_2 emissions (kg/year). Tradeoff/risk analysis decision approach is then applied to the decision database so that the optimal combination of device capacities can be determined with regard to three objectives: the minimization of both cost and emissions, and the maximization of system reliability.

The purpose of this sample study is to investigate the feasibility of applying ANN-based method for decision data expansion. For this regard, two test cases are defined as follows.

Case-1: The reference data set consists of 91 scenarios, and each of them is characterized by five decision variables: wind area (m^2), solar area (m^2), substation rating (kW), battery rating (kWh) and solar insolation condition (p.u). The architecture of MLP network used in this case thus has five input nodes, three output nodes, and the number of hidden nodes is initially equal to the node number on the input layer.

Case-2: The reference data set consists of 134 scenarios, and each of them is characterized by six decision variables: wind area (m^2), solar area (m^2), substation rating (kW), battery rating (kWh), solar insolation condition (p.u) and PV efficiency (%). The architecture of MLP network used in this case thus has six input nodes, three output nodes, and the number of hidden nodes is initially equal to the node number on the input layer.

In both cases, 60 scenarios are selected as the training data and the remaining scenarios, 31 in Case-1 and 74 in Case-2, are used as the testing data. The training data are randomly selected from the reference data set so that the testing data may contain some extreme points (extrapolation).

Table 4.3-1 gives the test results for both cases, where the overall approximation performance of ANN-based method is measured in terms of the average and the median of estimation errors associated with the testing scenarios. As a comparison, this table also gives the estimation errors using Linear Describing Function (LDF) or linear regression method, which can be regarded as a special form of Describing Function method.

Table 4.3-1 Summary of Test Results in Case-1 and Case-2

Case-1	ANN Method		LDF Method	
	Mean	Median	Mean	Median
Energy Cost	2.63%	2.49%	2.71%	1.99%
Reliability	1.48%	1.45%	9.32%	8.06%
SO_2 Emissions	2.92%	2.66%	5.06%	3.93%
Case-2	ANN Method		LDF Method	
	Mean	Median	Mean	Median
Energy Cost	2.88%	2.53%	2.17%	1.90%
Reliability	2.03%	1.44%	11.20%	10.41%
SO_2 Emissions	3.06%	2.35%	7.02%	5.12%

Fig 4-2 and Fig 4-3 show the test results graphically, where the estimated attribute values are plotted as opposed to the actual simulated results. It is easy to understand that, for 100% accuracy, all points should lie on the 45 degree line of exact correspondence since the scales on both axes being the same. The following can be obtained from the results in Table 4.3-1, Fig 4-2 and Fig 4-3:

- Excellent performance of ANN-based method has been observed in both cases. It can be seen that the estimation errors for all three attributes, in average, are below 3% or nearly so, and for about 50% of tested scenarios, the estimation errors are less than 2.5%.
- Both ANN-based method and LDF method work quite well for estimating the cost of energy production, indicating this attribute can be approximated by a linear function of the given decision variables.
- On the other hand, the reliability index (EENS) estimated using LDF method is totally unreliable due to the nonlinear dependence of system reliability on the given decision variables.
- For the estimation of SO_2 emissions, the approximation performance of ANN-based method is apparently superior to the results obtained using LDF method.

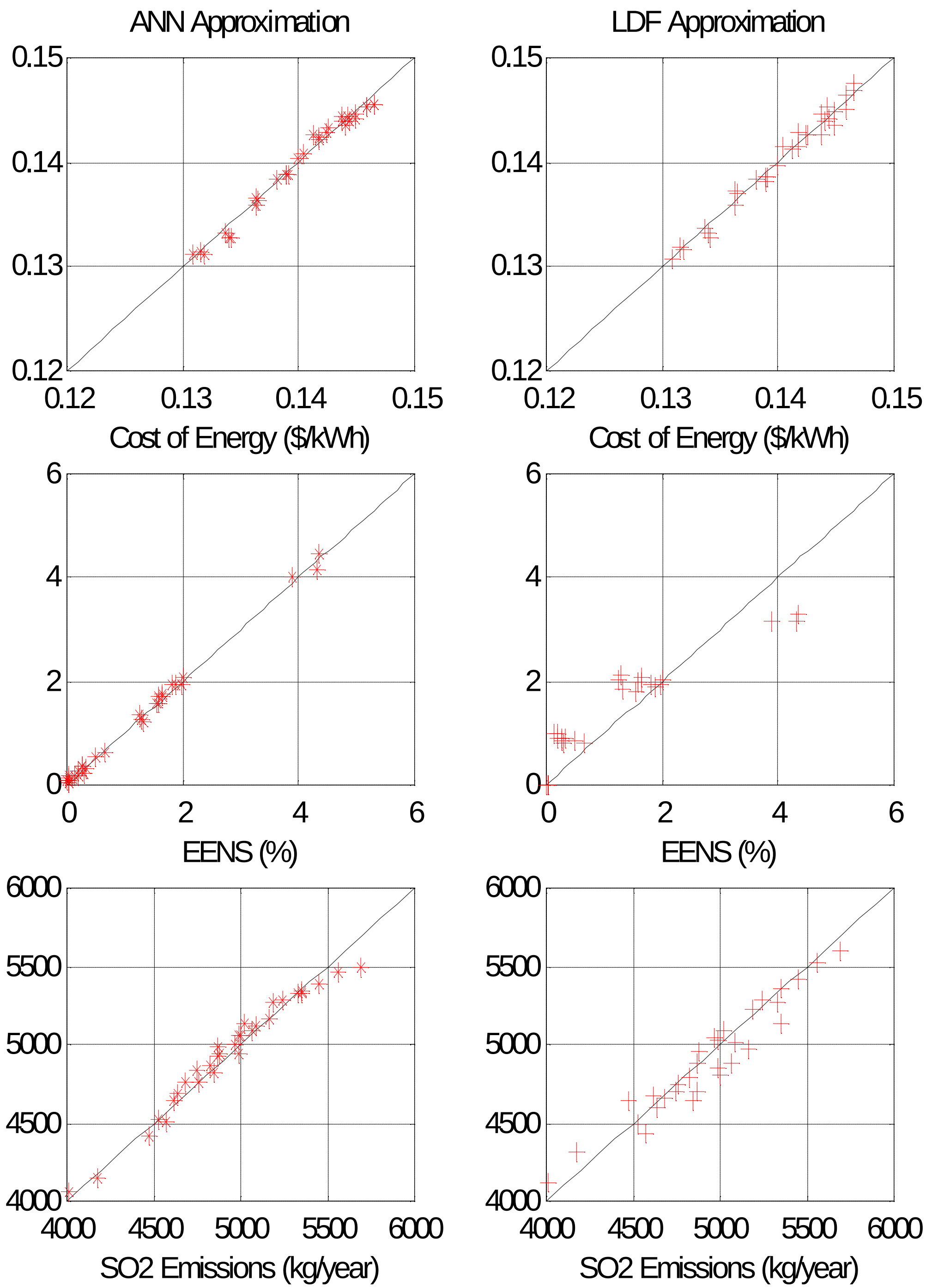

Figure 4-2 Approximation Performance (Case-1)

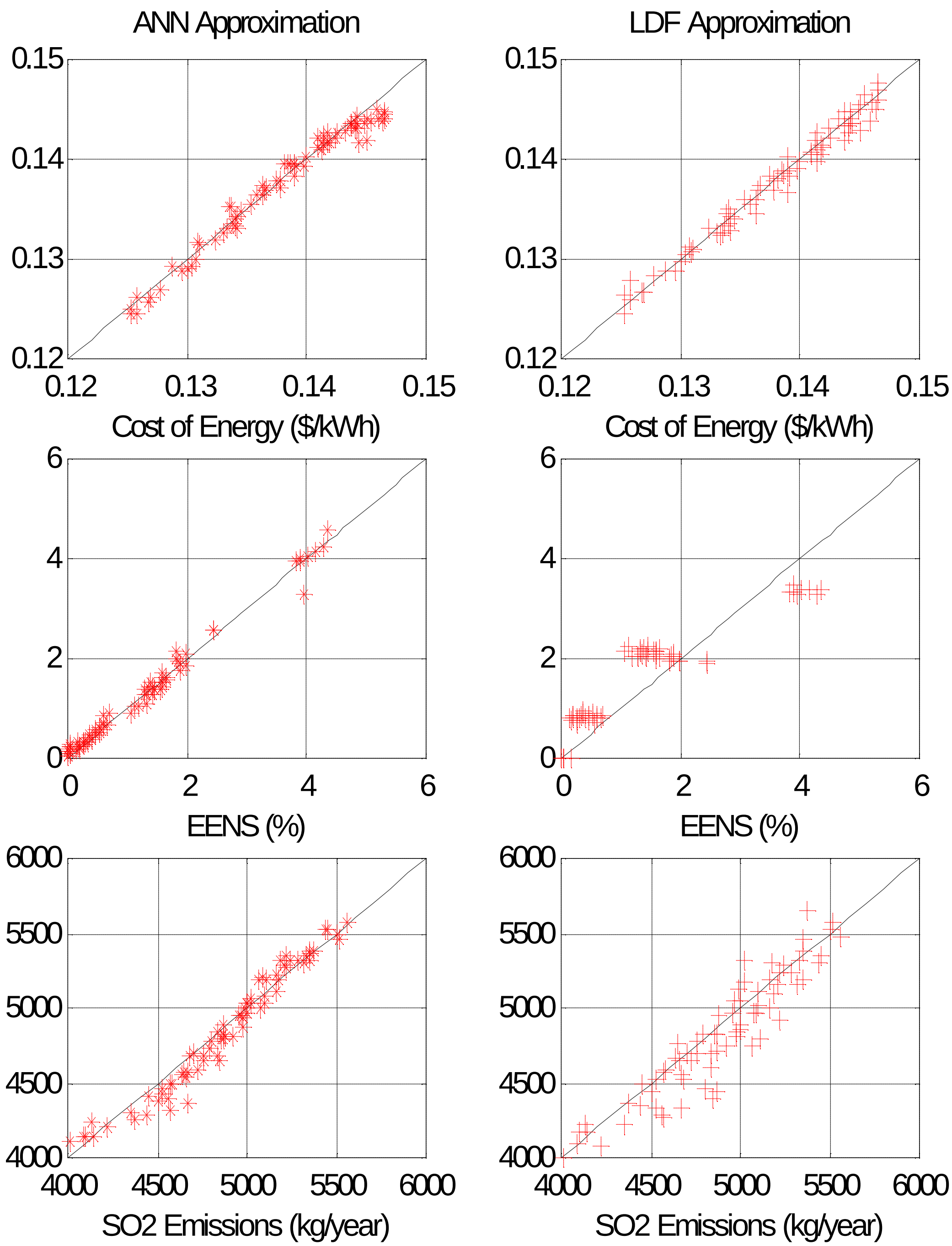

Figure 4-3 Approximation Performance (Case-2)

The accuracy of ANN model generalization can be improved by proper model refinements if the error statistics are not satisfactory or some extremely large errors are observed in the testing process. Extensive discussion on ANN model refinements is out of the scope of this feasibility study. As a matter of fact, the process of model refinement is not necessary for this sample study in view of the good performance of ANN model shown in Table 4-1. However, for the purpose of illustration, we will re-examine the previously studied cases with some minor model refinements. Here, we simply replace some scenarios in the testing data (which have shown large estimation errors) with the same number of scenarios selected randomly from the training data, thus the total testing scenarios unchanged.

Case-3: This case is created from Case-1 by exchanging two scenarios between the training data and the testing data.

Case-4: This case is created from Case-2 by exchanging four scenarios between the training data and the testing data.

Table 4.3-2 presents the test results of Case-3 and Case-4. An overall performance improvement can be observed by comparing Case-3 with Case-1, reflected by reduced average and median error indices for all three attributes. With reference to Case-2, the error size of energy cost in Case-4 has decreased from 2.88% to 2.25% in average and from 2.53% to 1.74% for the median. On the other hand, the estimation errors for reliability and SO_2 emissions in Case-4 are slightly higher than the error levels Case-2, showing the improved performance in the estimation of one attribute may negatively affect the estimation accuracy for other attributes. For this particular case, we may regard the performance of ANN model in Case-4 is better than that in Case-2 because the cost of energy supply usually has a higher priority than reliability and emissions in multi-attribute resource planning. Fig 4-4 and Fig 4-5 show the test results graphically.

Table 4.3-2 Summary of Test Results in Case-3 and Case-4

Case-3	ANN Method		LDF Method	
	Mean	Median	Mean	Median
Energy Cost	2.65%	1.99%	2.82%	2.49%
Reliability	1.47%	1.35%	9.36%	8.99%
SO_2 Emissions	2.43%	1.71%	5.10%	3.13%
Case-4	ANN Method		LDF Method	
	Mean	Median	Mean	Median
Energy Cost	2.25%	1.74%	2.20%	1.90%
Reliability	2.54%	1.99%	11.72%	11.57%
SO_2 Emissions	3.33%	2.99%	6.50%	5.29%

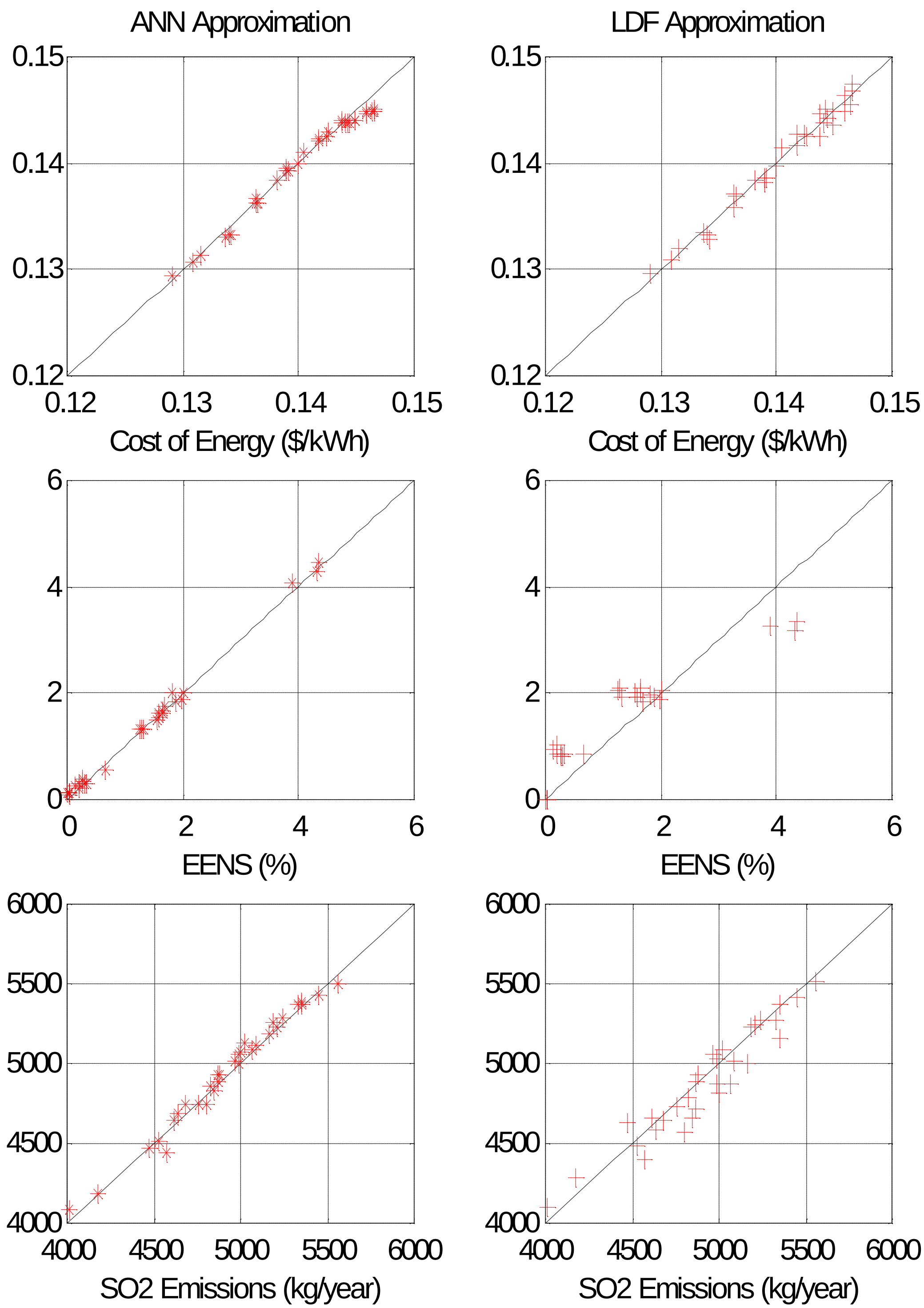

Figure 4-4 Approximation Performance (Case-3)

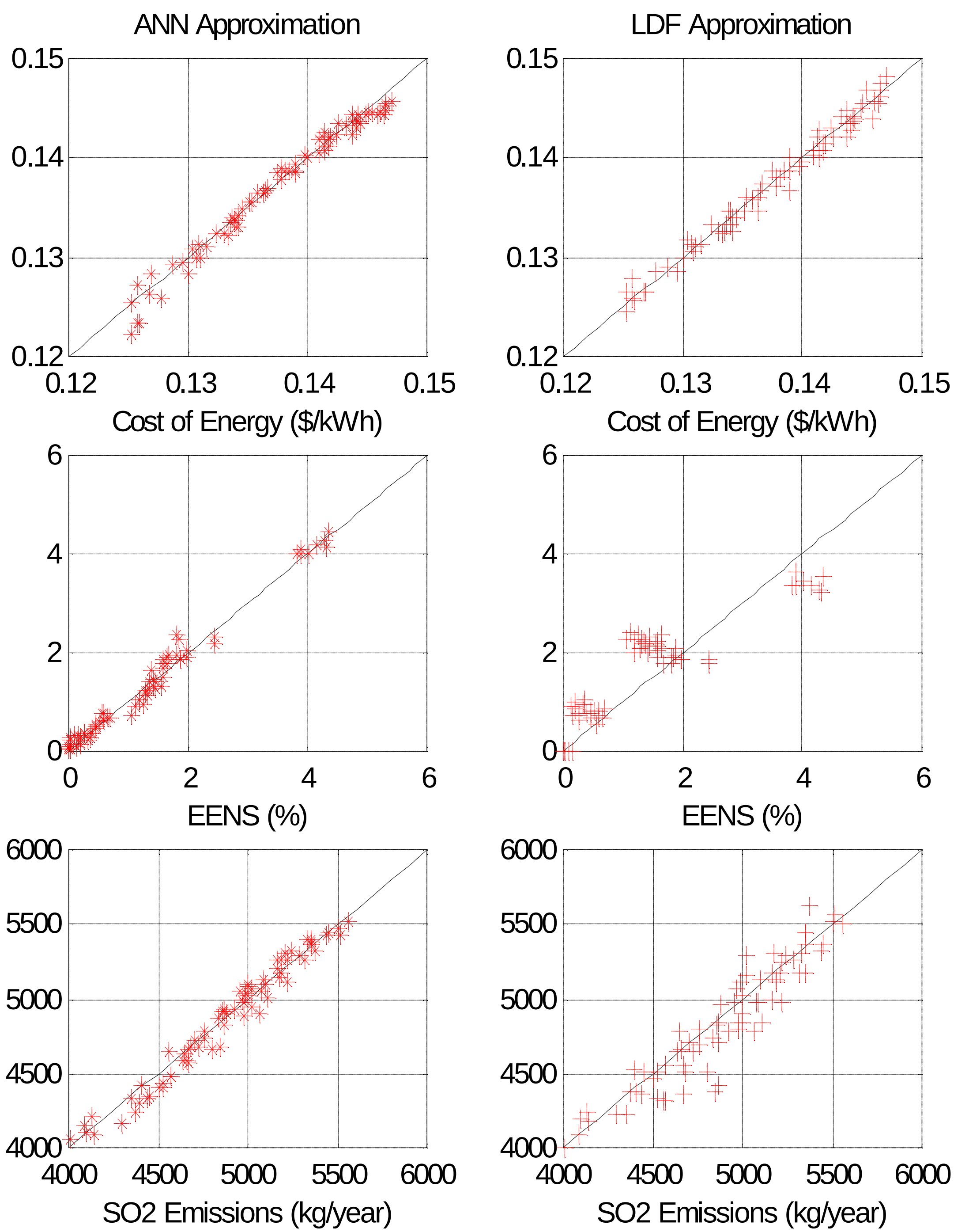

Figure 4-5 Approximation Performance (Case-4)

4.3.2 Evaluation of Third Party Generation

Third party generation or non-utility generation has become an important source of electric energy since 1980s and the ability to use this energy source is a major factor in the economics of utility system resource planning and operations. The worth of non-utility generation may be affected by a number of factors, such as existing utility generation mix, system load characteristics, different level of non-utility generation capacities, environmental considerations in generation dispatch, etc.

In [84], the technique of interdependent data analysis (IDA) is used for the evaluation of the consequences of incorporating non-utility generation into the utility systems. It shows that the actual operating cost savings for a target scenario that is not directly simulated can be estimated accurately based on the knowledge extracted from the base case library. In this example, we are going to compare the estimation results between using the ANN-based method and using the IDA technique.

This sample case consists of 65 non-utility generation scenarios, and each scenario is specified by four factors: the size and the number of IPP units, the capacity of total cogeneration facilities and an integer index indicating the system load characteristics. In the application of ANN-based method, the total IPP capacity (the product of unit size and the number of units) has been used as an additional factor. As with the first sample case, the structure of MLP network thus has five input nodes and five hidden nodes, equal to the number of decision variables. The attribute of concern is the actual operating cost savings contributed by non-utility generation capacities, which is the unique output node of MLP network.

Two test cases are created in this sample study based on the production simulation results under different generation dispatch policies: without considering the environmental impact (Case-1) vs. incorporating environmental penalty (Case-2). For each test case, 50 out of 65 scenarios are used as the base cases or training data and the remaining 15 scenarios are used as the target cases or testing data.

Tables 4.3-3 and 4.3-4 give the estimated operating cost savings as against the actual values for Case-1 and Case-2, respectively. In the tables, the percent errors are calculated with reference to the range of variation of production cost savings over all simulated scenarios. The estimation performance of ANN-based method and IDA technique is also illustrated graphically in Fig 4-6 and Fig 4-7.

It is clear from the test results that the estimation performance of ANN-based method is better than that achieved using IDA technique. For example, by using ANN-based method, the average of estimation errors is reduced from 4.59% to 2.66% in Case-1 and from 4.24% to 2.92% in Case-2. Similarly, with the use of ANN-based method, the median of estimation errors is decreased from 4.53% to 1.98% in Case-1 and from 4.01% to 2.21% in Case-2.

Table 4.3-3 Actual and Estimated Production Cost Savings ($'1000)

Case-1 Scenario No	Actual Savings	Estimated Savings		Percent Error	
		IDA	ANN	IDA	ANN
1	276.3	244.7	298.7	2.80	1.98
2	459.0	407.9	444.8	4.53	1.26
3	585.3	589.8	552.1	0.40	2.95
4	623.6	648.8	657.1	2.23	2.97
5	617.0	792.4	510.0	15.55	9.49
6	733.8	806.1	758.1	6.41	2.15
7	828.6	818.2	826.7	0.92	0.17
8	862.8	885.3	865.8	2.00	0.27
9	997.8	935.5	983.3	5.52	1.29
10	946.1	924.8	1019.7	1.89	6.53
11	1075.3	999.8	1081.2	6.69	0.52
12	1055.1	986.1	1023.5	6.12	2.80
13	1230.9	1309.8	1251.9	7.00	1.86
14	1129.4	1107.8	1173.1	1.92	3.88
15	1258.2	1313.5	1277.6	4.90	1.72
Max				*15.55*	*9.49*
Average				*4.59*	*2.66*
Median				*4.53*	*1.98*

Table 4.3-4 Actual and Estimated Production Cost Savings ($'1000)

Case-2 Scenario No	Actual Savings	Estimated Savings		Percent Error	
		IDA	ANN	IDA	ANN
1	248.7	220.2	290.2	2.63	3.83
2	390.2	346.7	390.0	4.01	0.02
3	526.8	530.1	543.3	0.30	1.52
4	530.1	551.5	556.1	1.97	2.39
5	586.2	752.4	532.8	15.32	4.92
6	623.7	685.2	674.7	5.67	4.70
7	704.3	695.5	680.3	0.81	2.21
8	819.7	841.0	823.2	1.96	0.32
9	848.1	795.2	915.5	4.88	6.22
10	851.5	832.3	926.3	1.77	6.90
11	914.0	849.8	910.1	5.92	0.36
12	949.6	887.5	961.4	5.73	1.09
13	1046.3	1113.3	1123.0	6.18	7.07
14	1072.9	1052.4	1093.6	1.89	1.91
15	1195.3	1247.8	1191.8	4.84	0.33
Max				*15.32*	*7.07*
Average				*4.26*	*2.92*
Median				*4.01*	*2.21*

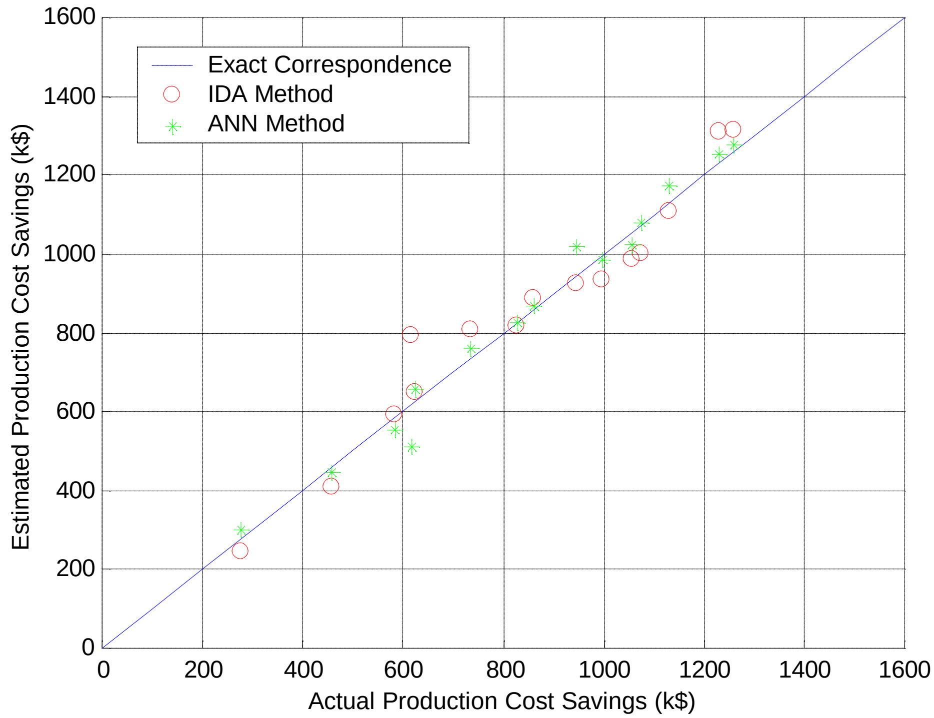

Figure 4-6 Comparison between ANN and IDA Methods (Case-1)

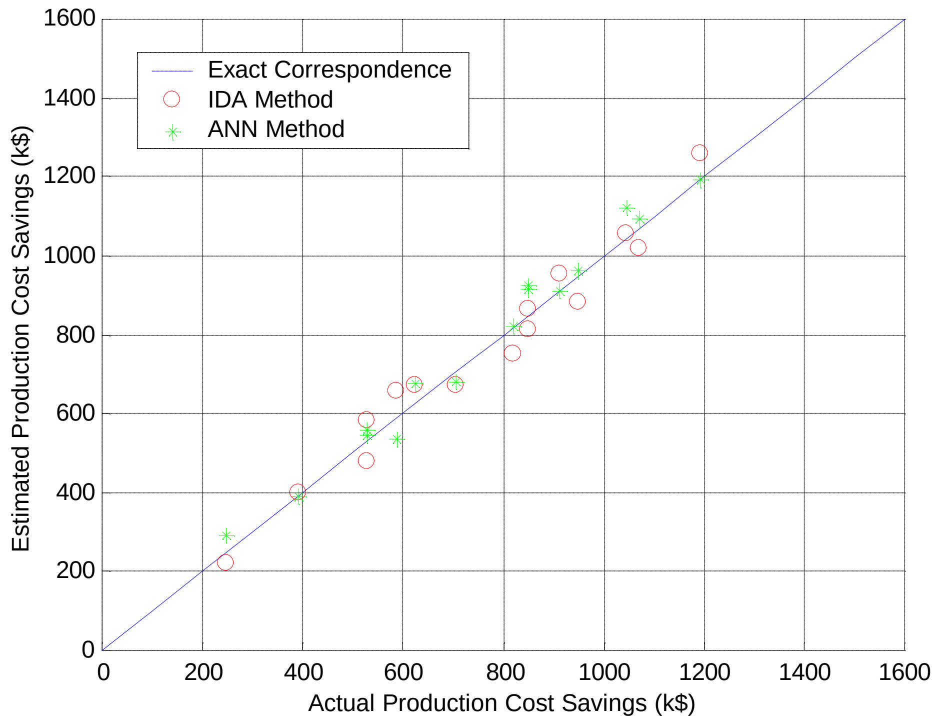

Figure 4-7 Comparison between ANN and IDA Methods (Case-2)

4.3.3 Strategic Planning for Electric Energy

The third sample study is based on the data from a MIT Energy Laboratory Report on strategic planning for electric energy [65]. Since this set of data has been used in the literature to compare the estimation performance of DF, HOLI and IDA methods for decision data expansion, it is thus worthwhile and convenient to compare the accuracy of ANN-based method with the results reported in the literature [74,83].

Being consistent with other studies, the reference data set used in this example consists of the same 69 scenarios selected from the list of electric energy expansion scenarios. Also, the same 50 scenarios, numbered from 1 to 50, are selected from the reference data set and used as the training data. The attribute of interest is the amount of coal consumption under different energy expansion strategies, which has been found being influenced by a number of relevant factors. These include coal conversion schedules, load growth rates, levels of energy purchase, rise in fuel prices, building a pumped storage plant, building a coal plant and continuing to operate a nuclear plant.

In the MLP network, six input nodes are used to model the influence of different combinations of relevant factors. The impact of fuel prices is not modeled because the 69 scenarios have shown a single fuel price rate. The annual electric load growth rate and the level of energy purchase are represented by the corresponding numerical values while the operation status of generating plants are represented by switching variables. Different coal conservation plans have been transformed into two appropriate scaling factors.

As with the previous sample studies, the MLP network used for this example has six input nodes and six hidden nodes, equal to the number of decision variables. The attribute of concern is the coal consumption, which is the unique output node of MLP network.

Table 4.3-5 gives the estimated coal consumption for the 19 testing scenarios with different estimation methods. In the table, the estimation errors are expressed by the absolute difference between the actual and the estimated values. Note that when applying HOLI method, four scenarios with star marks in the table have been identified being outside the interpolation region. Detailed analysis is thus required for these four scenarios. The performance of ANN-based method is also compared with the results obtained using DF, HOLI and IDA methods, respectively in Fig 4-8 through Fig 4-10.

This example once again shows the feasibility of applying ANN-based method for decision data expansion and its superior estimation performance over other techniques available from the literature.

Table 4.3-5 Estimated Coal Consumption (M'Tons) Using Different Methods

Scenario No	Actual Value	Estimated Value				Absolute Error			
		DF	HOLI	IDA	ANN	DF	HOLI	IDA	ANN
51	66	69	66	67	69	3	0	1	3
53	64	57	54	58	65	7	10*	6	1
54	93	80	63	95	92	13	30*	2	1
55	80	73	54	78	83	7	26*	2	3
57	52	45	40	44	52	7	12*	8	0
74	65	68	67	67	66	3	2	2	1
75	63	66	66	65	65	3	3	2	2
76	48	57	59	55	51	9	11	7	3
77	75	76	73	73	74	1	2	2	1
78	58	59	53	58	58	1	5	0	0
80	77	75	72	73	76	2	5	4	1
81	59	59	53	58	59	0	6	1	0
84	61	61	61	64	63	0	0	3	2
85	52	50	52	54	49	2	0	2	3
87	44	43	45	42	44	1	1	2	0
88	34	37	36	35	36	3	2	1	2
89	31	31	31	34	29	0	0	3	2
90	27	27	28	32	26	0	1	5	1
91	58	59	59	59	62	1	1	1	4

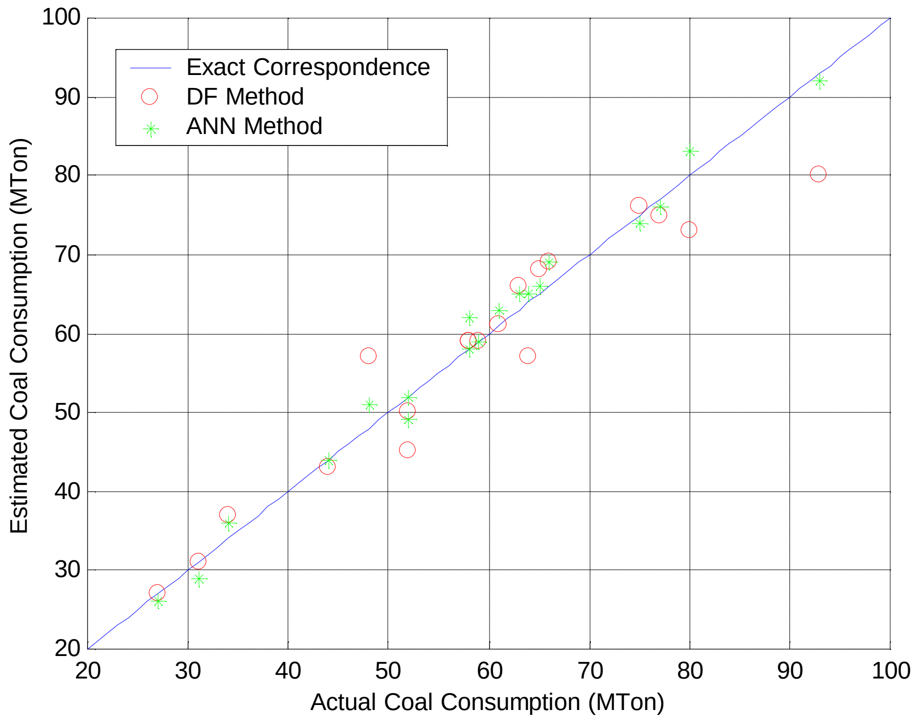

Figure 4-8 Comparison between ANN and DF Methods

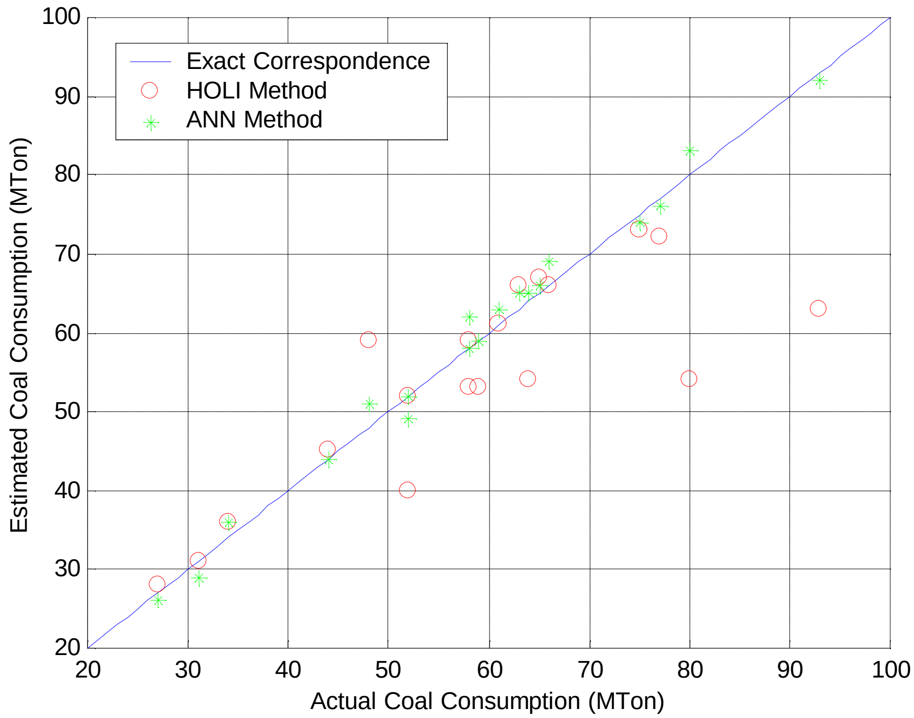

Figure 4-9 Comparison between ANN and HOLI Methods

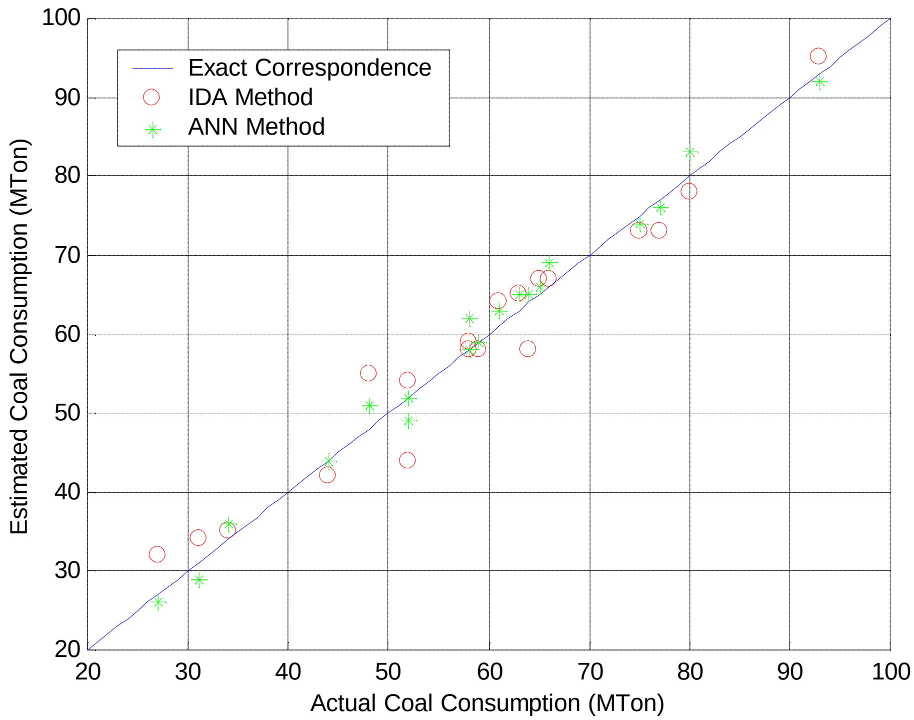

Figure 4-10 Comparison between ANN and IDA Methods

4.4 Conclusion

Application of artificial neural networks for power systems has been an active study area in recent years. This chapter discussed the feasibility of using ANN-based method for decision data expansion, which can be described as nonlinear input-output vector mapping problem. Based on the test results obtained from the illustrative examples, the following observations and conclusions may be obtained.

- The feasibility of using ANN-based method for decision data expansion has been confirmed. For a well-defined problem with adequate and properly selected training data, the quality of expanded decision database will be reliable.
- The approximation performance of ANN-based method has shown to be better than the results obtained using DF, HOLI and IDA methods.
- A general procedure can be followed in applying ANN-based method for decision data expansion, thus eliminating many concerns involved in the application of other techniques.
- The quality of training data is of significant importance to the application of ANN-based method. The training data must be representative and adequate, and proper data scaling and transformation are necessary.
- The accuracy of ANN model generally can be improved by proper model refinements. However, this would require user's experience and involve a trail and error mechanism.
- In some cases, the generalization process may become difficult if the size of training data is too small or unrepresentative or the problem itself is an ill-posed one.

In summary, the proposed ANN-based method for decision data expansion in strategic planning is feasible, easy to implement, and more accurate than the techniques available in the existing literature.

5 MADM Analysis with Imprecise Information

This chapter presents an interval-based multi-attribute decision making (MADM) approach in support of the decision process with imprecise information. The proposed decision methodology is based on the model of linear additive utility function but extends the problem formulation with the measure of composite utility variance. A sample study concerning with the evaluation of electric generation expansion strategies is provided showing how the imprecise data may affect the choice toward the best solution and how a set of alternatives, acceptable to the decision maker (DM), may be identified with certain confidence.

5.1 Introduction

MADM methods have been widely used in strategic planning of electric utilities which provides an efficient decision analysis framework to help the DM of electric utilities in selecting the best resource strategy with regard to the chosen attributes. A useful MADM model should be able to display tradeoffs among different attributes, both quantitative and qualitative, economic as well as non-economic, and quantify the preferences held by different interests. In many MADM problems, however, the information available to the DM is often imprecise due to inaccurate estimates of attribute values and inconsistent human judgments on attribute priorities. As such, the preference with regard to the ranking of different resource strategies determined using traditional MADM methods, which is based solely on the point value estimate, may not be adequate to distinguish between the outcomes from competing alternatives. It appears necessary to include the measure of variances into the decision process so as to increase the level of confidence in the final decision reached.

This chapter presents an interval-based MADM approach in support of the decision making process with imprecise information. Section 5.2 introduces a structured procedure for the construction of linear additive utility model, which is the best known and most used MADM model in electric utility planning studies, to facilitate the process of eliciting preference functions and weighting parameters. Section 5.3 discusses how the composite utility variance can be estimated properly by the technique of propagation of errors, accounting for individual errors from inaccurate attribute measurements and inconsistent priority judgments. Thus, given a desired confidence interval, the likely range of composite utility values can be determined, leading to the interval-based MADM approach. In Section 5.4, a sample case study is provided showing how the proposed decision methodology can be used in electric utility generation expansion analysis so as to increase the level of confidence for the selection of best resource strategy by examining a range of acceptable alternatives. Concluding remarks are given in Section 5.5.

5.2 Construction of Linear Additive Utility Models

5.2.1 Linear Additive Utility Function

One popular approach in dealing with MADM problems is defining an appropriate formulation that transforms an n-dimensional vector performance to a scalar performance measurement, usually termed as multi-attribute utility function (MUF). In general, the MUF model is comprised of the single utility functions or preference functions associated with the chosen attributes and the weighting parameters that reflect the relative importance of these attributes toward the overall planning goal or objective. Conceptually, the composite utility value is a nonlinear function of single utility functions and weighting parameters. However, a special form of MUF model, known as linear additive form, can be used if the condition of additive utility independence of attributes holds, thus greatly simplifying the procedure of model establishment. Less formally, this means that the contributions of an individual attribute to the composite utility is independent of other attribute values. Equation (5-1) below gives a general expression of linear additive utility model.

$$U(x) = \sum_{i=1}^{n} w_i \cdot U_i(x_i) \tag{5-1}$$

where $U(x)$ is the composite utility of each alternative characterized by the vector of attributes $\boldsymbol{x} = [x_1, \ldots, x_n]$, $U_i(x_i)$ is the single utility function with respect to the ith attribute, w_i is an appropriate weighting parameter for the ith attribute, representing its relative importance in comparison to other attributes and satisfying $Sw_i = 1$.

Linear additive utility models have been used for a variety of decision problems in electric utility planning, including generation resource acquisition assessment, energy-conservation program evaluation, selecting new generation technologies, integrated resource planning, and transaction selection in a competitive market [5,20,46,49,53]. Since the attributes considered in these studies, such as project investment, energy production cost, system reliability, environmental impact and the flexibility in resource development, cover quite different fields of interest, the condition of additive utility independence is generally satisfied.

There are two terms that are of concern in the construction of linear additive utility models: the single utility functions and the weighting parameters. These are usually determined through interviews with utility planners, performed by the DM, using techniques of decision analysis. In the following, a structured procedure is presented to facilitate the assessment of the single utility functions associated with individual attributes and the tradeoff among the conflicting attributes.

5.2.2 Assessment of Single Utility Functions

The single utility function, $U_i(x_i)$, represents the utility values which the DM attaches to each attribute and reflects his/her attitude toward taking a risk. To obtain a comparable basis, the utility value is often defined on a normalized scale as the attribute varies between its lower and upper bounds. The single utility function is usually evaluated by the certainty equivalence method as described in [72]. However, it has been realized that the convergence procedure in assessing a certainty equivalent is time-consuming and cumbersome [27]. Sometimes, it may be hard for the DM to determine a single value that would represent confidently his/her attitude. Instead, it would be more convenient for the DM to specify a boundary or several candidates around the true certainty equivalent. The DM's preferences may also be measured by a ratio-scale method [55,71]. But this method seems to work well only when there are a small number of alternatives.

We attempt to improve the assessment procedures for single utility functions by incorporating the pair-wise comparison analysis into the certainty equivalent method. The revised procedure for the assessment of single utility functions will now be described as follows.

First, we need to identify the range of attribute values. For electric utility resource planning, these are usually obtained from detailed studies including production costing simulation, investment optimization, reliability evaluation and environmental impact analysis for all alternatives. *Next*, we assess three certainty equivalent values for x_i with respect to $U_i(x_{.5})$, $U_i(x_{.75})$, and $U_i(x_{.25})$, respectively. To avoid the tedious convergence procedure, the DM may select a few candidate values, which are thought to be around the true certainty equivalent. By comparing each pair of these candidates for their closeness to the expected certainty equivalent, the judgment matrix can be formed from which the priority vector can be obtained by solving the corresponding eigenvalue problem. The certainty equivalent is then calculated as the weighted-average of these candidates

$$\overline{c} = c^T \cdot p \tag{5-2}$$

where, $\boldsymbol{c} = [c_1,c_2,...,c_m]$ is the vector of candidates and $\boldsymbol{p} = [p_1,p_2,...,p_m]$ is the corresponding priority vector. These three (x_i, $U_i(x_i)$) pairs, together with the end point utility values of 1 and 0, gives us five points on the single utility function for the *i*th attribute. *Finally*, we can fit a curve through these points to determine the corresponding equation for $U_i(x_i)$.

The above assessment procedure may be better than the traditional certainty equivalent method since the value of certainty equivalent is determined by examining several candidates on a compromise basis and therefore would increase the level of confidence in the resulting preference functions. This revised certainty equivalent method may be more reliable than the ratio-scale method because the DM's preference is evaluated over the entire range of attribute values.

In many MADM applications, the single utility function $U_i(x_i)$ in (5-1) may be replaced by the normalized attribute value r_i, reflecting a risk-neutral attitude of the DM. Such a special form of linear additive utility model can be expressed by

$$U_d(x) = \sum_{i=1}^{n} w_i \left| \frac{x_i - x_i^*}{x^r} \right| = \sum_{i=1}^{n} w_i r_i \tag{5-3}$$

where x_i and r_i are the measured and normalized values of *i*th attribute, x_i^r is the range of variation of measured attribute values with x_i^* as the optimal (maximal for benefit attributes and minimal for cost attributes).

Unlike Equation (5-1), where the best solution is the alternative for which the measured composite utility value is maximum, the most favored alternative determined by Equation (5-3) represents a minimum distance from the ideal point on the direction preferred by the DM. Thus, without any confusion, the term "Composite Utility" or $U(x)$ can be replaced by the term "Composite Distance" or $U_d(x)$ whenever appropriate.

5.2.3 Assessment of Attribute Priorities

A number of weighting-selection methods are available for MADM analysis, among them ratio-questioning and indifference tradeoff methods are most frequently used because they represent a good combination of reliability and easy-to-use [7]. Both methods need the input from the DM to prioritize attributes, but the ratio method directly asks for the relative importance between each pair of attributes while the indifference method indirectly infers the weighting information from tradeoff judgments.

The ratio-questioning method is often used in conjunction with the technique of analytical hierarchy analysis (AHP) to break up the complex priority assessment task into several evaluation stages, starting from the given attribute, through one or more intermediate evaluation levels, up to the overall evaluation level. In a multi-layer hierarchy, each layer influences the entities in the layer immediately above it. Beginning, then, from the second layer of the hierarchy, the DM will be asked to compare the relative importance between each pair of factors at that layer with respect to every connected factor on the upper layer. This process will create a set of judgment matrices for each layer. Next, the priority vectors associated with these judgment matrices are calculated by solving the corresponding eigenvalue problems. Equations are given in Appendix A, which shows how the composite priority vectors, i.e., the priority vector from the bottom layer with respect to the top layer or the normalized attribute weighting parameters can be calculated.

In the indifference tradeoff method, the DM needs to specify certain amount of one attribute, usually with reference to the range of attribute values, that is equivalent to a fixed improvement in another attribute. In other wards, this method concerns with how far the DM is willing to trade off one attribute with respect to another in a quantitative way. For instance, if 10% of the range of system reliability were judged to be equivalent to 20% of the range of environmental impact, then the system reliability improvement would be two times as important as the reduction of generation-related emissions. Alternatively, the DM may also be asked to specify appropriate tolerance levels, termed as "much worse" and "significant better", for each attribute in its natural units. These tolerance levels are then used to identify the non-dominated plans or acceptable plans with respect to the given attributes. Apparently, the weighting parameters in the MADM model (5-1) or (5-3) can be obtained by comparing the normalized tolerance levels for each pair of attributes.

The AHP based ratio-questioning method is favored in this study for the assessment o attribute priorities. *First of all*, it is a system approach taking care of various concerns for the preference of conflicting attributes. *Secondly*, it can compensate for the inconsistent human judgments by asking redundant questions and then retrieving the weighting parameters on a compromise basis using eigenvector prioritization method. *Additionally*, it can also incorporate the influence of the range of attribute values on the preference, a major feature of indifference tradeoff method, into the assessment process with properly revised ratio questions. The AHP-based weighting-selection approach will be further discussed in Section 5.4 where a three-layer hierarchy is constructed to evaluate the relative importance of interested attributes with respect to the least-cost planning objective.

5.3 Composite Utility Variance

5.3.1 Technique of Propagation of Errors

The technique of the propagation of errors can be used to examine the influence of inaccurate data on the ranking of candidate alternatives. The principle of the propagation of errors is described as: "Given some set of numbers and their errors, what is the error in some prescribed function involving these numbers?" [21,54]. For a function $y = f\ (x_1, x_2, \ldots, x_n)$, the general expression for propagation of errors is given by

$$s_y^{\ 2} = \sum_{i=1}^{n} \left(\frac{\P f}{\P x_i} s_{xi} \right)^2 \qquad (5\text{-}4)$$

where s_{xi} is the standard deviation of variable x_i and s_y is the standard deviation of the prescribed function $y = f\ (x_1, x_2, \ldots, x_n)$.

Accordingly, the composite utility variance for the linear additive utility model in (5-1) can be estimated as

$$s_u^2 = \sum_{i=1}^{n} (\frac{\partial U}{\partial w_i} s_{wi})^2 + \sum_{i=1}^{n} (\frac{\partial U}{\partial x_i} s_{xi})^2 = \sum_{i=1}^{n} [U_i^2(x_i) s_{wi}^2 + (w_i \frac{dU_i(x_i)}{dx_i})^2 s_{xi}^2] \qquad (5\text{-}5)$$

where s_u is the standard deviation of composite utility values; s_{xi} and s_{wi} are the standard deviations of the ith attribute and its weight, respectively. The error parameter s_{wi} is caused by inconsistent subjective judgments and the error parameter s_{xi} is due to inaccurate attributes measurements.

Similarly, the composite distance variance for the linear additive utility model in (5-3) can be estimated as

$$s_d^2 = \sum_{i=1}^{n} (\frac{\partial U_d}{\partial w_i} s_{wi})^2 + \sum_{i=1}^{n} (\frac{\partial U_d}{\partial r_i} s_{ri})^2 = \sum_{i=1}^{n} (r_i^2 s_{wi}^2 + w_i^2 s_{ri}^2) \qquad (5\text{-}6)$$

where s_d is the standard deviation of composite distance values; s_{ri} and s_{wi} are the standard deviations of the normalized ith attribute and its weight, respectively. Let m be the number of alternatives to be evaluated, the standard deviation s_{ri} for a specific alternative, say j, can then be estimated by

$$s_{ri}^{2} = \frac{1}{\left(x_i^{\max} - x_i^{\min}\right)^4}\left[s_{x_{ij}}^{2}\left(x_i^{\max} - x_i^{\min}\right)^2 + s_{x_i^{\max}}^{2}\left(x_{ij} - x_i^{\min}\right)^2 + s_{x_i^{\min}}^{2}\left(x_{ij} - x_i^{\max}\right)^2\right] \qquad (5\text{-}7)$$

where x_{ij} is the measured ith attribute for alternative j and the error parameter $s_{x_{ij}}$ is its standard deviation, $x_i^{\min} = \min\left\{ \left|x_{ij}\right|, \quad j = 1,2,\ldots m\right\}$, $x_i^{\max} = \max\left\{ \left|x_{ij}\right|, \quad j = 1,2,\ldots m\right\}$.

Less strictly, the composite utility values may be approximately measured by the normal distribution. Thus, given a desired level of confidence, the likely range of composite utility values corresponding to Equation (5-1) can be estimated as

$$(U - l_{a/2} s_u, U + l_{a/2} s_u) \qquad (5\text{-}8)$$

Similarly, the likely range of composite distance values corresponding to Equation (5-3) can be estimated as

$$(U_d - l_{a/2} s_d, U_d + l_{a/2} s_d) \qquad (5\text{-}9)$$

There are two major error sources in performing multi-attribute electric utility resource planning: the variance of production cost and the variance of priority assessment. These will be discussed briefly as follows.

5.3.2 Variance of Production Cost

Due to the uncertainties in the availability of generating units (i.e., unexpected outages) and the load variations over a certain time interval, the production cost of an electric power system is not a single deterministic value, but a random variable [97]. Its mean is the expected production cost and its probability distribution depends on the load patterns and the stochastic characteristics of the forced outages of the generating units in the system. The outputs of conventional production costing models include the expected energy production costs, system reliability indices and generation-related emissions.

In recent publications, the variance of production costs has been discussed extensively recognizing that the measure of production cost variance would be very useful input to the decision making process in comparing different generation expansion alternatives. Some efficient methods have been introduced for estimating this variance [59,67,97]. In this dissertation, we are not going to verify or compare these methods but rather to incorporate the concept of production cost variance, as the error parameter, into the corresponding equations to estimate the composite utility variance or the composite distance variance.

5.3.3 Variance of Priority Assessment

The AHP technique has been proved to be a reliable tool for the assessment of attribute priorities in MADM analysis. Statistical studies have been carried out at Virginia Tech to model the subjective errors in the creation of judgment matrix [31,82]. It has shown that the error associated with each judgment ratio can be approximated by a log-normally distributed error factor $e \sim (0, s^2)$. Study results also shown that a good estimate of the error parameter s^2 can be calculated by

$$s^2 = \frac{2}{(n-1)(n-2)} \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} y_{ij}^2 \tag{5-10}$$

where n is the size of the judgment matrix, $y_{ij} = ln\,(a_{ij}/w_{ij})$, a_{ij} represents the judgment ratio [i,j] of judgment matrix, $w_{ij} = w_i/w_j$ and $\boldsymbol{w} = [w_1, w_2, \ldots\ w_n]$ is the priority vector. It can be noted that the error parameter s^2 is calculated directly from the judgment matrix, since it involves only the judgment ratio a_{ij} and the priority ratio w_{ij}. The variances of the priorities associated with each judgment matrix at any layer of the hierarchy can then be estimated as

$$s_{wi}^2 = \frac{n^2-1}{n}\left[\sum_{i=-1}^{n} w_i^2 - w_i^2\right] s^2 w_i^2 \tag{5-11}$$

For a three-layer fully connected hierarchy, the variances of composite priorities from the bottom layer to the top layer, i.e., the attribute weighting parameters, can then be calculated as

$$\begin{bmatrix} (s_{1,3}^{1,1})^2 \\ (s_{2,3}^{1,1})^2 \\ (s_{3,3}^{1,1})^2 \\ (s_{4,3}^{1,1})^2 \end{bmatrix} = \begin{bmatrix} (p_{1,3}^{1,2})^2 & (p_{1,3}^{2,2})^2 & (p_{1,3}^{3,2})^2 & (p_{1,3}^{4,2})^2 \\ (p_{2,3}^{1,2})^2 & (p_{2,3}^{2,2})^2 & (p_{2,3}^{3,2})^2 & (p_{2,3}^{4,2})^2 \\ (p_{3,3}^{1,2})^2 & (p_{3,3}^{2,2})^2 & (p_{3,3}^{3,2})^2 & (p_{3,3}^{4,2})^2 \\ (p_{4,3}^{1,2})^2 & (p_{4,3}^{2,2})^2 & (p_{4,3}^{3,2})^2 & (p_{4,3}^{4,2})^2 \end{bmatrix} \begin{bmatrix} (s_{1,2}^{1,1})^2 \\ (s_{2,2}^{1,1})^2 \\ (s_{3,2}^{1,1})^2 \\ (s_{4,2}^{1,1})^2 \end{bmatrix}$$

$$+ \begin{bmatrix} (s_{1,3}^{1,2})^2 & (s_{1,3}^{2,2})^2 & (s_{1,3}^{3,2})^2 & (s_{1,3}^{4,2})^2 \\ (s_{2,3}^{1,2})^2 & (s_{2,3}^{2,2})^2 & (s_{2,3}^{3,2})^2 & (s_{2,3}^{4,2})^2 \\ (s_{3,3}^{1,2})^2 & (s_{3,3}^{2,2})^2 & (s_{3,3}^{3,2})^2 & (s_{3,3}^{4,2})^2 \\ (s_{4,3}^{1,2})^2 & (s_{4,3}^{2,2})^2 & (s_{4,3}^{3,2})^2 & (s_{4,3}^{4,2})^2 \end{bmatrix} \begin{bmatrix} (p_{1,2}^{1,1})^2 \\ (p_{2,2}^{1,1})^2 \\ (p_{3,2}^{1,1})^2 \\ (p_{4,2}^{1,1})^2 \end{bmatrix} \tag{5-12}$$

where $p_{i,j}^{k,l}$ and $s_{i,j}^{k,l}$ are the priority and standard deviation of ith factor at layer j with respect to kth factor at layer l, respectively.

5.4 Sample Study: Evaluation of Generation Expansion Strategies

5.4.1 Problem Formulation

The sample system used here is based primarily on a moderate-sized U.S. electric utility. The utility long-range generation resource expansion strategies include three main policy approaches: SO_2 emissions, demand-side management (DSM) and system reliability. Emissions policy considers the allowance purchase policy versus the use of scrubbers and fuel switching. DSM policy options are between go and no-go decisions. Approaches to system reliability include choices among high, base case and low capacity reserve margins. In all, these three approaches result in (2x2x3=) 12 alternative generation resource expansion strategies, and cost of energy supply, system reliability, environmental impact and resource flexibility are the four major attributes considered in the decision process for the selection of most desired resource strategy.

The utility system performance under different expansion strategies has been studied using the electric generation expansion analysis system (EGEAS) package. The simulation results give actual project costs in millions of dollars, the amounts of SO_2 emissions, the expected unserved energy (EUSE) in kilowatt-hour, and the numbers and capacities of gas-fired and coal-fired units during the planning period. Since the base energy requirement change with the DSM impacts, the values of different attributes are normalized with respect to the total energy requirement as shown in Table 5.4-1. Cost as give here includes the annual levelized investment costs, fuel costs, operating and maintenance costs, as well as the cost of allowances. A rather indirect measure of resource flexibility is used here, the ratio of coal to gas capacity, in view of the ease with which gas plants can be changed and the possibility of conversion of gas power plants to other types such as combined cycle power plants. The equivalent cost of the coal-to-gas ratio (CGR) is the ratio of coal to gas capacities. This is normalized to reflect an average cost that is equal to the average cost of different alternatives.

Table 5.4-1 System Simulation Results under Different Expansion Strategies

Expansion Strategy	Policy Description	Cost (c/kWh)	SO2 (Ton/GWh)	EUSE (%)	CGR (c/kWh)
1	Purchase, No DSM, Low EUSE	3.56	3.3803	0.1026	2.67
2	Purchase, DSM, Low EUSE	3.38	3.3716	0.1263	2.93
3	Purchase, No DSM, Base EUSE	3.49	3.3083	0.1707	2.07
4	Purchase, DSM, Base EUSE	3.31	3.3154	0.2034	2.13
5	Purchase, No DSM, High EUSE	3.34	3.3210	0.2861	3.32
6	Purchase, DSM, High EUSE	3.27	3.3097	0.2957	3.55
7	Controls, No DSM, Low EUSE	3.75	1.4868	0.1026	2.67
8	Controls, DSM, Low EUSE	3.54	1.5155	0.1243	2.93
9	Controls, No DSM, Base EUSE	3.67	1.4988	0.1549	2.96
10	Controls, DSM, Base EUSE	3.48	1.5251	0.2001	5.53
11	Controls, No DSM, High EUSE	3.54	1.5172	0.2935	3.32
12	Controls, DSM, High EUSE	3.45	1.5272	0.2637	7.70

5.4.2 Decision Model Establishment

After obtaining the simulation results of the 12 alternative generation expansion strategies, we can assess the single utility functions and the weighting parameters using the structured procedure described in Section 5.2 and then assemble them into the linear additive utility model as defined in Equation (5-1).

(1) Assessment of Single Utility Functions

Let us consider the utility function for reliability as an example. The values of attribute EUSE are calculated to be in the range between 0.1% and 0.3%. The lower bound of EUSE represents the best system performance in terms of the reliability of electric energy supply and therefore we have $U(0.1\%) = 1.0$. Conversely, the upper bound of EUSE indicates the worst situation of system reliability and thus we have $U(0.3\%) = 0$.

Next, we need to assess three certainty equivalent values in the range of EUSE measurements with respect to $U_i(x_{.5})$, $U_i(x_{.75})$, and $U_i(x_{.25})$.

The candidates for $x_{.5}$, with respect to $U(x_{.5}) = 0.5$, are selected to be $\boldsymbol{c}$ = [0.16, 0.18, 0.20, 0.22] (%). By comparing each pair of these candidates for their closeness to the expected certainty equivalent, the judgment matrix $[A]$ is formed

$$[A] = \begin{vmatrix} 1 & 1/3 & 1/7 & 1/3 \\ 3 & 1 & 1/5 & 1 \\ 7 & 5 & 1 & 5 \\ 3 & 1 & 1/5 & 1 \end{vmatrix}$$

These ratio scales reflect the independent assessments that:

- Candidate 1 (0.16% EUSE level) is slightly less likely than candidates 2 and 4 (0.18% and 0.22% EUSE levels), but very much less likely than candidate 3 (0.20% EUSE level)
- Candidate 2 is much less than candidate 3 and is as likely as candidate 4
- Candidate 3 is much more likely than candidate 4

Solving the eigenvalue problem associated with the above judgment matrix yields the priority vector $\boldsymbol{p}$ = [0.0624, 0.1514, 0.6348, 0.1514]. The certainty equivalent $x_{.5}$ is then computed as the weighted-average of these candidates

$$x_{.5} = [0.16, 0.18, 0.20, 0.22] \times [0.0624, 0.1514, 0.6348, 0.1514]^T = 0.1975\%$$

In a similar manner, the candidates for $x_{.75}$ and $x_{.25}$, with respect to $U(x_{.75}) = 0.75$ and $U(x_{.25}) = 0.25$, are selected to be [0.12, 0.13, 0.14, 0.15] (%) and [0.25, 0.26, 0.27, 0.28] (%), respectively. The corresponding certainty equivalents for these two reliability levels are determined to be $x_{.75} = 0.1293\%$ and $x_{.25} = 0.2643\%$.

These three (x_i, $U(x_i)$) pairs, along with the two end points, give us five points on the preference function of system reliability. We then fit these points by a third-order polynomial function, which represents the preference function for attribute EUSE.

This procedure is performed for all four attributes and the resulting single utility functions for cost, reliability (EUSE), SO_2 emissions and flexibility (CGR) are expressed below by $U_1(x_1)$, $U_2(x_2)$, $U_3(x_3)$ and $U_4(x_4)$, respectively.

$$U_1(x_1) = -2.7734x_1^3 + 27.7246x_1^2 - 93.9817x_1 + 108.8031$$

$$U_2(x_2) = -238.2481x_2^3 + 144.1302x_2^2 - 31.6743x_2 + 2.9599$$

$$U_3(x_3) = -0.1088x_3^3 + 0.8082x_3^2 - 2.3652x_3 + 3.0370$$

$$U_4(x_4) = (0.077 - x_4) / 0.0563$$

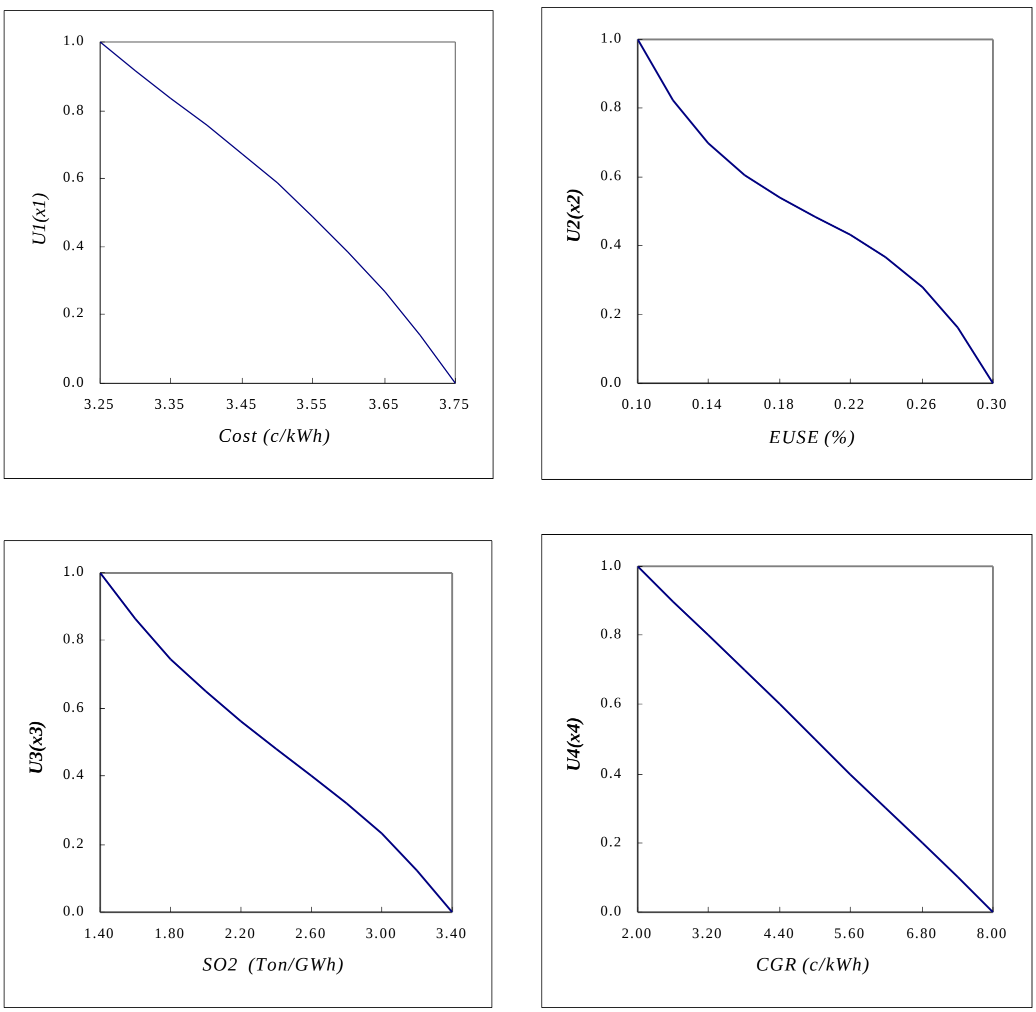

Figure 5-1 Single Utility Functions for Cost, Reliability, SO_2, and Flexibility

The shapes of these functions are sketched in Fig 5-1 and may be rationalized briefly as follows. The preference behavior of DM exhibited in the single utility function for cost, $U_1(x_1)$, corresponds to a strictly risk-aversion attitude. It is commonly believed that most utilities are risk aversive to the cost of energy supply. For system reliability, the DM has a risk-aversion attitude at high EUSE levels and a risk-seeking attitude at low EUSE levels as can be seen in the plot of $U_2(x_2)$. This is because, to the DM, the moderate EUSE levels around 0.2% are considered to be an acceptable system performance. A similar preference pattern can be observed for the SO_2 emissions, i.e., the plot of $U_3(x_3)$. In the plot of $U_4(x_4)$, the straight line represents a risk-neutral viewpoint toward the resource flexibility.

(2) Assessment of Attribute Priorities

Fig 5-2 illustrates a three-layer hierarchy used for attribute priority assessment. At the top of the hierarchy is the planning goal, which is defined as the least-cost planning in the present context. The second layer comprises four players involved in the decision process, i.e., the utility, the customers, the regulators and the general public. At the bottom layer of the hierarchy are four major interested attributes: resource flexibility, cost of energy supply, system reliability and SO_2 emissions.

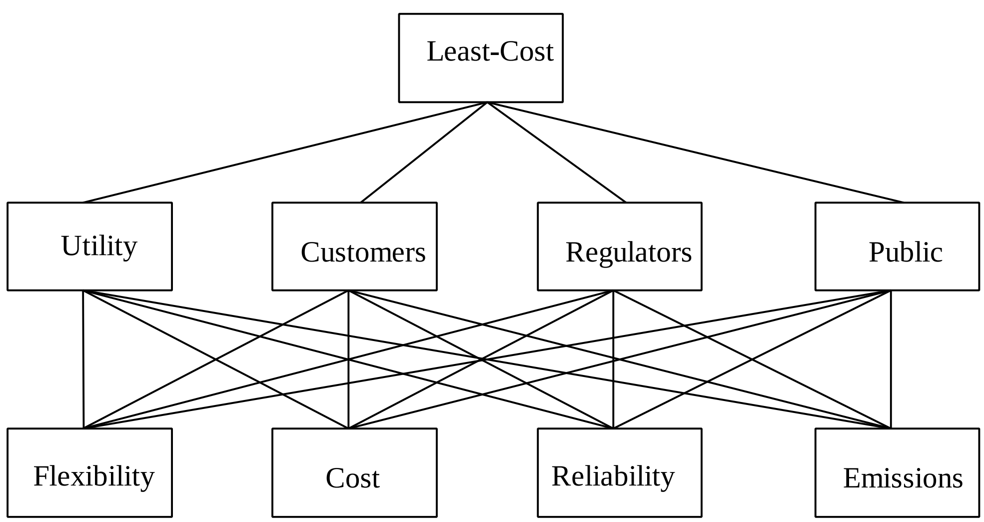

Figure 5-2 Hierarchy for Attribute Priority Assessment

According to the hierarchy in Fig 5-2, the assessment of attribute priorities will be proceeded in two evaluation levels by asking the DM two sets of ratio questions. One set of questions concerns with the relative importance of different players in implementing the least-cost planning strategy while the other set of questions concerns with the relative influence of different attributes on each individual player.

The relationship between the players and the least-cost planning goal can be determined by answering a straightforward question: What is the relative importance of one player with respect to the other in implementing the least-cost planning strategy? However, the direct comparisons of attributes should be avoided since the preferences held by the players may vary over the range of attribute values. For this reason, the pairwise comparisons can be performed between two well-defined hypothetical alternatives. One such alternative is defined by the attribute vector [x_1^-,…, x_i^+,…, x_n^-] while the other is assumed to have a attribute vector [x_1^-,…, x_h^+,…, x_n^-], with one attribute x_i or x_h at its maximum and all other attributes at their minimum.

Table 5.4-2 defines the four hypothetical alternatives used for this sample case study. Instead of asking what is the relative importance of the cost of energy supply with respect to the system reliability, the ratio question now would become clear: How much more preferable is a specific savings in the cost of energy supply than a specific improvement in system reliability? This question is asked for each pair of hypothetical alternatives with respect to each player. Appendix B shows the judgment matrices generated for each evaluation level of the hierarchy and the corresponding priority vectors calculated by solving respective eigenvalue problems.

Table 5.4-2 Definition of Hypothetical Alternatives

Hypothetical Alternative	Cost of Energy (c/kWh)	SO_2 Emissions (Ton/GWh)	EUSE (%)	CGR (c/kWh)
1	3.25	3.40	0.30	8.00
2	3.75	1.40	0.30	8.00
3	3.75	3.40	0.10	8.00
4	3.75	3.40	0.30	2.00

Table 5.4-3 gives the priority vectors for the second and third layers with respect to the least-cost planning goal. The priority vector of the second layer indicates the relative importance of each player in implementing the least-cost planning strategy in the order of utility, regulators, customers and general public. As for the composite priorities of attributes or the weighting parameters with respect to the planning objective, the minimization of energy production cost is ranked at the top followed by SO_2 emissions, system reliability, and flexibility in resource development.

Table 5.4-3 Composite Priority Vectors for Layers 2 & 3

Layer 2		Layer 3	
Player	Priorities	Attribute	Priorities
Utility	0.5738	Flexibility	0.0884
Customers	0.1310	Cost	0.4760
Regulators	0.2388	Reliability	0.1510
General Public	0.0563	Emissions	0.2846

(3) Linear Additive Utility Model

Finally, by assembling the single utility functions and the weighting parameters into the linear additive utility formulation defined in (5-1), we obtain the following MADM model for this particular decision making problem.

$$U(x) = 0.4760U_1(x_1) + 0.1510U_2(x_2) + 0.2846U_3(x_3) + 0.0884U_4(x_4)$$

5.4.3 Decision Analysis and Interpretations

In traditional MADM analysis, the goodness of alternatives is measured based on the expected composite utility values by substituting the system simulation results and the weighting parameters directly into the established MADM model. Both the expected composite utility values and the ranking of 12 generation expansion alternatives are given in Table 5.4-4 (see the second column and the last column). Apparently, the best solution determined by the point estimate of traditional MADM analysis is the alternative for which the measured composite utility value is maximal. It can be noted that the best solution (CDL) suggested by MADM analysis is not the one with the least cost of energy supply due to the contributions of SO_2 emissions and system reliability on the value of composite utility. The best solution supports the generation expansion strategy having SO_2 controls, DSM measures, and low EUSE or high capacity reserve margin.

Table 5.4-4 Estimated Composite Utility Values

Expansion Strategy	Point Estimate	Likely Range Estimate			Ranking
		(a)	(b)	(c)	
PNL	.4522	.4894, .4151	.4750, .4296	.5122, .3923	12
PDL	.5734	.5914, .5555	.6012, .5457	.6129, .5277	6
PNB	.4772	.4831, .4712	.4963, .4581	.5022, .4522	10
PDB	.6031	.6074, .5989	.6361, .5702	.6403, .5660	4
PNH	.5075	.5313, .4837	.5359, .4792	.5597, .4553	9
PDH	.5477	.5795, .5158	.5834, .5119	.6153, .4800	7
CNL	.4671	.4913, .4429	.5001, .4341	.5243, .4099	11
CDL	***.6978***	***.7172, .6783***	***.7306, .6649***	***.7501, .6454***	***1***
CNB	.5377	.5483, .5270	.5681, .5072	.5788, .4965	8
CDB	.6643	.6691, .6595	.6954, .6331	.7002, .6283	2
CNH	.5805	.6105, .5504	.6104, .5505	.6405, .5205	5
CDH	.6232	.6352, .6111	.6551, .5912	.6671, .5792	3

Note: P/C Allowance Purchase / Emission Control
N/D No DSM / DSM
L/B/H Low / Base / High EUSE Limit

To support the decision analysis with imprecise information, the likely ranges of composite utility values are estimated using the approximate error model introduced in Section 5.2. Toward that end, the subjective errors due to inconsistent attribute priority assessment are estimated using (5-10) through (5-12), and the error sizes of inaccurate attribute measurements are assumed from 2% to 4% of the value range of respective attributes. Then, the composite utility variances can be estimated by Equation (5-5) and the likely ranges of composite utility values can be estimated by Equation (5-8).

As shown in Table 5.4-4, the likely ranges of composite utility values are estimated with 90% confidence interval under three different conditions: *a*) considering the errors due to inaccurate attribute measurement only; *b*) considering the errors due to inconsistent priority assessment only; and *c*) considering both error sources.

The estimated likely ranges of composite utility values for the 12 expansion strategies are also plotted in Fig 5-3 through Fig 5-5, corresponding to three different conditions. In these graphs, each column corresponds to a specific expansion strategy and the dark section of the column represents the likely ranges of composite utility values.

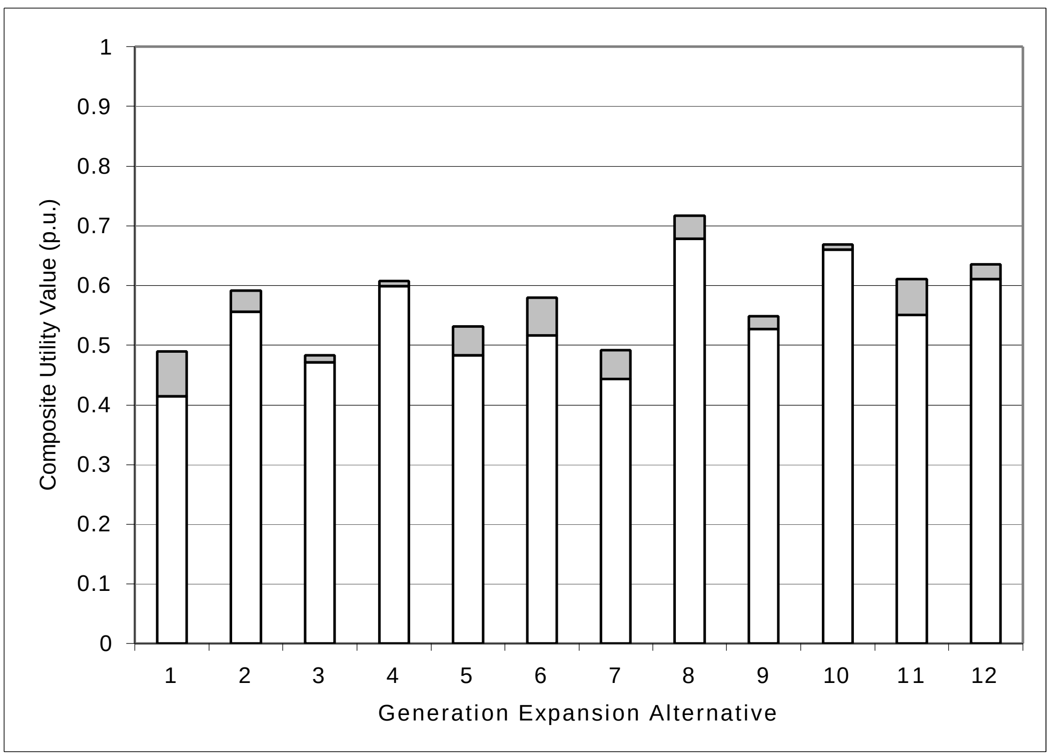

Figure 5-3 Likely Range of Composite Utility Value (Condition A)

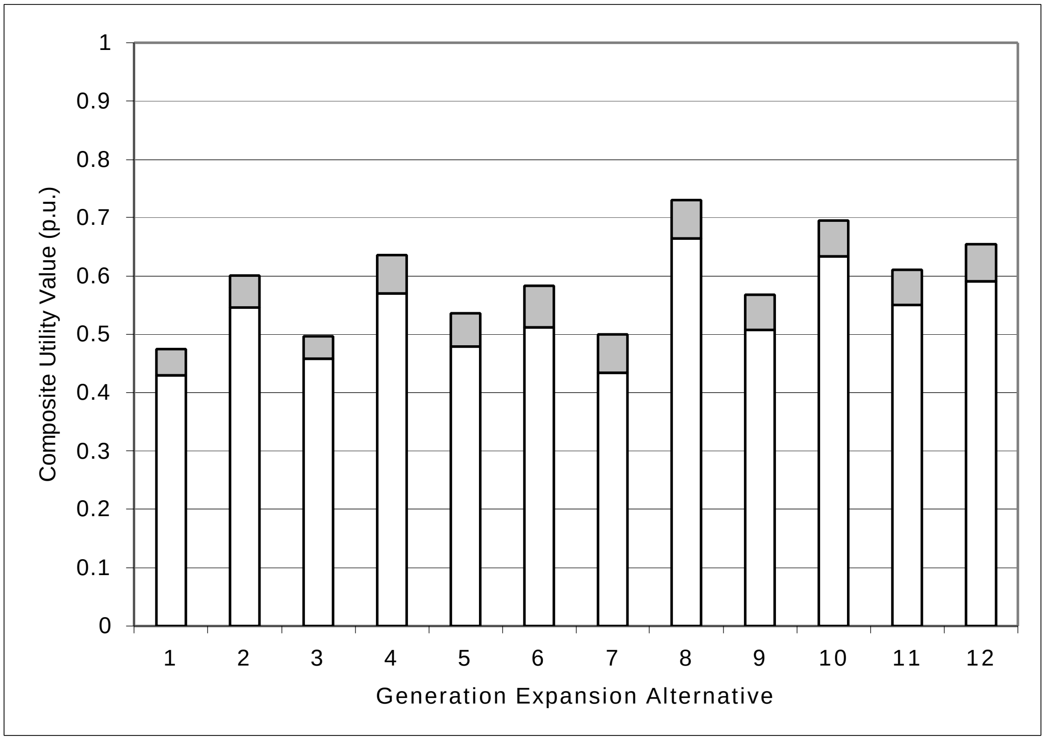

Figure 5-4 Likely Range of Composite Utility Value (Condition B)

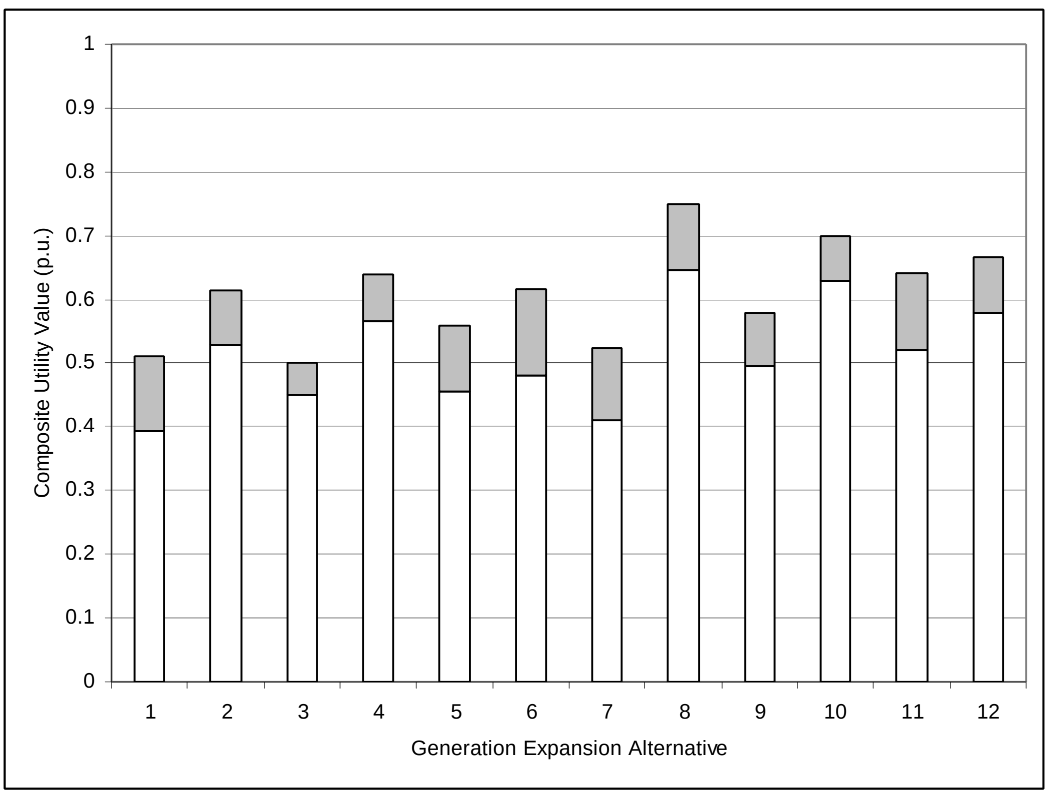

Figure 5-5 Likely Range of Composite Utility Value (Condition C)

The main contribution of interval-based MADM approach is to help the DM gain insight into how the imprecise data may affect the choice toward the best solution and how a set of acceptable alternatives may be identified with certain confidence. The following observations and conclusions may be obtained from the information provided in Table 5.4-4 and Fig 5-3 through Fig 5-5.

1. With concern only for the attribute errors, the best solution (CDL) determined by the point estimate of MADM analysis is still the unique optimal solution. There is no overlapping in the estimated value ranges between the best solution and other alternatives, meaning the decision achieved using expected composite utility values will not be affected by the variance of attribute measurements if the error size is within the given levels.
2. If the impact of inconsistent priority assessment is of concern, the alternative CBD will be tied for the first place with the best solution (CDL) because the value ranges of these two competing alternatives overlap each other. Thus, both CDL and CBD need to be considered in making the final decision.
3. In the situation when both error sources are taken into account, the likely ranges of composite utility values become bigger, and as a result, two competing alternatives (CBD & CDH) have fallen within the value range of the best solution (CDL). Thus, these two acceptable alternatives together with the best solution constitute the decision set from which a desired resource strategy can be identified. This will be further discussed as follows:
   - Both the best solution and two competing alternatives recommend the go decision for utility DSM programs. In this sample study, the load shape objectives of utility DSM programs have been catalogued into peak reduction, energy conservation and load factor improvement. The aggregate DSM effects have turned out to be cost-effective from the viewpoint of entire system operating performance, mainly due to avoided capacity costs and peak energy production savings.
   - All the acceptable alternatives support the control policy for SO_2 emissions. The control policy (scrubber and fuel switching) for SO_2 emissions is preferred over the allowance purchase policy in view of the relative contributions of cost savings and emission reductions.
   - The low EUSE, base case and high EUSE are favored respectively by one single alternative. However, in consideration of the preference ranking determined by the expected composite utility values, the alternatives with high system reliability levels (i.e., low EUSE and the base case) may be preferred.
   - Either CDL or CDB would represent a desired expansion strategy with the following policy approaches: implementing utility DSM programs, using SO_2 control technologies and ensuring adequate system reliability levels.

5.5 Conclusion

An interval-based MADM approach has been developed to enhance the decision making process with imprecise information. The main contributions from this part of research work include

- Providing a structured procedure to facilitate the evaluation of preference functions and the relative importance of attributes in the construction of linear additive utility models.
- Providing an approximate model to estimate properly the composite utility variance or composite distance variance, accounting for individual errors from inaccurate attribute measurements and inconsistent subjective judgments.
- Providing a confidence interval-based MADM decision approach to help the planner of electric utilities identify a desirable resource strategy by examining a range of acceptable alternatives.

Experience from the sample case study indicates that this enhanced MADM methodology can build insight on how the imprecise information may affect the choice toward the best solution and increase the level of confidence for the selection of a final resource strategy.

6 MADM Analysis under Uncertainty

This chapter presents an integrated MADM methodology for handling multi-attribute planning under uncertainty, which combines the attractive features of utility function model and tradeoff/risk analysis, two most commonly used decision methods in the utility industry. It is within the framework of tradeoff/risk analysis but introduces a novel multi-dimensional numerical knee-set searching algorithm based on the measure of composite distance, a special form of utility function model. Statistical background is provided for the selection of appropriate tolerance levels with which a range of acceptable plans or the conditional decision set can be determined. A sample study concerning with the optimal design of grid-linked renewable energy systems is provided to illustrate the concept of proposed decision methodology.

6.1 Introduction

For many years, uncertainty has been a major issue faced by electric power industry in their strategic planning. Some of the primary data, such as demand growth, fuel prices, capital costs, and regulatory standards, may have a profound influence on the course and outcomes of utility resource development, and it is very difficult to provide definite data as these parameters themselves are influenced by many uncertain conditions. For instance, the uncertainties associated with future demand forecasts could make the system generation facilities inadequate or excessive, both cases being unacceptable. In recent years, competitive markets are adding new uncertainties that make responsible decision-making for generation and transmission expansion projects more difficult. For instance, uncertainties in competitive generation capacity additions in terms of the siting, timing and operating parameters are much greater than before due to the deregulated power supply markets and the increased number of independent power producers. Consequently, the resource development strategies determined under particular series of base assumptions and constraints may not be sufficient to guarantee a sustained competitive advantage to the utility systems.

The utility industry has used a variety of decision analysis methods in their strategic planning to deal with multiple objectives and concerns for risk due to uncertainties. Essentially, the following questions should be addressed in the decision process.

- Which planning strategy or plan appears to be better than others
- What is the rationale of ranking concerning with a range of acceptable plans
- What is the relative importance of one attribute with respect to other attributers
- How the performance of each plan can be properly measured in the presence of uncertainties

Utility Function model and Tradeoff/Risk analysis are two most commonly used decision analysis methods in the electric power industry for multi-attribute planning in the presence of uncertainties

[66]. The concept of utility function model is to optimize a formulated function which transforms a multi-attribute decision problem into a scale performance measurement, i.e., the measure of composite utility or the measure of composite distance. With this method, the plans are ranked based on the rule of probability such that the best solution would be the plan for which the expected value is optimal. The concept of tradeoff/risk analysis is to treat all attributes individually and to identify the plans that significantly dominate other plans conditional on each specified future. With this method, the identified non-dominated plans are ranked based on the measure of robustness, i.e., the number of supporting futures.

Computer aided decision analysis packages either based on utility function model or within the framework of tradeoff/risk analysis are available, such as DETGEN, MIDAS and RISKMIN programs. These programs are developed especially for electric utility planning applications under the sponsorship of Electric Power Research Institute (EPRI) [16,61,62].

This chapter presents an integrated MADM methodology that combines the attractive features of utility function model and tradeoff/risk analysis and offers a structured, enhanced decision approach for handling multi-attribute planning under uncertainty. Conceptually, the proposed decision methodology is within the framework of tradeoff/risk analysis but it introduces a novel multi-dimensional numerical knee-set searching algorithm based on the measure of composite distance, a special form of utility function model. Section 6.2 summarizes the basic concepts of probabilistic evaluation approach and risk evaluation approach for multi-attribute decision making under uncertainty followed by a brief comparison between these two methods. Section 6.3 introduces the integrated MADM framework for decision making under uncertainty. In Section 6.4, a sample case study is provided concerning with the optimal design of grid-linked renewable energy systems. Concluding remarks are given in Section 6.5.

6.2 Multi-Attribute Planning under Uncertainty

6.2.1 Probabilistic Evaluation Approach

The concepts of utility function model have been discussed extensively in the previous chapter, which has shown to be very useful in comparing alternative plans that must consider several concerns. As for decision analysis under uncertainty, the utility function method is often used in conjunction with the decision tree modeling approach to provide a graphical interpretation of alternative planning strategies, decision variables and uncertainty factors. This decision process is usually termed as probabilistic evaluation approach by which the best solution is determined based on the expected performance of respective planning strategy under various future conditions, i.e., the expect value of composite utility.

Decision Tree Structure

Fig 6-1 below illustrates a typical decision tree model for utility generation expansion planning. Decision nodes marked rectangles fork into branches representing resource options. Chance nodes marked as circles fork into branches representing uncertainties. In the decision tree model, uncertainty is usually addressed with the use of discrete probability estimates for the occurrence of different conditions. The sum of probabilities on branches radiating from a chance node must be equal to 1.0. Each of the terminal branches of a tree terminates at the end point marking a unique scenario, i.e., a particular combination of options and uncertainty factors, that can be traced throughout the tree. In other words, a particular scenario is a complete path between the tree root and a terminal node.

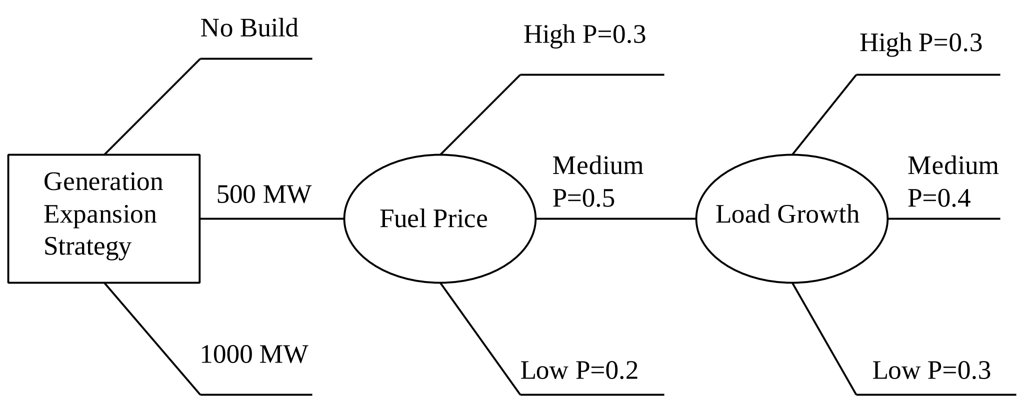

Figure 6-1 Typical Decision Tree Structure

Scenario Evaluation

For each scenario, a scalar value can be calculated by the utility function model defined in (5-1) or (5-3) as appropriate. This would provide an overall performance index, named as composite utility or composite distance, for that scenario taking into account the contributions from different attributes. The likelihood of each scenario is determined by multiplying the probability of uncertainty for each branch tracking back from the end point corresponding to that scenario toward the decision node at the beginning of the tree.

Expected Utility Value

The expected utility value associated with each planning strategy can then be determined as the sum of utility multiplied by the likelihood for each scenario relevant to that planning strategy as below.

$$U(x) = \sum_{k=1}^{m} p_k U_k(x) = \sum_{k=1}^{m} p_k \sum_{i=1}^{n} w_i \cdot U_{ki}(x_{ki}) \qquad (6\text{-}1)$$

where $U(x)$ is the expected utility value for each planning strategy or design alternative, $U_k(x)$ is the composite utility for scenario k characterized by the vector of attributes $\mathbf{x} = [x_{k1}, \ldots, x_{kn}]$, p_k is the corresponding probability, $U_{ki}(x)$ is the single utility function with respect to the ith attribute, w_i is an appropriate weighting parameter for the ith attribute, representing its relative importance in comparison to other attributes and satisfying $Sw_i = 1$.

Finally, the planning strategy or design alternative with the optimal (maximal or minimal as appropriate) expected value is selected as the best solution.

6.2.2 Risk Evaluation Approach

One popular risk evaluation approach for strategic resource planning is termed as tradeoff/risk analysis. This method does not pretend to find a unique "optimal" plan, rather it is an organized approach of evaluating relationships between attributes and uncertainties and allows the identification of robust plans that are acceptable (close to optimal) under a wide range of future conditions. The tradeoff/risk analysis consists of four main steps as described below [41,96]:

- Step 1: Formulate the problem properly, in terms of options, uncertainties and attributes
- Step 2: Develop a decision database by computing attributes for a larger number of scenarios
- Step 3: Use the tradeoff concept to identify the "decision set" – the set of plans left after all inferior plans have been rejected
- Step 4: Analyze the plans in the decision set to eliminate more plans and support the development of a final strategy

Problem Statement

The problem statement for MADM analysis under uncertainty generally involves identifying sets of options, uncertainties and attributes and creating range of scenarios to be examined. This has been discussed in Chapter 3.

Creation of Decision Database

The decision database contains the measured attributes for each individual scenario, both quantitative and qualitative, which are calculated using analytical planning models or determined with appropriate subjective judgments. In Chapter 4, an ANN-based method has been introduced which can reduce the amount of computations involved in the creation of decision database consisting of hundreds or thousands of scenarios.

Identification of Non-Dominated Plans

Definition 1 (Dominance)

> Let $x_i(P_1)$ and $x_i(P_2)$ be the values of the ith attribute for two plans P_1 and P_2 included in the decision database, where each plan is characterized by the vector of attributes $\mathbf{x} = [x_1, \ldots, x_n]$. If the objective is to minimize each attribute of the plan, then we can say that plan P_1 dominates (is better than) plan P_2 if $x_i(P_1)$ is less than $x_i(P_2)$ for every $i \in n$. More precisely,

- Conditional Strict Dominance: Plan P_1 strictly dominates plan P_2, conditional on a specific future, if $x_i(P_1)$ is better (less) than $x_i(P_2)$ for all attributes.
- Conditional Significant Dominance: Plan P_1 significantly dominates plan P_2, conditional on a specific future, if at least one attribute $x_i(P_2)$ is "much worse" than $x_i(P_1)$ and if no other attribute $x_j(P_2)$ is "significantly better" than $x_j(P_1)$.

A set of tolerance levels or significant parameters need to be appropriately selected by the utility planner which define what is meant by the term "much worse" or the term " significant better". These tolerance levels are selected independently for each attribute. For example, with attributes "total cost" and "loss of load probability (LOLP)", a planner might specify that a plan costing one million dollars more than another is much worse, but that a plan costing $100,000 more than another is not significantly better. Similarly, if the difference in LOLP between two plans is greater than 2 days/year one plan is much worse than the other, while if the difference is less than 0.5 days/year, two plans can be thought equivalent relative to the performance measure LOLP.

Definition 2 (Tradeoff Curve and Knee Set)

- Tradeoff Curve: Set of plans that are not strictly dominated by any other plan conditional on a particular future.
- Knee Set: Set of plans that are not significantly dominated by any other plan conditional on a particular future. Knee set is also termed as conditional decision set.

An example of tradeoff graphs with two attributes is illustrated in Fig 6-2. Each marker in the graph represents a particular plan with the corresponding values of attribute A and attribute B. In the tradeoff graph, the tradeoff curve and knee set can be determined using the dominance criteria defined above.

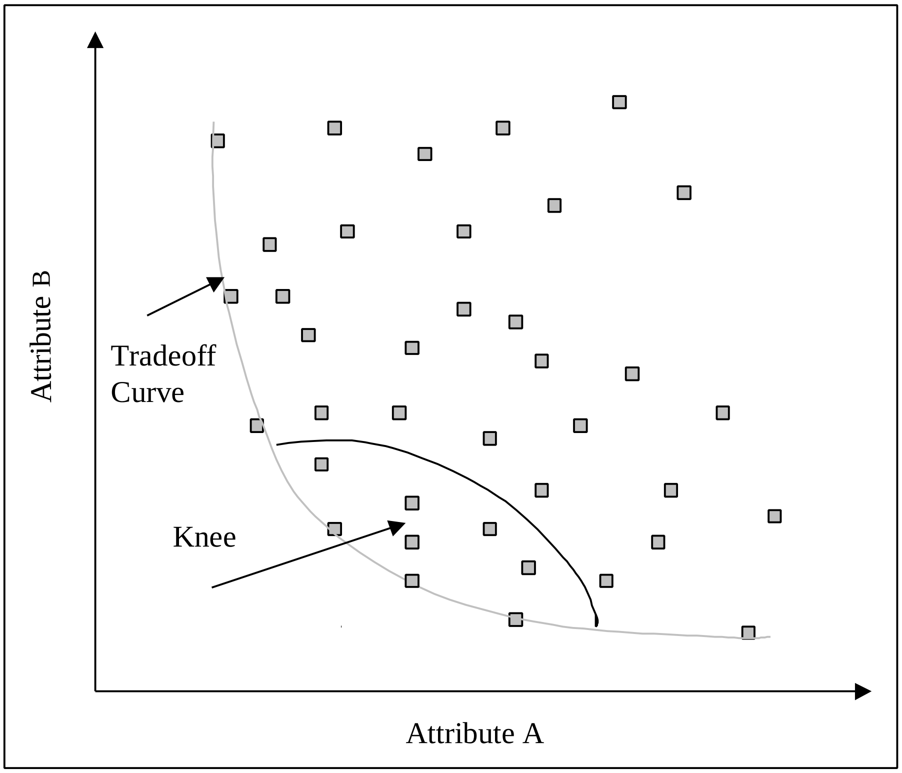

Figure 6-2 Tradeoff Graph with Two Attributes

It can be seen from the graph that the tradeoff curve forms the boundary between the sets of possible and unachievable attributes while the knee set contains plans on and near the knee of the tradeoff curve. The size of knee set, i.e., the number of plans whose performance is thought to be acceptable with respect to both attribute A and attribute B, is determined by the level of tolerances.

As can be seen from Fig 6-2, tradeoff graph comparing strategy performance across two attributes allows the planner to perform visual pair-wise comparison of all the plans under consideration and quickly identify the best alternatives – the plans included in the knee set. In fact, the tolerance for each attribute reflects how far the planner is willing to trade off one attribute with respect to another, or equivalently, indicates the planner's preference on the relative importance of different attributes.

However, finding the knee set with consideration of more than two attributes is not straightforward and performing tradeoff analysis graphically for each pair of attributes and for every specified future may not be realistic. Consequently, it turns out to be advantageous and even necessary in practical utility planning studies to use some well-defined numerical knee-set searching algorithms instead of visual examination.

<u>Decision Set Analysis</u>

Definition 3 (Global Decision Set)

> If uncertainties are modeled as unknown but bounded variables without probability assignments, then the global decision set is the set of plans that are left after all inferior plans have been eliminated.

To be more clear, plan P_1 remains in the global decision set only if there is no other plan which dominates plan P_1 (strictly or significantly as appropriate) for all possible futures. Finding the global decision set is obviously much harder than finding all the conditional decision sets. As a practical matter, the global decision set can be determined approximately by the union of the conditional decision sets.

Decision set analysis supports the final strategy of resource development by identifying robust plans, robust and inferior options. In tradeoff/risk analysis, the robustness of a plan is measured in terms of the frequency with which it appears on the global decision set. In other words, the number of supporting futures determines the final ranking of alternative planning strategies. A plan that is 100% robust is a plan that is in the conditional decision set of knee set for all futures. Robust and inferior options are the discrete option values that are nearly always (robust) or rarely (inferior) in the decision set.

In the case when no plan is completely robust, i.e., there is no any single plan that is optimal or nearly so for all possible futures, hedging to reduce the risk must be applied. This is usually the real situation in electric utility planning due to conflicting objectives and diverse future forecasts. One practical and effective risk-mitigating approach is to reassemble the identified robust resource options into new plans that may be expected to perform better or more robust than any original plans.

6.2.3 Comparison between Two Methods

The following gives a brief summary of the similarities and differences between the utility function method and the tradeoff/risk method in performing multi-attribute decision analysis under uncertainty.

Similarities

- Both methods require that the user define the decision problem properly by identifying sets of options and uncertainties, and specify how these options and uncertainties are combined to generate a range of scenarios.
- Both methods allow the user to analyze the performance of alternative planning strategies based on the measure of attribute values and the preference information regarding the relative importance of different attributes.
- Both methods can determine the best solution or optimal plan with respect to the given attributes in the presence of uncertainties.

Differences

- The advantages of utility function method are that it is based on the rule of probability and that it can suggest the best solution to the planner for which the expected utility value is optimal under the influences of various future conditions. This method requires establishing a well-defined utility function and assigning probability value for each uncertainty.
- There are two concerns in applying the utility function method for strategic planning. *First*, it is difficult to show the relative performance of the plans with respect to different attributes under different future conditions and thus may obscure the effect of catastrophic event with low probability. *Second*, the traditional utility function methods do not provide a strategy for the identification of acceptable plans.
- The advantages of tradeoff/risk method are that it provides information on how each of the plans will perform under various future conditions and that it uses the measure of robustness to characterize the risk aversion attitude of utility planners. This method require the planner to specify two tolerance parameters for each attribute with which a decision set containing plans that do not significantly dominated by any other plans can be identified. This method allows the analysis of uncertainties without explicitly specifying probabilities.
- There are two concerns in applying the tradeoff/risk method for strategic planning. *First*, the cost for providing robustness may be too high being planned solely on the basis of possibility of occurrence of some extremely conditions. *Second*, there is no proper statistical background to justify the selection of tolerance levels. Appropriate tolerance parameters are significant important in performing tradeoff analysis and the identification of acceptable plans.

6.3 Integrated MADM Methodology

Another major study task of this dissertation is to develop an integrated MADM methodology, which would combine the attractive features of utility function model and tradeoff/risk analysis and offer a structured and enhanced decision framework for handling multi-attribute planning under uncertainty. The main motivations of developing an integrated decision methodology are as follows.

- Both utility function and tradeoff/risk methods have been widely used in the electric utility industry, but they differ from each other in the philosophy of decision criteria and the interpretations of decision process. It would be desirable if the final decision is supported by both decision methods as a consistent check, and it would be better to consider the information provided from each method as complementary views of the same problem, rather than regard them as competing contradictory attitudes of the planners.
- It is essentially important in strategic resource planning to identify a range of acceptable plans with the given attributes. In the tradeoff/risk analysis, this is determined by searching for non-dominated plans based on some specified tolerance parameters. A confidence interval-based MADM methodology has been introduced in Chapter 5, which provides meaningful statistical background for the selection of tolerance levels. This interval-based MADM approach would be preferred in the case when the relative ranking of candidate alternatives are needed.

As with the tradeoff/risk analysis method, the proposed MADM framework can also be described by the following main steps.

- Formulating the decision problem properly
- Creating a reliable decision database
- Identifying decision sets after eliminating all inferior plans
- Analyzing the decision sets to support the final resource strategy.

However, the proposed MADM framework differs from the traditional tradeoff/risk analysis approach in the following two important aspects:

- It provides a novel multi-dimensional numerical knee-set searching algorithm based on the measure of composite distance, a special form of utility function model, together with statistical background for the selection of appropriate tolerance level.
- It provides a decision making platform through which the competing resource alternatives can be evaluated either based on the rule of probability (i.e., probabilistic evaluation approach or expected performance) or in a risk aversion perspective (i.e., risk evaluation approach or robustness performance).

Multi-Dimensional Knee-Set Searching Algorithm

1. Define the tradeoff region after eliminating all inferior plans due to unacceptable performance of one or more attributes.
2. Define the MADM model as in (6-1), which is identical to the additive utility function model (5-3) but with minor different interpretations

$$U_d(x) = \sum_{i=1}^{n} w_i \left| \frac{x_i - x_i^*}{x^r} \right| = \sum_{i=1}^{n} w_i r_i \tag{6-2}$$

   where, $U_d(\boldsymbol{x})$ is the composite distance for a particular plan measured from the ideal solution $x^* = [x_i^*, x_2^* ..., x_n^*]$, x_i and r_i are the measured and normalized values for the ith attribute, x_i^r is the range of the ith attribute values with x_i^* as the optimal, w_i is an appropriate weighting parameter for the ith attribute.

3. Compute the value of composite distance, both the point estimate and the likely range estimate, for each feasible plan, assuming the errors from attribute measurements and priority judgments can be properly estimated using the techniques discussed in Chapter 5.
4. Identify the best plan for which the value of composite distance is minimal, $U_{d,,min.}$
5. Determine the knee set, conditional on the specified future, which contains all data points satisfying

$$U_d - l_{a/2} s_d \leq U_{d,\min} + l_{a/2} s_{d,\min} \tag{6-3}$$

   where, $l_{d/2}$ is the standard deviation of normal distribution with a desired confidence interval, say 90% or 95%, s_d and $s_{d,min}$ are the estimated errors of composite distances corresponding to the plan being examined and the best plan identified in step 4.

Fig 6-3 below may be helpful to illustrate the conceptual knee-set searching process as discussed above when only two attributes involved.

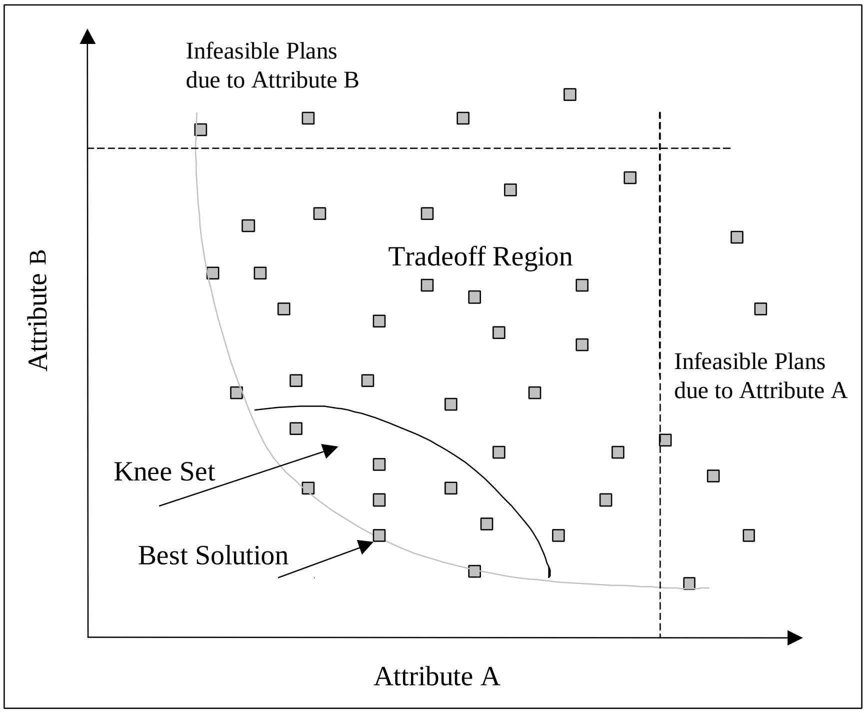

Figure 6-3 Conceptual Procedures in Knee-Set Searching

The significance of above knee-set searching algorithm is twofold. *First*, it provides a statistical background for the selection of an appropriate tolerance level in comparing alternative plans. Unlike the methods used in [40,96] where the tolerance levels, termed as "much worse" and "significant better", need to be specified for each attribute by the DM, the proposed approach estimates the variance of MADM model concerning the errors due to inaccurate attribute measurements and inconsistent priority judgments. *Second*, it ranks the acceptable plans contained in the knee set based on the measure of composite distance. This ranking information may be useful in making more precise discriminations among competing alternatives.

<u>Hybrid MADM Decision Methodology</u>

Hybrid decision methodology would be very helpful, as a consistent check, in support of important resource investment decisions. This dissertation suggests applying the probabilistic evaluation approach in parallel with the risk evaluation approach on the common decision database, aiming at identifying a desirable plan or plans that are acceptable not only based on the rules of probability but from the risk aversion perspective. As we discussed earlier, the risk evaluation approach will determine a set of acceptable plans based on the measure of robustness while the probabilistic evaluation approach will determine a set of acceptable plans based on the measure of expected performance. In the most desirable situation, the DM would be satisfied with one specific plan as the best solution from among the intersection of the acceptable plans recommended independently by two decision approaches as. In the case when one method is favored over the other, the hybrid decision analysis may still be useful to make more precise discriminations among competing alternatives.

6.4 Sample Study: Design of Grid-Linked Renewable Energy Systems

6.4.1 Problem Formulation

This sample study is primarily based on the decision problem introduced in [70], which concerns with the optimal design of hybrid solar-wind power systems (HSWPS). The system under design consists of four energy sources: wind turbine generators, PV arrays, storage batteries and a grid-linked substation. The candidate site under consideration is the American University of Beirut (AUB) campus where time series data are available for hourly wind speeds, solar insolation and load demand. The main goal behind proposing the HSWPS is to increase the penetration level of solar and wind energy technologies in the total generation mix. Three objectives are considered for the selection of suitable system components: the minimization of both cost and emissions, and the maximization of system reliability.

The study begins with the determination of priority order of three design objectives (attributes). AHP technique is used for attribute priority assessment since there are many factors influencing the planner's preference on the relative importance of different objectives with regard to the main goal, whether technical, political, economical, or even social. Fig 6-4 below illustrates the hierarchy for attribute priority assessment.

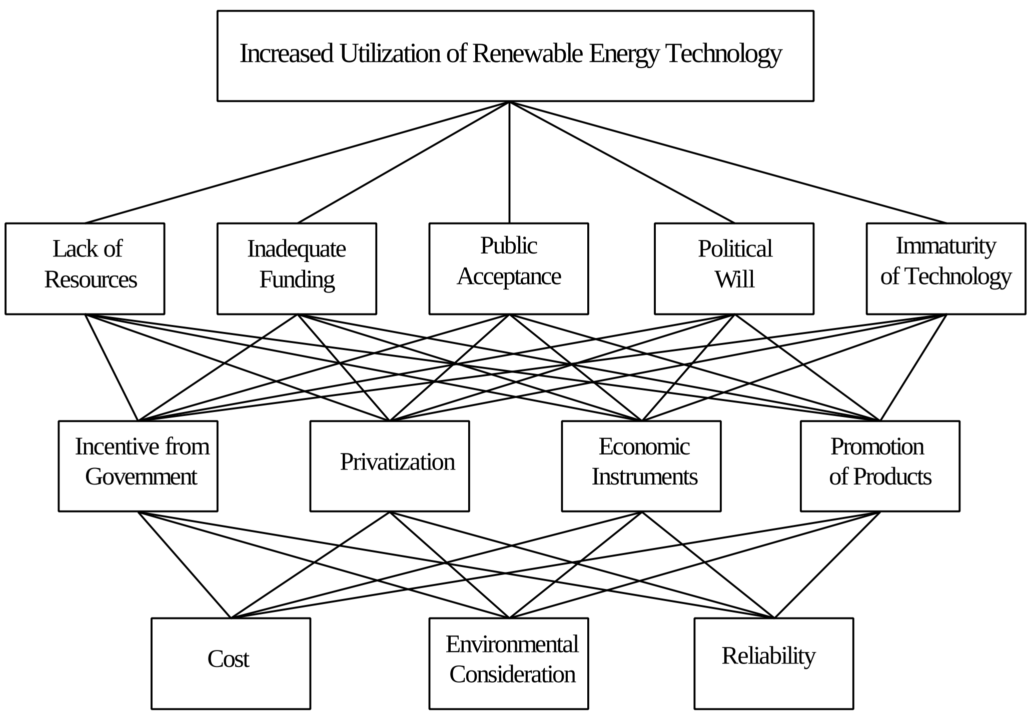

Figure 6-4 Hierarchy for Attribute Priority Assessment

As can be seen from Fig 6-4, the hierarchical structure of the HSWPS problem consists of four layers descending from the main goal, down to the constraints, and then down to the policies affecting the constraints, and finally down to the outcomes which represent the objectives (attributes). Starting, then, from the second layer of the hierarchy, specific ratio questions will be asked to the decision maker concerning the relative importance between each pair of factors at that layer with respect to every factor on the upper layer. Appendix B gives the judgment matrices corresponding to each evaluation level after consultation with the electric utility, design offices and private consultants using the scale of relative importance for ranking one factor over the other recommended in [89]. Appendix B also gives the local priority vector associated with each judgment matrix for each evaluation level calculated using the eigenvector prioritization method. The global priority vector, i.e., the composite priority vector from the bottom layer with respect to the top layer, is computed by combining the priority vector at the top evaluation level with the net priority vector of levels below. The resulting global priority vector indicates that minimizing the cost of energy supply is ranked the first (0.5006), followed by system reliability (0.3094) and then environmental concerns (0.1901).

Table 6.4-1 shows the range and step of variation for each design variable from which hundreds alternative plans can be generated. The decision problem considers sixteen futures accounting for the influences from uncertainty factors in economic situation, resource availability and load growth. Given the range and variation step of the design variables and possible futures, several thousands scenarios are created and studied using detailed energy production simulation model. The outputs of this chronological simulation model include the cost of energy production ($/kWh), expected energy unserved (%), and SO_2 emissions (kg/year). Tradeoff/risk analysis method is then applied to the decision database to determine the optimal combination of device capacities based on the measure of robustness.

Table 6.4-1 Range and Step of Variation of the Design Variables

	Wind Area (m^2)	Solar Area (m^2)	Substation Rating (kW)	Battery Rating (kWh)
Min	20000	0	200	500
Max	75000	20000	900	1000
Step	5000	5000	100	500

In this sample study, we reformulate the decision problem with only four futures selected for uncertainty modeling. These selected futures, as shown in Table 6.4-2, share the base case assumptions in wind speed, load growth, and economic factors, but differ with each other in the level of solar insolation and PV efficiency.

Table 6.4-2 Description of Selected Futures

Future	Solar Insolation (p.u.)	PV Efficiency (%)	Grid Energy Charge ($/kWh)	PV Cost ($/$m^2$)	Interest Rate (%)	Wind Speed (p.u.)	Load Growth (%)
A	0.9	12	0.08	450	12	1.0	0
B	1.1	12	0.08	450	12	1.0	0
C	0.9	17	0.08	450	12	1.0	0
D	1.1	17	0.08	450	12	1.0	0

6.4.2 Decision Analysis and Interpretations

The main results of performing MADM analysis with the proposed decision methodology for the reformulated decision problem will be presented. The discussion will focus on the determination of tradeoff region, identification of conditional and global decision sets, and decision set analysis.

(1) Determination of Tradeoff Region

Tables B-1 through B-4 in Appendix B list the feasible plans under different futures. In the tables, each feasible plan is characterized by four design variables, i.e., wind area (m^2), solar area (m^2), battery capacity (kWh) and substation capacity (kW), along with three decision attributes, i.e., cost of energy production (\$/kWh), expected energy unserved (%), and SO_2 emissions (kg/year). These feasible plans are determined after eliminating all inferior plans due to unacceptable performance of one or more attributes. At this prescreening stage, all plans with the cost of energy production higher than 0.15 \$/kWh and/or with the EENS index greater than 5% are rejected.

Thus, the set of feasible plans for each specified future condition constitute the tradeoff region within which the compromise between conflicting attributes can be achieved with the use of AHP based ratio-questioning weighting-selection method and then the MADM model as in (6-2) can be established.

For a decision problem with three attributes, graphical representation of tradeoff region usually requires a 3-D graph. Alternatively, we can use three 2-D plots to exhibit the relationship between each pair of attributes. Fig 6-5 below shows the tradeoff region for future A with three 2-D graphs: EENS vs. cost, SO_2 emission vs. cost and SO_2 emission vs. EENS. In these plots, attributes are given in their natural units.

(2) Identification of Decision Set

First of all, the value of composite distance is calculated for every plan contained by the tradeoff region using Equation (6-2). *Next*, the variance of composite distance is estimated using the approximate error model introduced in Chapter 5. In this sample study, the errors due to inconsistent priority judgments are assumed to be 10% of the expected values and the errors resulting from inaccurate attribute measurements are assumed up to 5% of the range of attribute values. *Then*, Equation (6-3) is applied to identify the decision set, conditional on the specified future, by searching for the plans which may overlap with the minimum distance solution under 90% confidence interval. *Finally*, the global decision set can be approximately determined as the union of conditional decision sets.

As with Fig 6-5, Fig 6-6 below displays the conditional decision set for future A with three 2-D graphs: EENS vs. cost, SO_2 emission vs. cost and SO_2 emission vs. EENS. Table 6-3 lists the top 10 acceptable plans for each future along with the preference ranking determined by the point estimate of composite distance. For future C, only eight plans have been found overlapping with the minimum distance solution at the given error size, therefore totally nine plans are listed in the table.

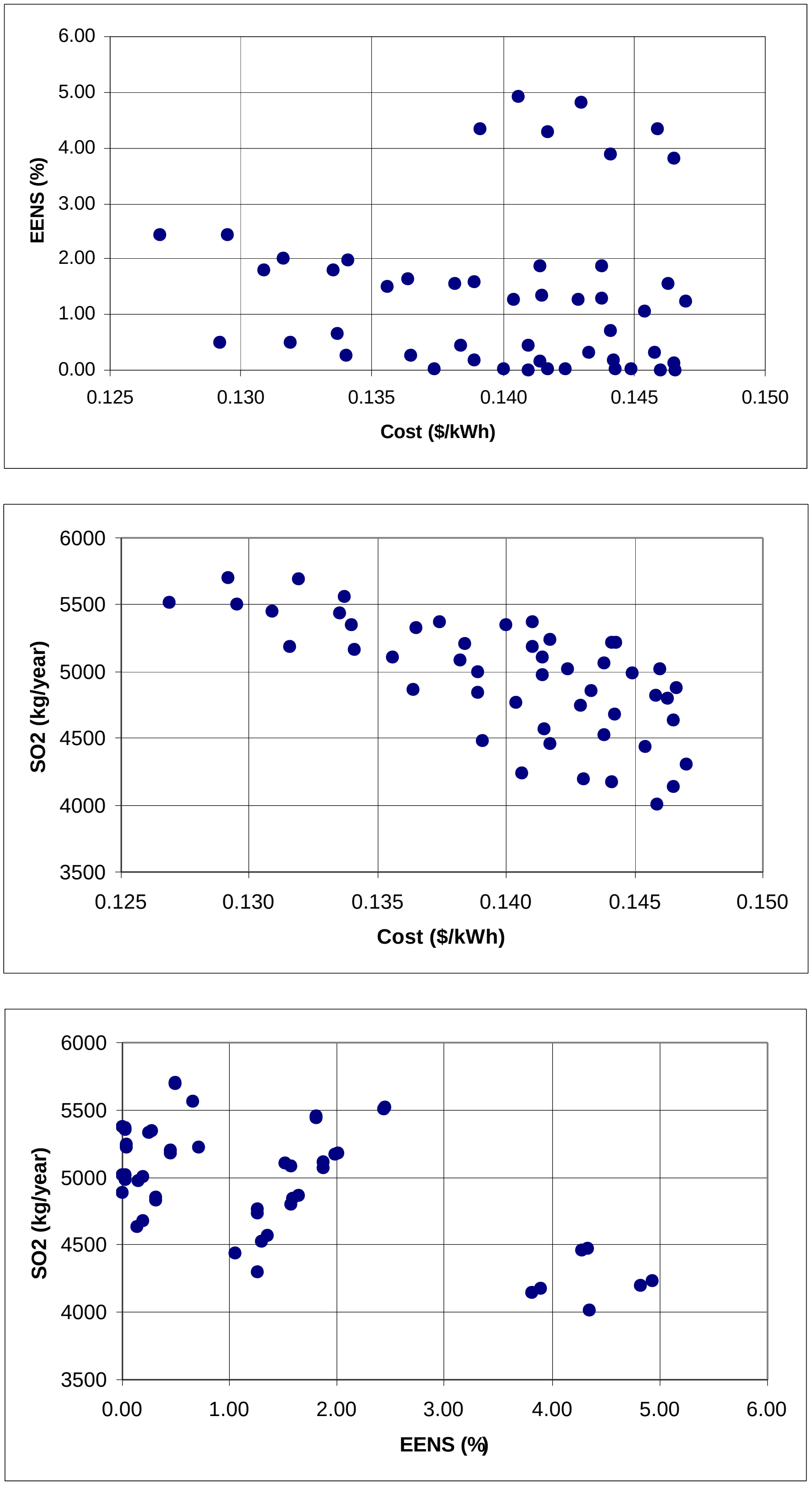

Figure 6-5 Tradeoff Region or Feasible Plans for Future A

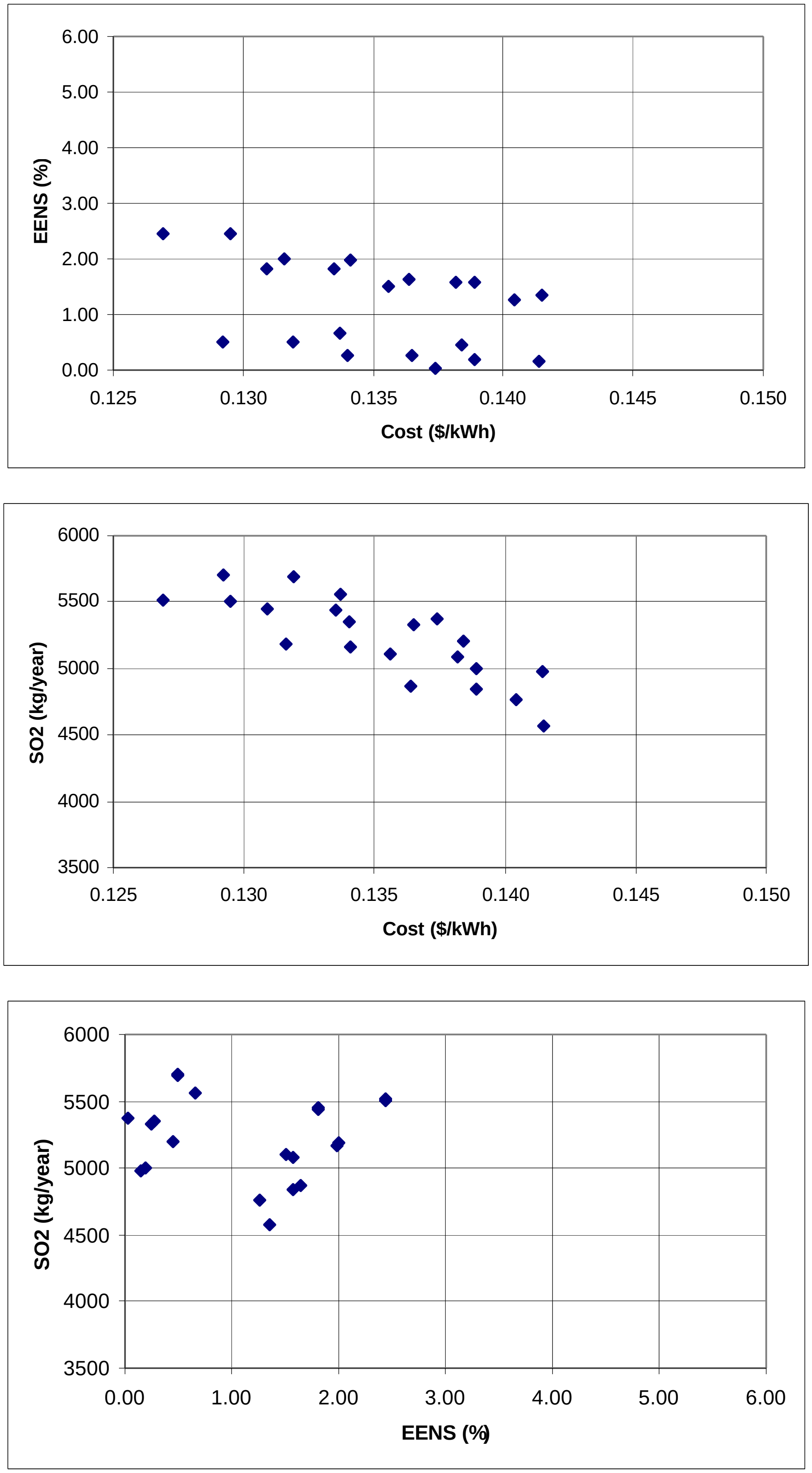

Figure 6-6 Conditional Decision Set for Future A

Table 6.4-3 Top 10 Acceptable Plans for Each Future

	Wind Area (m^2)	Solar Area (m^2)	Substation Rating (kW)	Battery Rating (kWh)	Cost ($/kWh)	EENS (%)	SO2 (kg/year)	Ranking
Future A	45000	0	500	500	0.1269	2.4406	5519	1
	45000	0	600	500	0.1292	0.4941	5702	2
	50000	0	500	500	0.1316	2.0025	5186	3
	50000	0	600	500	0.1340	0.2680	5349	4
	45000	0	500	1000	0.1295	2.4373	5508	5
	30000	5000	500	500	0.1309	1.8062	5454	6
	45000	0	600	1000	0.1319	0.4904	5691	7
	55000	0	500	500	0.1364	1.6408	4867	8
	50000	0	500	1000	0.1341	1.9834	5168	9
	35000	5000	500	500	0.1356	1.5124	5105	10
Future B	30000	5000	500	500	0.1290	1.6760	5208	1
	35000	5000	500	500	0.1338	1.4046	4866	2
	30000	5000	600	500	0.1319	0.5710	5312	3
	30000	5000	500	1000	0.1316	1.6677	5187	4
	50000	0	500	500	0.1316	2.0025	5186	5
	50000	0	600	500	0.1340	0.2680	5349	6
	35000	5000	600	500	0.1367	0.3932	4961	7
	40000	5000	500	500	0.1387	1.1760	4536	8
	35000	5000	500	1000	0.1364	1.4046	4840	9
	30000	5000	600	1000	0.1345	0.5710	5290	10
Future C	30000	5000	500	500	0.1257	1.5746	5004	1
	25000	5000	500	500	0.1227	1.8680	5343	2
	25000	5000	600	500	0.1256	0.6968	5453	3
	25000	5000	500	1000	0.1253	1.8614	5323	4
	35000	5000	500	500	0.1324	1.3248	4672	5
	30000	5000	600	500	0.1304	0.5117	5104	6
	35000	5000	500	1000	0.1349	1.3246	4368	7
	30000	5000	500	1000	0.1301	1.5752	4978	8
	35000	5000	400	500	0.1308	4.2791	4395	9
Future D	20000	5000	500	500	0.1154	1.9979	5359	1
	25000	5000	500	500	0.1204	1.7129	5028	2
	20000	5000	600	500	0.1184	0.7859	5473	3
	30000	5000	500	500	0.1253	1.4362	4707	4
	25000	5000	600	500	0.1233	0.6008	5133	5
	25000	5000	600	1000	0.1228	1.7116	4994	6
	30000	5000	400	500	0.1236	4.4925	4421	7
	30000	5000	500	1000	0.1278	1.4335	4664	8
	30000	5000	600	500	0.1283	0.4471	4800	9
	25000	5000	600	1000	0.1258	0.6008	5098	10

From Fig 6-5 and Fig 6-6, it can be noted that the conditional decision set or the acceptable plans are mainly compromised of those feasible plans having low energy production cost. It can also be noted that some plans with very low EENS index or with very low SO_2 emissions but relatively high cost have been eliminated. Further, by examining the conditional decision set, the DM can determine whether this set of plans would be acceptable in terms of the given attributes. In some cases, it may be necessary for the DM to re-evaluate the weighting parameters.

Based on Table 6-3, the main contributors to the optimal energy mix corresponding to future A are utility supply and wind technology. The solar resource option is only recommended by 2 out of 10 high ranked acceptable plans. On the contrary, the contribution from solar resource becomes significant in future D mainly due to the increased PV efficiency. It can also be seen that the desired penetration level of wind technology is much lower for future D as compared to the size recommended in future A. Future B and future C may represent two intermediate situations. It is apparent that, by comparing future A with future C and comparing future B with future D, increasing PV efficiency would be very beneficial to the overall performance of HSWPS in terms of all of three design objectives.

(3) Decision Set Analysis

Table 6.4-4 gives the relevant information about the global decision set. Only the plans supported by at least two futures are listed in the table, (G1 through G13). The preference ranking of these plans in the supporting future is also provided. For example, excellent performance can be expected for plan G2 in two futures, C and D, and in both futures this plan is ranked at the second place with reference to the minimum distance solution. However, the plan G2 is not included in the decision sets associated with future A and future B.

Table 6.4-4 Summary of Global Decision Set

Plan #	Wind Area (m^2)	Solar Area (m^2)	Substation Rating (kW)	Battery Rating (kWh)	Preference Ranking in Supporting Futures			
					A	B	C	D
G1	25000	5000	500	500			2	2
G2	25000	5000	600	500			3	5
G3	*30000*	*5000*	*500*	*500*	*6*	*1*	*1*	*4*
G4	*30000*	*5000*	*500*	*1000*	*14*	*4*	*8*	*8*
G5	*30000*	*5000*	*600*	*500*	*11*	*3*	*6*	*9*
G6	*35000*	*5000*	*500*	*500*	*10*	*2*	*5*	*11*
G7	35000	5000	500	1000	20	9	7	
G8	35000	5000	600	500	18	7		
G9	40000	5000	500	500	19	8		
G10	50000	0	500	500	3	5		
G11	50000	0	500	1000	9	14		
G12	55000	0	500	500	8	11		
G13	50000	0	600	500	4	6		

The analysis of the global decision set may conclude the following observations from which the "optimal" design strategy of HSWPS can be decided.

- Four robust plans, G3 through G6, are identified from the global decision set. These plans are acceptable for all considered futures and thus will be recommended as the candidate alternatives for the final decision making.
- All of the identified robust plans involve four energy sources indicating the complementary characteristics of these resource options in the routine system operations.
- These candidate plans reflect a conservative design attitude in utilizing wind and solar technologies and emphasize the importance of adequate storage capacity and grid supply.
- As for the best strategy, plan G3 may be regarded as more attractive than others in view of its preference ranking.
- Among other three candidate alternatives, plan G6 seems to be superior to plan G4 and plan G5 because the ranking of G6 is higher than G4 and G5 under majority (3 out of 4) of supporting futures.

Table 6.4-5 shows the variation of attribute values associated with the candidate design alternatives (G3 though G6) under different future conditions.

Table 6.4-5 Range of Attribute Values under Different Future Conditions

Plan #	Wind Area (m^2)	Solar Area (m^2)	Substation Rating (kW)	Battery Rating (kWh)	Range of Attribute Values		
					Cost ($/kWh)	EENS (%)	SO2 (kg/year)
G3	30000	5000	500	500	0.1253 ~ 0.1309	1.4362 ~ 1.8062	4707 ~ 5454
G4	30000	5000	500	1000	0.1278 ~ 0.1335	1.4335 ~ 1.8062	4664 ~ 5439
G5	30000	5000	600	500	0.1283 ~ 0.1319	0.4471 ~ 0.6511	4800 ~ 5562
G6	35000	5000	500	500	0.1304 ~ 0.1356	1.1889 ~ 1.5124	4402 ~ 5105

The information contained in Table 6-5 may be helpful in providing some insights into the performance of each candidate plan under various future conditions. From this table, it is clear that the plan G3 is preferred by the MADM model mainly due to reducing the cost of energy production is the dominated design objective. On the other hand, either plan G5 or plan G6 may be selected as the best solution if the DM would consider the improved system reliability index in plan G5 or the reduced SO_2 emission in plan G6 is more important to the low cost advantage associated with plan G3.

More precise discriminations among candidate design alternatives can be investigated using probabilistic analysis models. One commonly used probabilistic evaluation model, which is a combined utility function and decision tree modeling approach for handling multi-attribute planning under uncertainty, has been discussed in Section 6.2.1. Such probabilistic evaluation approach will determine the expected performance for each design strategy considering the influence of various uncertainty factors. Now let us continue the above HSWPS example and assuming uncertainties are modeled with discrete probability distributions.

Since probability distribution assignment is really a subjective matter, therefore, instead of giving a single set of values, it would be a good idea for the probabilistic analysis to be conducted in a manner by investigating the solution mapping space for a range of probability distributions [94]. In this illustrative example, we will examine the expected performance of robust plans under five specified probability distributions. The base case assumes an equal chance, i.e., 0.25 to each future condition, while in other four cases, Cases-1 through Case-4, one future is assumed twice more likely to occur than other three futures. For example, in Case-1, a probability value 0.40 is allocated to future A and other three futures are assigned a value of 0.20 each. Table 6.4-6 shows the results of probabilistic analysis.

Table 6.4-6 Expected Performance of Robust Plans

Plan #	Base Case	Case-1	Case-2	Case-3	Case-4
G3	0.3954	0.4029	0.3863	0.3896	0.4026
G4	0.4661	0.4718	0.4573	0.4709	0.4641
G5	0.4588	0.4626	0.4491	0.4630	0.4605
G6	0.4595	0.4626	0.4488	0.4634	0.4632

From Table 6-6, it is apparent that plan G3 is more attractive than other candidate alternatives while plan G4 seems not competitive to other in the selection of a final design strategy, in view of their consistent performance ranking under assumed likelihood of occurrence of different futures. On the other hand, the preference order between plan G5 and plan G6 may change under different future realizations.

6.5 Conclusion

An integrated MADM framework has been introduced for dealing with multi-attribute planning under uncertainty.

- It is within the framework of tradeoff/risk analysis but introduces a novel modeling approach for multi-dimensional tradeoff surface based on the measure of composite distance, a special form of additive utility function model.
- It provides statistical background for the selection of appropriate tolerance levels with which a range of acceptable plans can be determined for each specified future condition.
- It can determine for each specific future condition a best solution or the optimal plan and relative ranking information for the identified acceptable alternatives.
- It allows the DM to analyze the decision sets for the choice of best resource strategy both based on the rules of probability (i.e., probabilistic evaluation approach) and in a risk aversion perspective (i.e., risk evaluation approach).

7 Screening Applications

This chapter discusses two potential screening applications at the preliminary study stage of strategic planning of electric utilities as to identify cost-effective demand-side resource options and optimal generation expansion planning schemes.

7.1 Cost Effective DSM Options

Demand-side management (DSM) is becoming a universally accepted means for reducing utility capacity needs, improving system reliability performance and mitigating generation-related emissions. DSM screening models are designed to build portfolios of potentially cost-effective DSM programs. A technique has been developed which utilizes the load duration curve model in an efficient way to integrate utility DSM effects into the planning models properly without using the not-so-realistic chronological load-modification process. Such a simplified method provides the opportunity to screen a large number of DSM options and obtain a reliable estimate of their potential capacity and operational benefits. A few select cost-effective DSM portfolios may then be evaluated with supply-side alternatives in utility integrated resource planning models.

7.1.1 Avoided Cost of DSM

There are many possible ways of implementing DSM options. Cost-benefit analysis has been used in demand-side planning by which myriad options are compared based upon their net benefits [80]. Since individual demand-side resource options are usually small compared to the supply-side alternatives, marginal cost has been traditionally employed for such analysis, which is the utility cost associated with providing one additional unit of energy or power demand. When the resource contribution from DSM programs is expected to be large or the combined effects of bundled programs need to be investigated, avoided cost would provide a more accurate measure than marginal cost [45]. In general, avoided cost is the economic value or the cost of conventional supplies that are avoided by implementing DSM programs. The significant advantages of using avoided cost over marginal cost are the consideration of DSM load shape impacts and environmental improvements. As such, avoided cost analysis is a comprehensive measure for valuing demand-side options in utility integrated resource planning from the viewpoint of the entire system performance. Resources costing less than the avoided cost are considered cost-effective and should be implemented.

To estimate the avoided cost, the current practice in the utility industry is to develop a base resource plan and a number of alternate plans in which DSM programs are included. The avoided costs are the difference in total costs between the base plan and each individual alternative. Basically, the avoided cost of DSM consists of avoided capacity cost, avoided energy cost and avoided environmental externalities associated with electricity service. Depending on the study objective and planning period, the value of DSM may be evaluated by short-, intermediate- and long-term avoided costs. Generally, short- and intermediate-term avoided costs are estimated under the condition when the system capacity is unchanged, and therefore only production costing and reliability analysis are performed for such analysis. Long-term avoided cost, on the other hand, refers to the situation in which utilities undergo a capacity expansion progress. Thus, in addition to the optimization and production costing analysis, uncertainties that influence the effects of DSM need to be investigated.

There are many available capacity-expansion and production costing models such as WASP, EGEAS, MIDAS, IRP-Manager, and PROVIEW, into which DSM impacts may be incorporated as a part of the utility-resource planning process using either chronological or load-duration curve methods. The choice of an appropriate simulation model is of prime importance, depending on the tradeoff between the study objectives and the requirements of computations and data. For short-term avoided cost, chronological dispatch models are necessary to investigate the system operational performance when demand-side options, especially peak reduction programs, are implemented. However, because of excessive computation and data requirements, the chronological dispatch approaches are not widely used for intermediate- and long-term resource planning in comparison to the LDC-based probabilistic production simulation models. In applying LDC-based models, the load duration curve should be modified to incorporate utility DSM impacts. Since detailed impacts are hard to predict as DSM activities are diverse and are not consistent from one day to another, it would not be realistic to regenerate a LDC by integrating DSM impacts into the chronological load data. On the other hand, direct modifications of load-duration curves by reducing peak demand and total energy are inadequate and could result in excessive errors for production costing and reliability analysis.

7.1.2 Screening Methodology

Engineering methods are usually employed in the utility industry to estimate energy and demand effects from individual DSM programs. These methods provide projections of reduced peak demand, on-peak energy and total energy consumption over an extended period of time based on DSM load impacts, market segments and market penetration [2,15]. A useful screening technique will be described below which utilizes the load duration curve model in an efficient way to integrate the output of engineering methods into the production simulation models so as being able to evaluate the avoided costs for a large number of DSM options or their combinations.

<u>Multi-Section LDC Modeling</u>

It has been identified that the load duration curve can be represented with adequate accuracy by a four-segment exponential function as shown in Fig 7-1, consisting of four time blocks: peak-load duration ($block_1$), intermediate-load duration ($block_2$ and $block_3$) and base-load duration ($block_4$). For convenience in probabilistic production costing simulation, the axes of the LDC are usually reversed leading to the so-called inverted load duration curve (ILDC). The mathematical expression of this ILDC is given as

$$F_i(x) = T_i + (T_{i+1} - T_i)\left(1 - \frac{x - C_{i+1}}{C_i - C_{i+1}}\right) \times \exp\left\{\left(\frac{x - C_{i+1}}{C_i - C_{i+1}}\right) \sum_{n=1}^{7} A_n \left[\frac{AR_i - (T_{i+1} - T_i) C_{i+1}}{(C_i - C_{i+1})(T_{i+1} - T_i)} - 0.5\right]^n \right\}$$

$$\text{for } i = 1,2,3,4 \qquad (7\text{-}1)$$

where x = load level, T_i = number of hours during which the load equals or exceeds the relative load level C_i, AR_i = energy consumed in the ith time block, and A_n = coefficients in the reversion series of polynomial (n = 1, 2, 3, 4, 5, 6, 7).

Generally speaking, the ranges of different time blocks are specific to utilities, based on their load-duration patterns and experiences. For simplicity, however, the shares of peak-, intermediate-, and base-load periods are defined in the following way: T_3 = number of hours during which the load equals or exceeds the average load, T_5 = total number of hours in the period, $T_1 = 0$, $T_2 = T_2/2$, and $T_4 = (T_3+T_5)/2$. Specifically, C_1, C_3, and C_5 are peak, average and base loads, respectively. For each period of the year (one month or one quarter), the hourly chronological load data are arranged in increasing order. This series constitutes the reference ILDC with associated duration for each load level. The model parameters (e.g., T_i, C_i and AR_i) are then determined according to specified definitions.

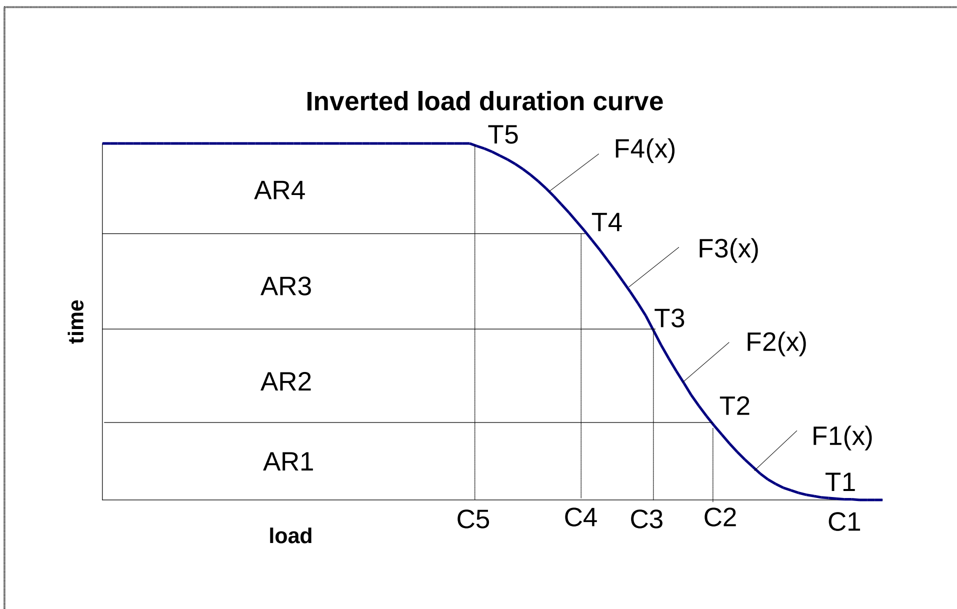

Figure 7-1 Inverted Load Duration Curve Model

<u>Screening Procedure</u>

The procedure for modeling DSM load shape impacts and estimating avoided costs associated with DSM activities will now be described.

- Identify a set of DSM options. Each of these options could be a combination of utility DSM programs such as direct load control, interruptible and/or time-of-use rates, energy storage, energy-efficient appliances, etc.
- Estimate power and/or energy reductions using engineering methods. Reductions in peak demand and energy savings are estimated by utilizing the expected penetration levels and unit impacts of individual programs or end-use technologies.

- Aggregate the effects of bundled DSM programs in a block-by-block manner (in terms of MW and MWh). This will result in a revised ILDC for all periods of the year.
- Determine the avoided cost of demand-side activities by employing the conventional production costing analysis for this modified ILDC and comparing the difference with the reference resource plan.

7.1.3 Example Applications

Conceptual application of the above screening technique has been illustrated in [86] where the capacity credits and system reliability improvements from utility DSM activities have been investigated. The sample system is based on a moderated-sized US electric utility and the selected utility DSM options include peak-reduction options and energy-conservation options. Capacity credit is defined as the difference between the capacity needs of the reference system (without DSM) and the modified system (with some DSM) while keeping the reliability level unchanged. Capacity credit is thus a measure of the amount of generation capacity that could be saved by DSM. This fact may become manifest as a reduced or deferred need for new and costly capacity additions that are necessary to meet system-reliability criteria. DSM programs have immediate benefits on utility system operational performance, including system reliability improvements; production cost savings and emission reductions. As an illustration, reliability improvement due to the use of DSM activities is calculated. This improvement is measured as the percentage reduction of loss of load probability (LOLP) while keeping the generation capacity unchanged. That is, the equivalence of the reference and the modified systems is determined subject to maintaining the original LOLP value.

The exercise with this example has shown the convenience and usefulness of proposed screening techniques in identifying cost-effective utility DSM options, resulting in significant savings of computational time and manpower dedicated to such activities. The study also provides some insight on capacity values of DSM activities: (i) Capacity values depend mainly on the amount of on-peak energy savings, which is a product of peak reduction and effective hours of that activity. (ii) There is a strong correlation between the effectiveness of peak reduction and system load factor. For periods with the same capacity-reserve margin, lower load factors generally result in higher levels of capacity displacement. (iii) The initial efforts in peak reduction always contribute more to the capacity credit than later efforts. As the amount of peak reduction increases, the effectiveness of capacity displacement will decrease to some extent.

In another example study [87], the proposed screening technique has been used to evaluate the economic potentials of aggregate utility DSM activities where the total economic value or the avoided cost of DSM is calculated based on energy production savings, reduced capacity needs and CO_2 emissions. This study approach would give a system value for the planned DSM load shape objectives and thereby provide a reliable criterion for screening potential candidate programs. Study results indicate that the interactive effects of DSM activities should be considered since it may reduce the economic values of bundled DSM programs as compared to the additive value contributed by individual resource options.

7.2 Robust Optimization for Generation Capacity Expansion

Robust optimization modeling approach is a recent contribution from the literature of Operation Research and Management Science, which is designed to develop an optimal resource plan under uncertainty. This section will review the general formulation of robust optimization and discuss its potential application in generation expansion planning of electric utilities.

7.2.1 General Formulation of Robust Optimization

Models for planning under uncertainty in complex and dynamic environments had been proposed shortly after the development of linear programming in the 1950s. However, the computational complexity of the resulting mathematical programs prohibited their applications. In the 1980s, the interest in models for planning under uncertainty was renewed in the Operation Research and Management Science literature, either in the form of stochastic programming (SP) or in the form of robust optimization (RO) due to the widespread availability of high-performance computers.

Stochastic programming models have been studied for four decades and experienced extensive applications in electric utility industry to solve a multistage decision problem when some parameters are known through probability distributions. This modeling approach yields a solution that guarantees a long-run optimal performance when the potentially realized macroeconomic scenarios are encountered repeatedly with the frequency of appearance of each scenario according to the assumed probability distribution.

Robust optimization modeling approach is based on stochastic programming but extends the problem formulation with the introduction of higher moments of the objective value and the consideration of appropriate feasibility penalty functions. It integrates multi-objective programming formulation with a scenario-based description of problem data such that the tradeoff between solution robustness and model robustness could be measured and a compromise solution can be achieved. What follows is a summary of the concepts of robust optimization modeling approach introduced in [48,77].

In order to define the general formulation of robust optimization, two sets of variables are defined as below.

$x \in R^{n1}$, denotes the vector of decision or design variables whose optimal value is not conditioned on the realization of uncertainty parameters. Variables in this set cannot be adjusted once a specific realization of the data is observed.

$y \in R^{n2}$, denotes the vector of control variables that are subjected to the adjustment once the uncertain parameters are observed. Their optimal value will be determined based on both the realization of uncertain parameters and the optimal value of the design variables.

To start with, the following deterministic optimization model is considered, which is formulated as a general linear programming problem (LP).

[LP]	Minimize	$c^T x + d^T y$	(7-2)
		$x\ \hat{I}\ R^{n1}\quad y\ \hat{I}\ R^{n2}$	
	Subject to	$Ax = b$	(7-3)
		$Bx + Cy = e$	(7-4)
		$x, y\ ^3\ 0$	(7-5)

To define the robust optimization problem, a set of scenarios $W = (1, 2, 3, \ldots, S)$ are introduced. With each scenario $s\ \hat{I}\ W$, associate the set $\{d_s, B_s, C_s, e_s\}$ of realizations for the coefficients of the control constraints and the probability of the scenario p_s ($\mathring{a}\, p_s = 1$). According to the concept of robust optimization, the optimal solution of the mathematical program (7-2) through (7-5) will be robust with respect to optimality if it is remains "close" to optimal for any realization of the scenario $s\hat{I}\ W$. This characteristic is termed solution robust. The solution is also robust with respect to feasibility if it is "almost" feasible for any realization of $s\hat{I}\ W$. This characteristic is termed model robust.

In real-world applications, it is unlikely that any solution to the above mathematical program will remain both feasible and optimal for all scenario indices. Only in the case when the system that is being modeled has substantial redundancies built in, then it is might be possible to find solutions that remain both feasible and optimal. Robust optimization modeling approach is designed explicitly for handling such multi-scenario optimization problems, which measures the tradeoff between solution and model robustness and provides a compromise solution strategy.

Toward that end, for each scenario $s\hat{I}\ W$, introduce a set $\{y_1, y_2, \ldots, y_s\}$ of control variables and also introduce a set $\{z_1, z_2, \ldots, z_s\}$ of error vectors that will measure the unfeasibility allowed in the control constraints. A general formulation of robust optimization modeling approach can then be expressed as

[RO]	Minimize	$\sigma(x, y_1, \ldots, y_s) + \omega\rho(z_1, \ldots, z_s)$	(7-6)
	Subject to	$Ax = b$	(7-7)
		$B_s x + C_s y_s + z_s = e_s$ *for all* $s\ \hat{I}\ W$	(7-8)
		$x\ ^3\ 0, \quad y_s\ ^3\ 0$ *for all* $s\ \hat{I}\ W$	(7-9)

It can be noted that the general RO model is formulated in a multi-objective programming form with a scenario-based description of problem data. In the objective function, the first term measures the solution or optimality robustness while the second term is a measure of feasibility or model robustness. The goal programming weight ω is used to derive a spectrum of solutions that tradeoff solution robustness for model robustness.

It is also noted that, with multiple scenarios, the objective function $x = c^T x + d^T y$ in (7-2) now becomes a random variable taking the value $x_s = c^T x + d_s^T y_s$ with probability p_s. Hence, there is no longer a single choice for an aggregate objective. If the mean value $\sigma(\cdot) = \sum p_s x_s$ is chosen as the objective function, then this general RO formulation is degenerated into the objective function used in classical stochastic programming models. In other words, stochastic programming is a special case of robust optimization.

Several suitable alternatives to the representations of functions $s(x, y_1, \ldots, y_s)$ and $r(z_1, \ldots, z_s)$ have been discussed in [7]. The recommended choice of functions $\sigma(\cdot)$ is given in (7-10) which involves the mean plus a constant λ times the variance.

$$\sigma(x, y_1, y_2, \quad , y_s) = \sum p_s x_s + \lambda \sum p_s \left(x_s - \sum p_s x_s\right)^2 \qquad (s = 1,2,\ldots,S) \qquad \text{(7-10)}$$

The introduction of higher moments is one of the distinguishing features of RO from SP. In the low risk situation it might be acceptable to take the expected value as the objective function. However, this choice is inappropriate for moderate and high-risk decisions under uncertainty. The expected value objective ignores both the DM's risk-averse attitude and the distribution of the objective value x_s. Including outcome variance as a surrogate for risk, the robust optimization model naturally leads to a minimization of expected outcome for a given level of risk. As such, robust optimization approach can yield a solution that is relatively insensitive to the potential realization of macroeconomic parameters over the planning horizon. This is usually a reflection of risk-averse preference of the utility planner.

The second term $\rho(z_1, \ldots, z_s)$ is a feasibility penalty function which is used to penalize any violation of the control constraints under some of the scenarios. The introduction of penalty function distinguishes the robust optimization approach from stochastic programming models in the treatment of constraints. Stochastic programming models aim at finding the design variables x such that for each realized scenario a control variable setting y_s is possible that satisfies all the constraints. For systems with some redundancy such a solution might always be possible. However, for many engineering applications, it is not unusual when there is no such a pair (x, y_s) feasible for every scenario. As a matter of fact, in many applications, the violation of constraints may be allowed to some extent in order to find a much more economical plan. The robust optimization, through the use of error terms and the penalty function, will lead to an optimal solution that violates the constraints by the least amount.

7.2.2 RO Modeling for Generation Expansion Planning

Robust GEP Model

As the first exercise of RO modeling approach in electric utility planning studies, a conceptual robust optimization model has been introduced for power systems capacity expansion under uncertain load forecasts [7]. The proposed robust model for generation expansion planning (RO-GEP) is described by the following equations.

[RO-GEP]

Minimize

$$\sum_{s\in S} p_s \xi_s + \lambda \sum_{s\in S} p_s \Big(\xi_s - \sum_{s'\in S} p_{s'} \xi_{s'}\Big)^2 + \omega \sum_{s\in S} p_s \Big(\sum_{i\in I} (z_{1i}^s)^2 + \sum_{j\in J} (z_{2j}^s)^2\Big) \quad (7\text{-}11)$$

Subject to

$$x_i - \sum_{j\in J} y_{ij}^s + z_{1i}^s = 0 \qquad \text{for all } i \in I,\ s \in S \qquad (7\text{-}12)$$

$$\theta_i \sum_{i\in I} y_{ij}^s - d_j^s + z_{2j}^s = 0 \qquad \text{for all } j \in J,\ s \in S \qquad (7\text{-}13)$$

$$x_i \geq 0, \quad y_{ij}^s \geq 0 \qquad \text{for all } i \in I,\ j \in J,\ s \in S \qquad (7\text{-}14)$$

where the function ξ_s is defined as

$$\xi_s = \sum_{i\in I} c_i x_i + \sum_{j\in J} \theta_j \sum_{s\in S} f_i y_{ij}^s \qquad (7\text{-}15)$$

The objective function of the RO-GEP model is composed of three terms: the expected cost over all possible scenarios, the variance of the cost and a penalty function for feasibility deviations. Two types of errors are included in the penalty function: surplus capacity and unmet demand. Unmet demand clearly has an adverse effect on society by imposing shortage of electricity supply. Surplus capacity means capital resources are not being utilized efficiently. By varying the weighting parameters, i.e., λ and ω, a measure of solution and model robustness can then be obtained, leading to a compromise solution.

Numerical example has been provided in [77] to show the difference between the robust optimization and the classical stochastic programming in terms of expected cost, standard deviation and expected excess capacity. This will be discussed in Section 7.2.3 together with the results using a reformulated RO-GEP model.

<u>Reformulated Robust GEP Model</u>

While the above robust optimization model for generation expansion planning (RO-GEP) provides a promising modeling approach for handling uncertainties with the tradeoffs between solution robustness and model robustness, it does not show an efficient way on how to find a desirable compromise solution from the resulting multi-objective optimization problem. For the given numerical example, it has been seen that the recommended robust solution is reached after examining a great range of λ and ω combinations, a very time-consuming process. Furthermore, there is no meaningful interpretation for the selected weighting parameters, and the quadratic penalty function may not best represent the attitude of utility planner toward taking a risk due to feasibility violation. In the following, we will present a reformulated robust optimization model for generation expansion planning (Re-RO-GEP), which maintains all useful properties of original RO-GEP model but has a flexible structure for tradeoff analysis.

[Re-RO-GEP]

Minimize $$\sum_{s \in S} p_s x_s + \; l \times STD(x, y_1, ..., y_s) + w \times EEC(z_1, ..., z_s) \qquad (7\text{-}16)$$

$$x_s = \sum_{i \in I} c_i x_i + \sum_{j \in J} q_j \sum_{s' \in S} f_i y_{ij}^s \qquad (7\text{-}17)$$

$$STD = sqrt(\sum_{s \in S} p_s (x_s - \sum_{s' \in S} p_{s'} x_{s'})^2) \qquad (7\text{-}18)$$

$$EEC = \sum_{s \in S} p_s \sum_{i \in I} c_i z_{1i}^s \qquad (7\text{-}19)$$

Subject to

$$x_i - \sum_{j \in J} y_{ij}^s + z_{1i}^s = 0 \qquad \textit{for all } i \in I,\ s \in S \qquad (7\text{-}20)$$

$$q_i \sum_{i \in I} y_{ij}^s - d_j^s + z_{2j}^s = 0 \qquad \textit{for all } j \in J,\ s \in S \qquad (7\text{-}21)$$

$$x_i \geq 0, \quad y_{ij}^s \geq 0 \qquad \textit{for all } i \in I,\ j \in J,\ s \in S \qquad (7\text{-}22)$$

$$\sum_{s \in S} p_s x_s \leq EC_0 \qquad (7\text{-}23)$$

$$sqrt(\sum_{s \in S} p_s (x_s - \sum_{s' \in S} p_{s'} x_{s'})^2) \leq STD_0 \qquad (7\text{-}24)$$

$$\sum_{s \in S} p_s (\sum_{i \in I} x_i - Peak^s) \leq EEC_0 \qquad (7\text{-}25)$$

There are two advantages of the reformulated RO-GEP model as compared to the original one in dealing with the tradeoff between solution robustness and model robustness. *First*, we believe it may be more convenient to express the objective function using all dollar-valued terms or normalized attribute values, measured as functions of design and control variables. This would allow the DM to associate decision attributes with properly defined preference or penalty functions and assign weighting parameters with meaningful interpretations. Here, for this particular GEP problem, we have replaced the variance of the cost with the corresponding standard deviation and the violation of capacity balance with the expected cost incurred due to unutilized generation capacity. In some other GEP studies, the shortage of energy supply may be valued approximately by utility-specific outage costs and the environmental impact may be valued properly by market-based taxes or allowances. *Second*, the reformulated RO-GEP model includes constraints or targets for some decision attributes, as shown in (7-23) through (7-25). This would provide a reasonable tradeoff region within which a desirable compromise can be found between solution robustness and model robustness. For this particular GEP example, we use the solution obtained from stochastic programming, which is the optimal resource development plan with minimal expected cost, as the reference to determine appropriate levels of allowed increase in expected cost and required reduction in standard deviation and expected excess capacity.

7.2.3 Example Applications

The following shows the solutions of SP model, RO model and the reformulated RO model, using MATLAB Optimization Toolbox, for a simple GEP problem which involves the development of an optimal resource plan considering the impact of uncertainty in the forecast of electricity demand.

Problem Description

The sample test system used here is the same as the one discussed in [28,77]. The test system considers four supply resource options, referred to as A, B, C and D. The relevant cost data associated with these resource options are given in Table 7.2-1, including annual levelized capital cost and operating cost. These cost data reflect low capital cost/high operating cost, high capital cost/low operating cost, medium capital cost/medium operating cost and zero capita cost and extremely high operating cost, allowing for the explicit incorporation of a shortage cost $200 per energy unit.

Table 7.2-1 Supply Resource Options and Cost Data

Resource Options	Capital Cost ($/MW)	Operating Cost ($/MWh)
A	200	30
B	500	10
C	380	20
D	0	200

The test system considers four demand scenarios over two operating modes (i.e., peak and base) assumes an equal chance for each future condition (i.e., 0.25 to each scenario). Fig 7.2-2 describes the linear approximation of load-duration curve model and Table 7.2-2 gives the parameters of load-duration curve for each of the scenarios.

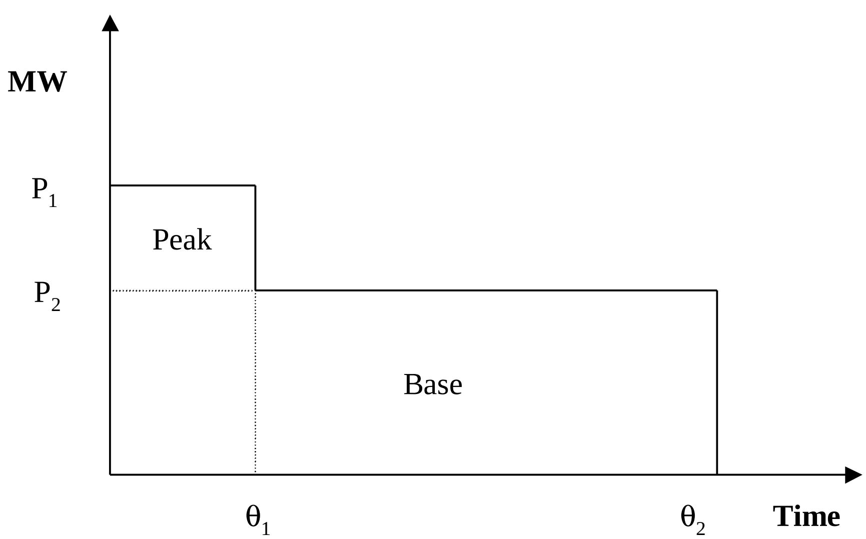

Figure 7-2 Linear Approximation of Load Duration Curve

Table 7.2-2 Load-Duration Curve Model Parameters

Scenario #	Scenario Probability	Demand (MW)		Duration (H)	
		P_1	P_2	θ_1	θ_2
1	0.25	12	8	6	24
2	0.25	10	8 2/3	6	24
3	0.25	10 2/3	9	6	24
4	0.25	10 3/4	8 1/4	6	24

SP and RO Solutions

This study first re-examined the optimal solutions obtained using the stochastic programming model and the robust optimization model. Table 7.2-3 below shows the results from these two modeling approaches. It has been confirmed that the optimal solution obtained from classical SP model is identical to the RO solution with parameters $\lambda = 0$ and $\omega = 0$. As with [7], the recommended RO solution is calculated by setting $\lambda = 0.01$ and $\omega = 512$.

Table 7.2-3 SP Solution and Recommended RO Solution

GEP Model	Scenario				Expected Cost	Standard Deviation	Expected Excess Capacity
	1	2	3	4			
SP	7560	7320	7620	7380	7470	124	1.1458
RO	7792	7691	7734	7672	7722	46	0.7783

GEP Model	Supply Resource Options		
	A	B	C
SP	3.33	8.67	0
RO	3.21	8.00	0.42

Compared to the optimal solution determined by SP model, the recommended RO solution is "almost" optimal for any realization of the demand scenarios while at the same time reducing the standard deviation by 60% and expected excess capacity by 30%. Of course, this improved performance is with expanse of increasing the expected cost from $7470 to $7722.

Re-RO Solutions

In the following, we will show the flexibility of reformulated RO-GEP model in performing tradeoff analysis between solution robustness and model robustness. The optimal solution obtained from SP model is used here as the reference to select appropriate levels of allowed or required changes in expected cost, standard deviation and expected excess capacity.

Table 7.2-4 presents the results of reformulated RO-GEP model at the given constraints where the standard deviation and expected excess capacity determined from the SP solution are assumed acceptable while the expected cost is allowed to increase by $300 above the reference level $7470. The information contained in the table clearly illustrates how the choice of weighting parameters will affect the compromise solution while observing the given constraints. An example solution is given by setting $\lambda = 2.0$ and $\omega = 3.0$, which implies the relative importance of the standard deviation of cost and the cost due to unutilized generation capacity has been regarded as being two times or three times higher as compared to the expected cost.

Table 7.2-4 Re-RO-GEP Model Solution (1)

Scenario						Expected Cost	Standard Deviation	Expected Excess Capacity
λ	ω	1	2	3	4			
0.5	0.5	7560	7320	7620	7380	7470	124	1.1458
0.5	1.0	7561	7320	7620	7397	7470	124	1.1442
0.5	2.0	7607	7359	7612	7364	7485	124	1.0841
0.5	3.0	7783	7489	7656	7489	7604	124	0.7273
0.5	5.0	7899	7606	7628	7606	7685	124	0.5858
1.0	0.5	7590	7433	7590	7433	7512	78	1.1458
1.0	1.0	7590	7411	7590	7411	7501	89	1.1458
1.0	2.0	7590	7412	7590	7412	7502	88	1.1458
1.0	3.0	7783	7489	7656	7489	7604	124	0.7273
1.0	5.0	7899	7606	7628	7606	7685	124	0.5858
2.0	2.0	7606	7697	7688	7535	7632	66	1.1049
2.0	*3.0*	*7611*	*7784*	*7683*	*7744*	*7705*	*66*	*0.9632*

		Supply Resource Options		
λ	ω	A	B	C
0.5	0.5	3.33	8.67	0
0.5	1.0	3.33	8.66	0
0.5	2.0	3.29	8.64	0
0.5	3.0	3.58	8.00	0
0.5	5.0	3.44	8.00	0
1.0	0.5	3.17	8.83	0
1.0	1.0	3.17	8.83	0
1.0	2.0	3.17	8.83	0
1.0	3.0	3.58	8.00	0
1.0	5.0	3.44	8.00	0
2.0	2.0	3.22	8.73	0
2.0	*3.0*	*3.70*	*8.12*	*0*

Constraints:
(1) EC ≤ \$7470 + \$300
(2) STD ≤ \$124
(3) EEC ≤ 1.1458 MW

As far as the constraints on decision attributes are of concern, there will be three possible situations depending on the defined tradeoff region.

(1) Active Constraints Table 7.2-5 presents the results of reformulated RO-GEP model for the situation when the standard deviation and expected excess capacity are required to be controlled within \$100 and 0.9 MW respectively and only \$100 increase is allowed for the expected cost with reference to the SP solution. It has been found the solutions obtained with different weighting parameter are almost identical in this case, showing the existence of feasible solution at the given constraints and no further improvement can be made for standard deviation or expected excess capacity due to active constraints.

Table 7.2-5 Re-RO-GEP Model Solution (2)

Scenario						Expected Cost	Standard Deviation	Expected Excess Capacity
λ	ω	1	2	3	4			
0.0	0.0	7666	7466	7666	7466	7566	100	0.9
0.5	0.5	7666	7466	7666	7466	7566	100	0.9
1.0	1.0	7666	7471	7666	7467	7569	98	0.9
1.0	2.0	7666	7467	7666	7467	7567	100	0.9
2.0	2.0	7666	7474	7666	7474	7570	96	0.9

		Supply Resource Options			
λ	ω	A	B	C	Constraints:
0.0	0.0	3.62	8.14	0	(1) EC ≤ \$7470 + \$100
0.5	0.5	3.62	8.14	0	(2) STD ≤ \$100
1.0	1.0	3.62	8.14	0	(3) EEC ≤ 0.9 MW
1.0	2.0	3.62	8.14	0	
2.0	2.0	3.62	8.14	0	

(2) Compromise Solution Table 7.2-6 presents the results of reformulated RO-GEP model for the situation when the standard deviation and expected excess capacity are required to be controlled within \$100 and 0.9 MW respectively and \$200 increase is allowed for the expected cost with reference to the SP solution. It has been found further reductions in standard deviation and expected excess capacity can be achieved in this case because of the relaxed constraint on expected cost. Compromise between solution robustness and model robustness can be determined by varying the weighting parameters associated with standard deviation and expected excess capacity.

Table 7.2-6 Re-RO-GEP Model Solution (3)

Scenario						Expected Cost	Standard Deviation	Expected Excess Capacity
λ	ω	1	2	3	4			
0.0	0.0	7666	7466	7666	7466	7566	100	0.9
0.5	0.5	7666	7466	7666	7466	7566	100	0.9
1.0	1.0	7666	7654	7666	7654	7600	6	0.9
1.0	3.0	7764	7526	7661	7526	7619	100	0.7514
2.0	2.0	7668	7668	7668	7668	7668	0	0.89

		Supply Resource Options			
λ	ω	A	B	C	Constraints:
0.0	0.0	3.62	8.14	0	(1) EC ≤ \$7470 + \$200
0.5	0.5	3.62	8.14	0	(2) STD ≤ \$100
1.0	1.0	3.62	8.14	0	(3) EEC ≤ 0.9 MW
1.0	3.0	3.60	8.00	0	
2.0	2.0	3.63	8.12	0	

(3) Infeasible Solution If only \$50 increase is allowed for the expected cost, no feasible solution can be obtained for this GEP problem which satisfies simultaneously the constraints on

expected cost, standard deviation and expected excess capacity. In this case, the tradeoff region needs to be re-defined by relaxing some attribute constraints.

7.2.4 Further Discussions

We have discussed the application of reformulated RO-GEP model for handling the tradeoff between solution and model robustness in generation expansion strategy under uncertainty. In general, the proposed modeling and solution approach involves a two-stage optimization process: stochastic programming and robust optimization. The solution of stochastic programming provides a reference resource plan that minimizes the total expected cost. With this information, the utility planners can determine how far the expected cost might be allowed to increase in order to reduce the variance of cost and the excess of installed capacity to certain preferred levels. This set of attribute constraints or preferred targets will define the tradeoff region for robust optimization process. In the process of robust optimization, the feasibility of tradeoff region needs to be confirmed by examining the range of weighting parameters. Within the feasible tradeoff region, a good compromise solution can then be obtained by finding a set of appropriate weighting parameters that would best represent the utility planner's preference on the relative importance between solution and model robustness. More research efforts are needed to investigate the instability problem that may be caused by the non-differential model structure due to the term of standard deviation and how the methods introduced in [47,68] might be used to solve this problem.

It is suggested to use the RO-GEP modeling approach in strategic planning to determine an appropriate system capacity expansion scheme or resource mix that will perform well under a variety of future conditions. This robust generation expansion strategy can then be used as a reference plan from which a range of candidate generation expansion configurations or project schedules can be developed and evaluated using detailed utility planning tools.

It should also be pointed out that the numerical example used here is only for the purpose of illustration. For practical electric utility resource planning studies, greater variety of physical and resource restrictions should be considered, such as limitation on power allocation, demand met for each load block, resource availability, and global and regional environmental impacts. Uncertainty modeling may be extended to include demand forecasts, fuel prices, capital investments, and environmental protection regulations.

8 Conclusion

8.1 Summary of Present Work

In this dissertation, we have developed an enhanced MADM framework for strategic resource planning of electric utilities. Study efforts have focused on four technical issues identified to be essentially important to the success of strategic planning. These include decision data expansion, MADM analysis with imprecise information, MADM analysis under uncertainty and screening applications. Main contributions from this dissertation work are summarized as follows.

ANN-Based Decision Data Expansion Technique

An automatic learning method has been introduced for decision data expansion which takes advantage of the flexibility of artificial neural networks in nonlinear input-output vector mapping and offers an efficient approach to reduce the amount of computations involved in the creation of decision database. The performance of proposed method has been demonstrated through three illustrative examples. Test results have shown that the proposed method for decision data expansion is feasible, easy to implement, and more accurate than the techniques available in the existing literature.

Confidence Interval-Based MADM Methodology

An interval-based MADM methodology has been developed in support of the decision process with imprecise information. The developed MADM methodology is based on the model of linear additive utility function but extends the problem formulation with the measure of composite utility variance, accounting for individual errors from inaccurate attribute measurements and inconsistent priority judgments. This enhanced MADM methodology would help the DM gain insight into how the imprecise data may affect the choice toward the best solution on one hand and how a set of acceptable alternatives may be identified on the other. Sample study is provided involving the evaluation of long-range utility generation expansion strategies. Experience from this example indicates the increased level of confidence for the final selected resource development strategy.

Integrated Decision Making Framework

An integrated MADM framework has been developed to handle complicated decision problems involving multiple attributes and uncertainties. The proposed MADM framework combines attractive features of tradeoff/risk analysis, utility function formulation and analytical hierarchy process, and thus provides a structured and enhanced decision analysis methodology with the following advantages.

- The AHP technique has been incorporated into the construction procedure of MADM formulation to facilitate the assessment process of preference functions and weighting parameters for the given attributes.

- A novel multi-dimensional numerical knee-set searching algorithm has been developed, which is based on the measure of likely range of composite distance, to identify acceptable plans or designs with respect to the given attributes under the specified future condition.
- The proposed MADM framework supports hybrid decision analysis with which alternative resource strategies can be examined both based on the rules of probability and from the perspective of robustness, providing a consistency check for the final resource development strategy.

Screening Applications

A useful screening technique has been developed for estimating the avoided cost of demand-side options, which integrates the aggregate DSM load shape impacts into the planning models in an efficient way thus avoiding the not-so-realistic chronological load-modification process. A few select cost-effective DSM portfolios may then be evaluated with supply-side alternatives in utility integrated resource planning models.

The general formulation of robust optimization for generation expansion planning (RO-GEP) under uncertainty has been discussed, followed by a reformulated RO-GEP modeling approach to facilitate the tradeoff between solution robustness and model robustness. The solution of robust optimization provides useful information regarding desirable generation mix for the target years over the planning horizon with which appropriate generation expansion configurations can be scheduled and evaluated using detailed and project-oriented utility planning models, such as WASP and EGEAS.

While this dissertation provides useful insight into the decision making process for strategic resource planning of electric utilities, it has limitations in its scope and the depth. For instance, it does not provide an example showing how the developed MADM framework can be used to support market driven resource investment decisions and how this enhanced MADM methodology can be used to develop a flexible resource strategy. These two important issues will be discussed in the next section as recommended future works.

8.2 Recommended Future Work

Flexible Resource Development

In recent years, the concept of flexibility has been recognized by electric utilities as an efficient resource development strategy to manage the risk associated with uncertainty factors [13,24]. Unlike the concept of robustness, which aims at developing a resource plan which can perform well under most, if not all, future conditions, a flexible resource plan allows easy and inexpensive changes to be made if future conditions deviate from the base assumptions. Some commonly flexibility enhancement options in utility integrated resource planning may include smaller commitments, adaptability and deferring decisions.

Conceptually, the developed MADM framework in this dissertation, which is a combined scenario analysis and external optimization modeling approach [9], is capable of evaluating various risk management strategies in strategic resource development, both robustness and flexibility. It is realized that multi-stage decision analysis would be required to address the influences of various uncertainty factors and flexibility enhancement options. However, the application of multi-stage decision analysis is restricted by its computational complexity which increases exponentially as the number of uncertainties, decision options and time periods represented in the decision model are increased. Thus, a practical solution is to develop a two-stage decision analysis model, a compromise between the simplified one-period modeling approach and the complicated multi-stage modeling approach. We should focus on the decision to be made at the first stage of decision process and examine the outcomes of different planning strategies over the entire planning horizon with proper flexibility enhancement measures implemented at the end of the first time period. This two-stage decision analysis model would provide a way of incorporating flexibility measures into the planning process and therefore adapting the course of resource development to changing conditions.

Market-Based Planning Approach

Deregulation and competition are forcing electric utilities and new players to perform market driven resource investment decisions [56,90]. For a vertically integrated utility, the need for new generation and transmission capacity is usually determined by an engineering reliability criterion based on a least-cost planning strategy. In competitive electric markets, the timing and type of new generation additions are driven more by expectations of market prices, generating plant capital and operating costs and resulting profit margins. The investment decisions on transmission expansion are more likely driven by a combination of traditional transmission-related reliability criteria and market-based opportunities for energy trading. Hence, new analytical models need to be developed and new decision attributes need to be defined in support of market-based investment decision making process. For this regard, advanced decision analysis technique, such as the MADM methodology developed in this dissertation, would be very helpful in market-based generation and transmission planning process by providing a structured project evaluation framework for performing uncertainty analysis and risk management.

Strategic planning in deregulated markets requires the integration of financial and engineering analysis that can simultaneously consider the economics and physical laws of power generation and transmission throughout the grid. Such an integrated engineering and economic analysis tool should help the industry to efficiently identify and evaluate potential generation and transmission opportunities in terms of project location and optimal project rating/capacity.

Deregulation and competition expose the responsible planner for generation and transmission investments to new uncertainties. For instance, uncertainties in competitive generation capacity additions in terms of the siting, timing and operating parameters are much greater than before due to the deregulated power supply markets and the increased number of independent power producers. Different power market structures and transmission tariffs may also have significant influences on the operating performance of new generation and transmission facilities in terms of loading conditions, investment cost recovery and financial profits. As such, uncertainty analysis and risk assessment are becoming much more important than before and major generation and transmission investment decisions must consider a great range of scenarios associated with different expansion strategies and projected market conditions.

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Appendices

A Analytic Hierarchy Process

The analytic hierarchy process (AHP) introduced by Saaty [1] is a structured approach for dealing with complicated multi-attribute decision problems. In AHP, the decision problem is broken up into layers, each layer influencing the entities in the layer immediately above it. Beginning, then, from the second layer of the hierarchy, the DM will be asked to compare the relative importance between each pair of factors at that layer with respect to every connected factor on the upper layer. For example, the following ratio questions may be asked in the assessment of attribute priorities: How much stronger or important does this attribute contribute to, dominate, influence, satisfy, or benefit the overall design objective than does the attribute with which it is being compared? This process will create a judgment matrix ***A*** with a row and a column for each attribute. For a decision problem with *n*-layer hierarchy, a set of judgment matrices will be generated for each of *n-1* evaluation levels.

Creation of Judgments

To create a judgment matrix with m factors, at least (m-1) ratio questions need to be asked. However, in compensation for any bias or inconsistency, redundant pair-wise comparisons are usually performed thus increasing the ratio questions up to $m(m-1)/2$.

If we denote the relative importance of ith factor with respect to jth factor by a_{ij}, then the relative importance of jth attribute with respect to ith factor would be $1/a_{ij}$, and the importance of every factor with itself (a_{ii}) is equal to one. The matrix obtained in this way is called "reciprocal judgment matrix" or "pair-wise comparison matrix" as given below.

$$\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \Rightarrow \mathbf{A} = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ 1/a_{12} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 \end{bmatrix} \quad \text{(A-1)}$$

For the entries of the judgment matrix, a set of integer numbers are recommended by Saaty [10] to represent the relative importance of one factor with respect to another. The table below gives the scales and their descriptions used for pair-wise comparisons.

Table A-1 Scales and Descriptions

Intensity of importance	Definition	Explanation
1	Equal importance	Two attribute contribute equally to the objective
3	Weak importance of one over another	Experience and judgment slightly favor one criterion over another
5	Essential or strong importance	Experience and judgment strongly favor one criterion over another
7	Demonstrated importance	An attribute is strongly favored and its dominance is demonstrated in practice
9	Absolute importance	The evidence favoring one attribute over another is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate values	When compromise is needed between the two adjacent judgments

Eigenvalue Prioritization Method

The eigenvalue prioritization method is a unique technique to determine the relative ranking of factors associated with each judgment matrix by normalizing the principal eigenvector ***p*** of judgment matrix ***A*** which is obtained by solving the following eigenvalue problem

$$\mathbf{A} \cdot \mathbf{p} = l_{\max} \cdot \mathbf{p} \qquad \text{(A-2)}$$

where λ_{max} is the principal or the largest real eigenvalue of judgment matrix ***A***. For a n-layer hierarchy, the composite priority vector form the bottom layer with respect to the top layer can be calculated using the following matrix equation:

$$\begin{bmatrix} p_{1,n}^{1,1} \\ p_{2,n}^{1,1} \\ \cdots \\ p_{n,n}^{1,1} \end{bmatrix} = \begin{bmatrix} p_{1,n}^{1,n-1} & p_{1,n}^{2,n-1} & \cdots & p_{1,n}^{m_{n-1},n-1} \\ p_{2,n}^{1,n-1} & p_{2,n}^{2,n-1} & \cdots & p_{2,n}^{m_{n-1},n-1} \\ \cdots & \cdots & \cdots & \cdots \\ p_{m_n,n}^{1,n-1} & p_{m_n,n}^{2,n-1} & \cdots & p_{m_n,n}^{m_{n-1},n-1} \end{bmatrix} \cdots \begin{bmatrix} p_{1,3}^{1,2} & p_{1,3}^{2,2} & \cdots & p_{1,3}^{m_2,2} \\ p_{2,3}^{1,2} & p_{2,3}^{2,2} & \cdots & p_{2,3}^{m_2,2} \\ \cdots & \cdots & \cdots & \cdots \\ p_{m_3,3}^{1,2} & p_{m_3,3}^{2,2} & \cdots & p_{m_3,3}^{m_2,2} \end{bmatrix} \begin{bmatrix} p_{1,2}^{1,1} \\ p_{2,2}^{1,1} \\ \cdots \\ p_{m_2,2}^{1,1} \end{bmatrix} \quad \text{(A-3)}$$

where m_i is the number of elements at layer i and $p_{i,j}^{k,l}$ is the priority of element i at layer j with respect to element k at layer l.

B Judgment Matrices and Priority Vectors

B.1 Judgment matrices and the computed priority vectors for the hierarchy shown in Fig. 5-2.

Level 2.1:	*The Least-Cost Objective*				
Utility	1	5	3	7	0.5738
Customers	1/5	1	1/2	1/3	0.1310
Regulators	1/3	2	1	5	0.2388
General Public	1/7	3	1/5	1	0.0564

Level 3.1:	*The Utility*				
Flexibility	1	1/5	1/2	1/3	0.0838
Cost	5	1	4	3	0.5462
Reliability	2	1/4	1	1/2	0.1377
Emissions	3	1/3	2	1	0.2323

Level 3.2:	*The Customers*				
Flexibility	1	1/7	1/2	1/3	0.0783
Cost	7	1	3	2	0.5073
Reliability	2	1/3	1	1/2	0.1517
Emissions	3	1/2	2	1	0.2628

Level 3.3:	*The Regulators*				
Flexibility	1	1/3	1/2	1/3	0.1091
Cost	3	1	2	1	0.3509
Reliability	2	1/2	1	1/2	0.1891
Emissions	3	1	2	1	0.3509

Level 3.4:	*The General Public*				
Flexibility	1	1/3	1/2	1/7	0.0722
Cost	3	1	2	1/3	0.2179
Reliability	2	1/2	1	1/5	0.1228
Emissions	7	3	5	1	0.5872

B.2 Judgment matrices and the computed priority vectors for the hierarchy shown in Fig. 6-4

Level 2.1: Increased Utilization of Renewable Energy Technologies

Lack of Resource	1	1/7	3	1	1/3	0.0921
Inadequate Funding	7	1	9	5	1	0.4327
Public Acceptance	1/3	1/9	1	1/5	1/5	0.0389
Political Will	1	1/5	5	1	1/5	0.1032
Immaturity of Technology	3	1	5	5	1	0.3330

Level 3.1: Lack of Resources

Incentive from Government	1	1/7	1/5	1/9	0.0406
Privatization	7	1	3	1/3	0.2853
Economic Instruments	5	1/3	1	1/3	0.1490
Promotion of Products	9	3	3	1	0.5252

Level 3.2: Inadequate Funding

Incentive from Government	1	1/7	1/9	1/9	0.0351
Privatization	7	1	1/3	1/5	0.1446
Economic Instruments	9	3	1	1	0.3755
Promotion of Products	9	5	1	1	0.4447

Level 3.3: Public Acceptance

Incentive from Government	1	1/7	1/9	1/9	0.0368
Privatization	7	1	1	1	0.2933
Economic Instruments	9	1	1	1/3	0.2425
Promotion of Products	9	1	3	1	0.4275

Level 3.4: Political Will

Incentive from Government	1	7	7	5	0.6569
Privatization	1/7	1	1/3	1/3	0.0569
Economic Instruments	1/7	3	1	3	0.1776
Promotion of Products	1/5	3	1/3	1	0.1086

Level 3.5: Immaturity of Technology

Incentive from Government	1	1/3	1/3	1/3	0.0927
Privatization	3	1	3	5	0.5356
Economic Instruments	3	1/3	1	1	0.1942
Promotion of Products	3	1/5	1	1	0.1775

Level 4.1: Incentive from the Government

Cost	1	7	3	0.6694
Environmental Consideration	1/7	1	1/3	0.0879
Reliability	1/3	3	1	0.2426

Level 4.2: Privatization

Cost	1	7	5	0.7147
Environmental Consideration	1/7	1	1/5	0.0668
Reliability	1/5	5	1	0.2185

Level 4.3: Economic Instruments

Cost	1	7	5	0.7147
Environmental Consideration	1/7	1	1/5	0.0668
Reliability	1/7	5	1	0.2185

Level 4.4: Promotion of Products

Cost	1	1/5	1/7	0.0778
Environmental Consideration	5	1	1	0.4353
Reliability	7	1	1	0.4869

C Feasible Plans and Conditional Decision Sets

Table C-1 Feasible Plans for Future A

Plan #	Wind Area (m^2)	Solar Area (m^2)	Substation Rating (kW)	Battery Rating (kWh)	Cost ($/kWh)	EENS (%)	SO2 (kg/year)
1	20000	10000	500	500	0.1414	1.8757	5111
2	20000	10000	500	1000	0.1438	1.8714	5068
3	20000	10000	600	500	0.1441	0.7041	5221
4	25000	10000	500	500	0.1463	1.5655	4804
5	30000	5000	500	500	0.1309	1.8062	5454
6	30000	5000	500	1000	0.1335	1.8062	5439
7	30000	5000	600	500	0.1337	0.6511	5562
8	35000	5000	500	500	0.1356	1.5124	5105
9	35000	5000	500	1000	0.1382	1.5701	5084
10	35000	5000	600	500	0.1384	0.4550	5204
11	35000	5000	600	1000	0.1410	0.4551	5183
12	35000	5000	700	1000	0.1443	0.0349	5223
13	35000	5000	700	500	0.1417	0.0349	5243
14	40000	5000	400	500	0.1391	4.3270	4476
15	40000	5000	400	1000	0.1417	4.2721	4456
16	40000	5000	500	500	0.1404	1.2626	4763
17	40000	5000	500	1000	0.1429	1.2620	4739
18	40000	5000	600	500	0.1433	0.3199	4852
19	40000	5000	600	1000	0.1458	0.3196	4827
20	40000	5000	700	500	0.1466	0.0030	4882
21	45000	0	500	500	0.1269	2.4406	5519
22	45000	0	500	1000	0.1295	2.4373	5508
23	45000	0	600	1000	0.1319	0.4904	5691
24	45000	0	600	500	0.1292	0.4941	5702
25	45000	5000	400	500	0.1441	3.8985	4173
26	45000	5000	400	1000	0.1465	3.8155	4139
27	45000	5000	500	500	0.1454	1.0502	4440
28	50000	0	500	500	0.1316	2.0025	5186
29	50000	0	500	1000	0.1341	1.9834	5168
30	50000	0	600	500	0.1340	0.2680	5349
31	50000	0	600	1000	0.1365	0.2512	5331
32	50000	0	700	500	0.1374	0.0336	5371
33	50000	0	700	1000	0.1400	0.0336	5351
34	50000	0	800	500	0.1410	0.0030	5374
35	55000	0	500	500	0.1364	1.6408	4867
36	55000	0	500	1000	0.1389	1.5808	4843
37	55000	0	600	500	0.1389	0.1904	5003
38	55000	0	600	1000	0.1414	0.1513	4977
39	55000	0	700	500	0.1424	0.0324	5018
40	55000	0	700	1000	0.1449	0.0324	4988
41	55000	0	800	500	0.1460	0.0010	5021
42	60000	0	400	1000	0.1430	4.8229	4195
43	60000	0	400	500	0.1406	4.9284	4235
44	60000	0	500	1000	0.1438	1.2980	4525
45	60000	0	500	500	0.1415	1.3512	4570
46	60000	0	600	500	0.1442	0.1870	4680
47	60000	0	600	1000	0.1465	0.1435	4634
48	65000	0	400	500	0.1459	4.3469	4009
49	65000	0	500	500	0.1470	1.2554	4299

Table C-2 Feasible Plans for Future B

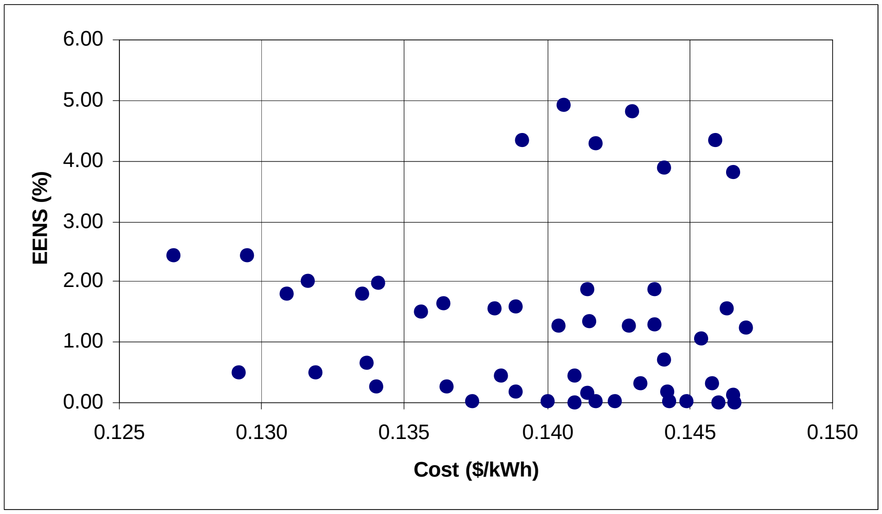
Plan #	Wind Area (m^2)	Solar Area (m^2)	Substation Rating (kW)	Battery Rating (kWh)	Cost ($/kWh)	EENS (%)	SO2 (kg/year)
1	20000	10000	500	500	0.1391	1.5943	4833
2	20000	10000	500	1000	0.1412	1.5495	4744
3	20000	10000	600	1000	0.1440	0.6010	4833
4	20000	10000	600	500	0.1420	0.6010	4926
5	20000	10000	700	500	0.1453	0.2219	4961
6	25000	10000	400	1000	0.1450	3.9583	4217
7	25000	10000	500	500	0.1444	1.3339	4570
8	30000	5000	500	1000	0.1316	1.6677	5187
9	30000	5000	500	500	0.1290	1.6760	5208
10	30000	5000	600	1000	0.1345	0.5710	5290
11	30000	5000	600	500	0.1319	0.5710	5312
12	30000	5000	700	500	0.1352	0.1002	5356
13	35000	5000	500	1000	0.1364	1.4046	4840
14	35000	5000	500	500	0.1338	1.4046	4866
15	35000	5000	600	500	0.1367	0.3932	4961
16	35000	5000	600	1000	0.1392	0.3932	4935
17	35000	5000	700	500	0.1401	0.0333	4994
18	35000	5000	700	1000	0.1426	0.0333	4969
19	35000	5000	800	500	0.1436	0.0010	4997
20	40000	5000	400	500	0.1373	4.0415	4267
21	40000	5000	400	1000	0.1397	3.9399	4242
22	40000	5000	500	1000	0.1412	1.1757	4502
23	40000	5000	500	500	0.1387	1.1760	4536
24	40000	5000	600	500	0.1417	0.3020	4618
25	40000	5000	600	1000	0.1442	0.3017	4584
26	40000	5000	700	500	0.1451	0.0030	4646
27	45000	5000	400	500	0.1423	3.6745	3973
28	45000	5000	400	1000	0.1447	3.5306	3934
29	45000	5000	500	500	0.1438	0.9768	4226
30	50000	0	500	500	0.1316	2.0025	5186
31	50000	0	500	1000	0.1341	1.9834	5168
32	50000	0	600	500	0.1340	0.2680	5349
33	55000	0	500	500	0.1364	1.6408	4867
34	55000	0	500	1000	0.1389	1.5808	4843
35	55000	0	600	500	0.1389	0.1904	5003
36	55000	0	600	1000	0.1414	0.1513	4977
37	55000	0	700	1000	0.1449	0.0324	4988
38	55000	0	700	500	0.1424	0.0324	5018
39	60000	0	500	500	0.1415	1.3512	4570
40	60000	0	500	1000	0.1438	1.2980	4525
41	60000	0	600	500	0.1442	0.1870	4680
42	65000	0	400	500	0.1459	4.3469	4009

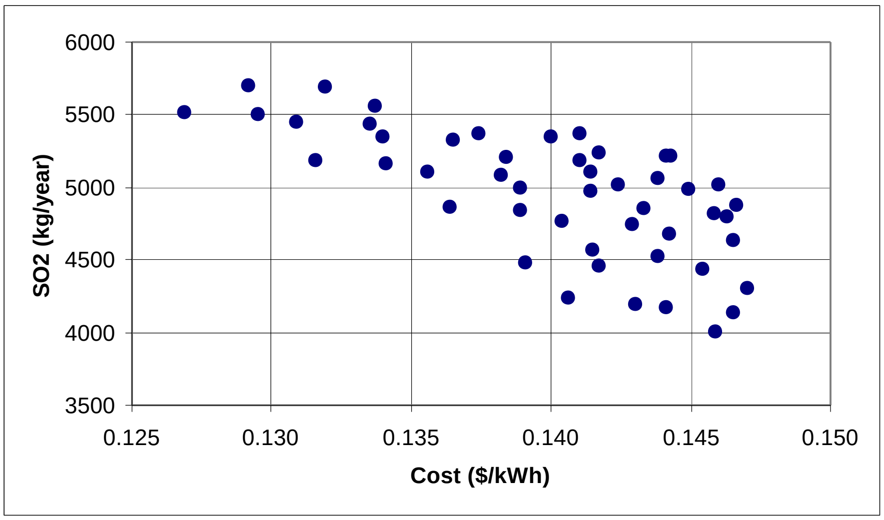
Table C-3 Feasible Plans for Future C

Plan #	Wind Area (m^2)	Solar Area (m^2)	Substation Rating (kW)	Battery Rating(kWh)	Cost ($/kWh)	EENS (%)	SO2 (kg/year)
1	20000	10000	500	1000	0.1397	1.3961	4558
2	20000	10000	500	500	0.1378	1.4426	4670
3	25000	5000	500	500	0.1227	1.8680	5343
4	25000	5000	500	1000	0.1253	1.8614	5323
5	25000	5000	600	500	0.1256	0.6968	5453
6	30000	5000	500	500	0.1257	1.5746	5004
7	30000	5000	500	1000	0.1301	1.5752	4978
8	30000	5000	600	500	0.1304	0.5117	5104
9	30000	5000	600	1000	0.1330	0.5117	5077
10	30000	5000	700	500	0.1338	0.0924	5143
11	30000	5000	700	1000	0.1363	0.0924	5117
12	35000	5000	400	500	0.1308	4.2791	4395
13	35000	5000	400	1000	0.1333	4.1635	4371
14	35000	5000	500	500	0.1324	1.3248	4672
15	35000	5000	500	1000	0.1349	1.3246	4368
16	35000	5000	600	500	0.1354	0.3694	4762
17	35000	5000	600	1000	0.1378	0.3695	4727
18	35000	5000	700	500	0.1387	0.0326	4793
19	40000	5000	400	500	0.1358	3.9034	4092
20	40000	5000	400	1000	0.1382	3.7558	4061
21	40000	5000	500	500	0.1374	1.1117	4352
22	55000	0	500	500	0.1364	1.6408	4867
23	55000	0	500	1000	0.1389	1.5808	4843
24	55000	0	600	500	0.1389	0.1904	5003

Table C-4 Feasible Plans for Future D

Plan #	Wind Area (m^2)	Solar Area (m^2)	Substation Rating (kW)	Battery Rating (kWh)	Cost ($/kWh)	EENS (%)	SO2 (kg/year)
1	20000	5000	500)	500	0.1154	1.9979	5359
2	20000	5000	600	500	0.1184	0.7859	5473
3	25000	5000	500	500	0.1204	1.7129	5028
4	25000	5000	500	500	0.1233	0.6008	5133
5	25000	5000	600	1000	0.1228	1.7116	4994
6	25000	5000	600	1000	0.1258	0.6008	5098
7	25000	5000	700	500	0.1267	0.1581	5174
8	25000	5000	700	1000	0.1291	0.1581	5139
9	30000	5000	400	500	0.1236	4.4925	4421
10	30000	5000	400	1000	0.1260	4.3346	4392
11	30000	5000	500	500	0.1253	1.4362	4707
12	30000	5000	500	1000	0.1278	1.4335	4664
13	30000	5000	600	500	0.1283	0.4471	4800
14	30000	5000	600	1000	0.1307	0.4471	4757
15	30000	5000	700	500	0.1317	0.0838	4843
16	35000	5000	400	500	0.1288	4.0131	4137
17	35000	5000	400	1000	0.1310	3.8747	4097
18	35000	5000	500	500	0.1304	1.1889	4402
19	35000	5000	500	1000	0.1328	1.1971	4349





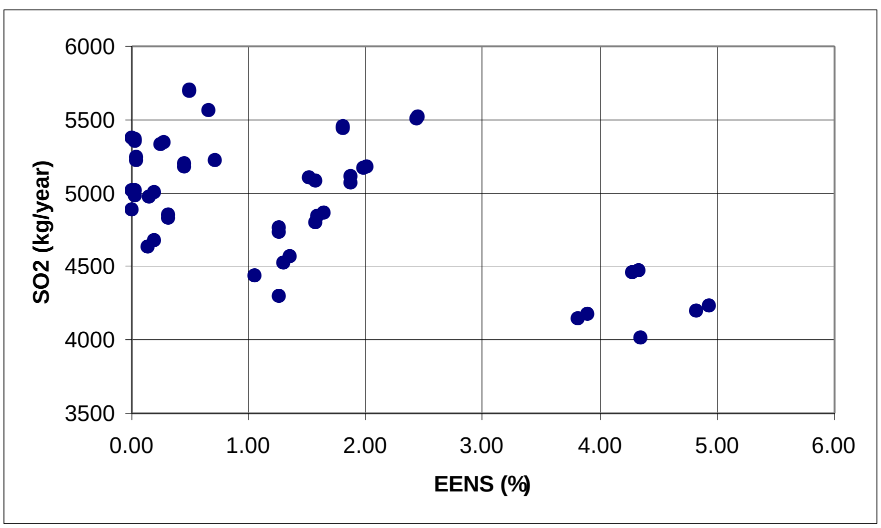


Figure C-1 Tradeoff Region or Feasible Plans for Future A

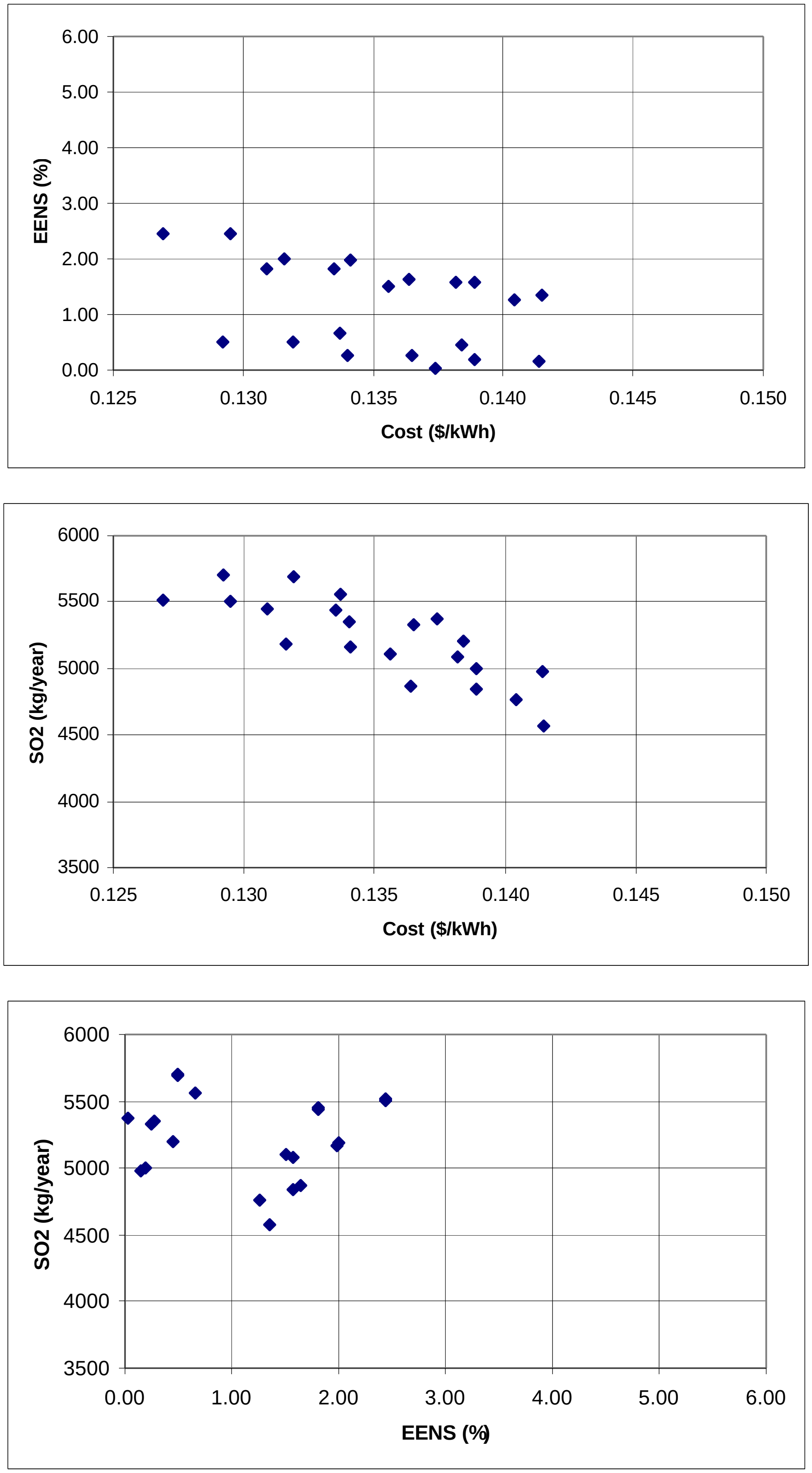


Figure C-2 Conditional Decision Set for Future A

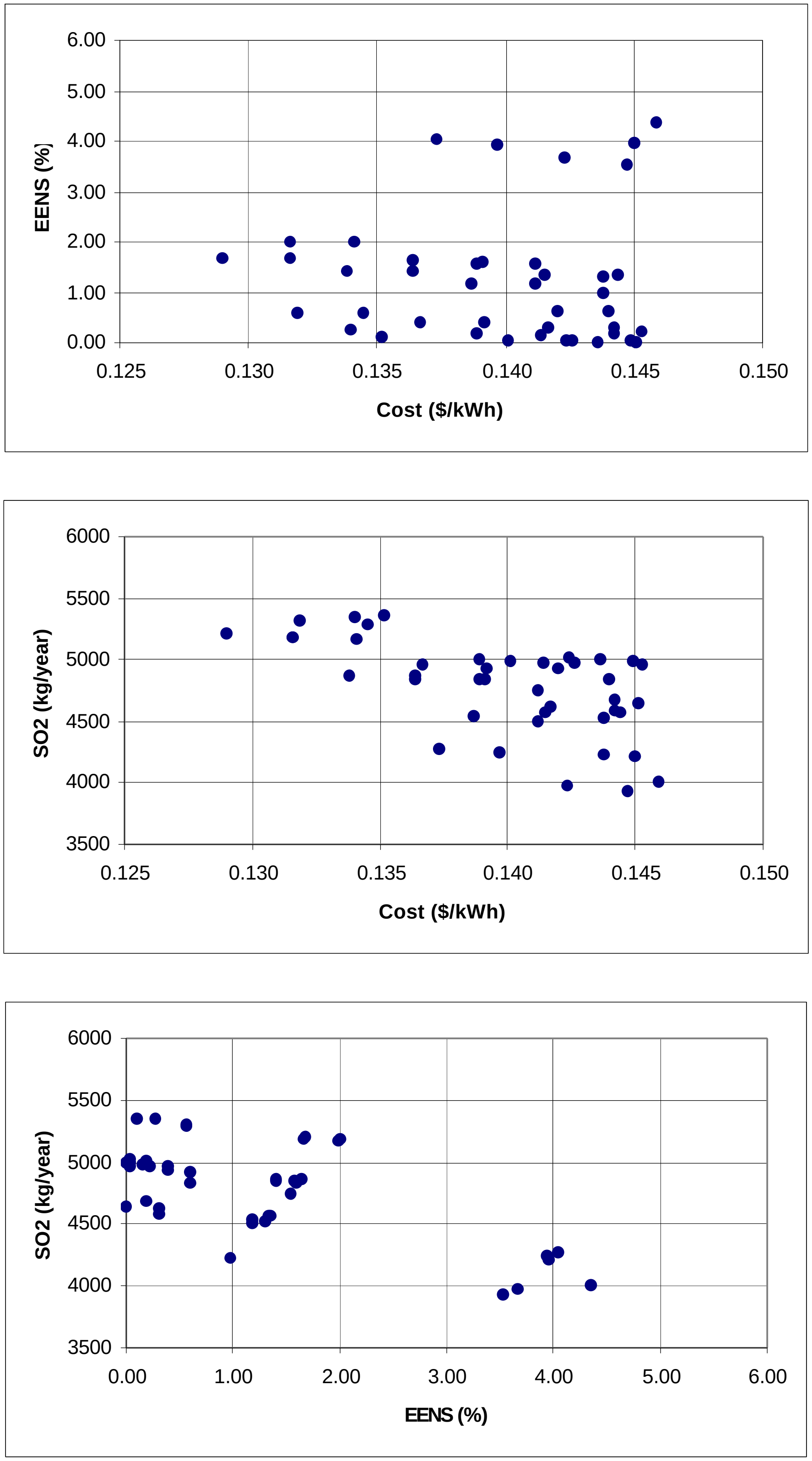


Figure C-3 Tradeoff Region or Feasible Plans for Future B

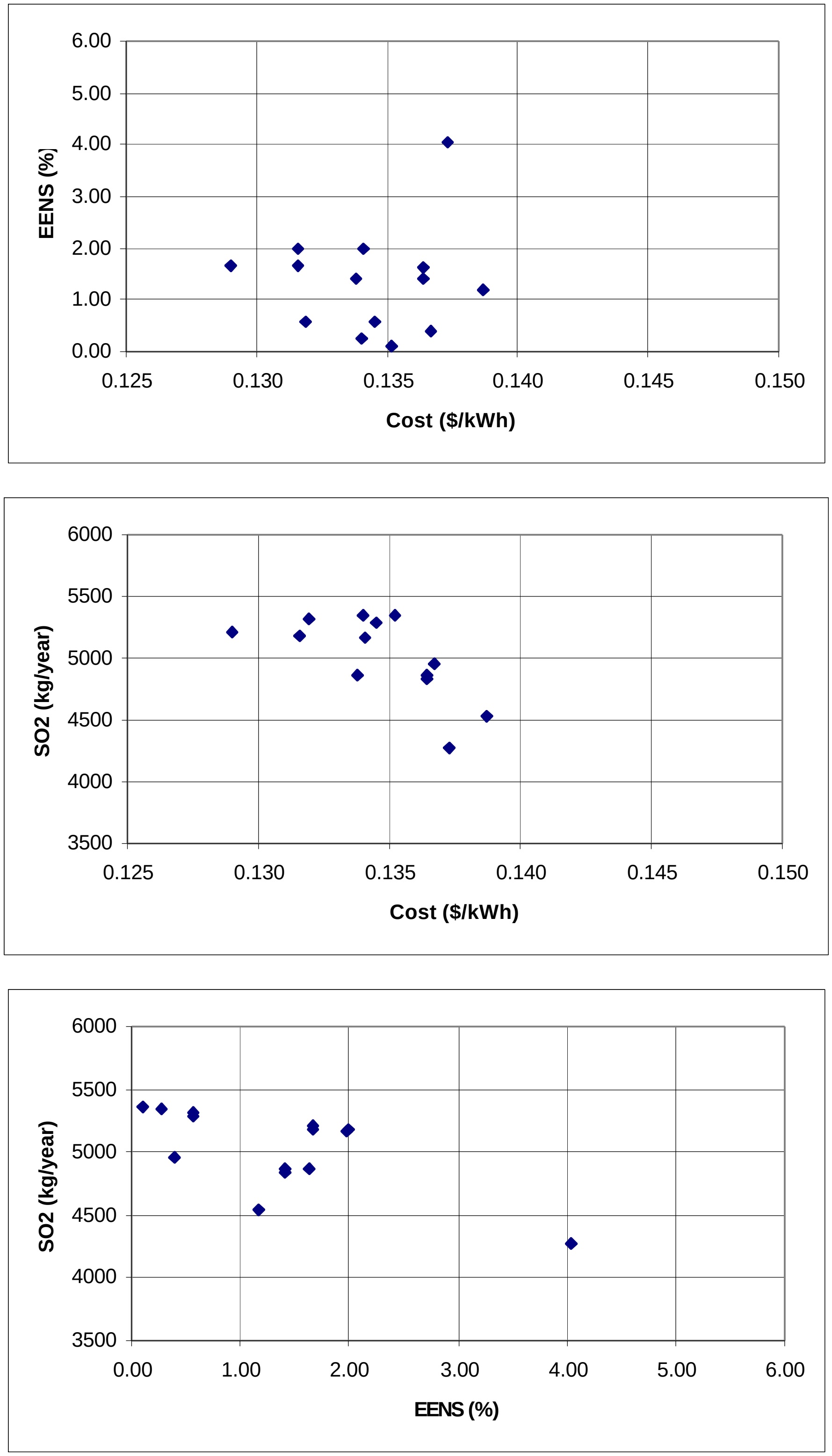


Figure C-4 Conditional Decision Set for Future B

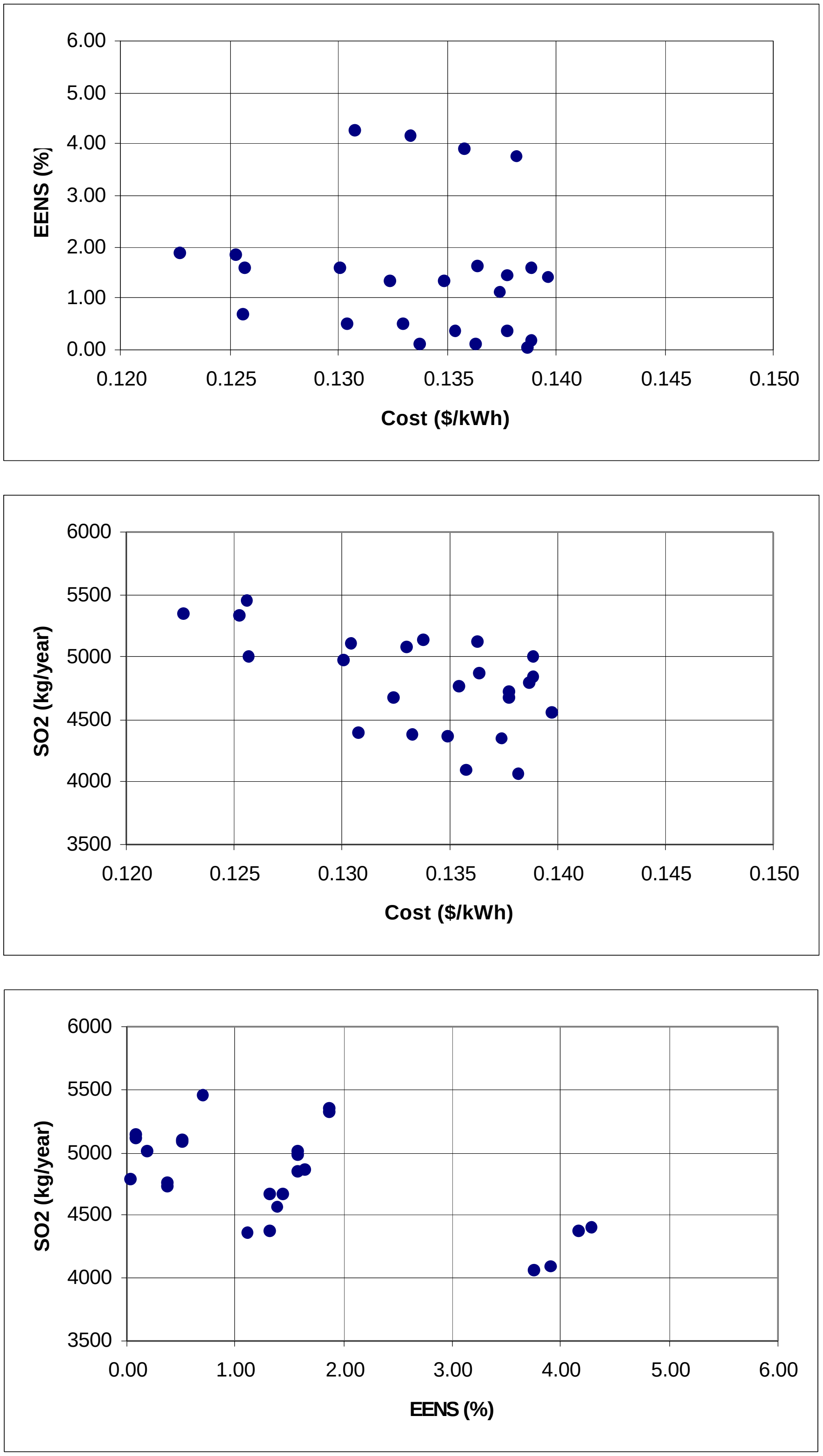


Figure C-5 Tradeoff Region or Feasible Plans for Future C

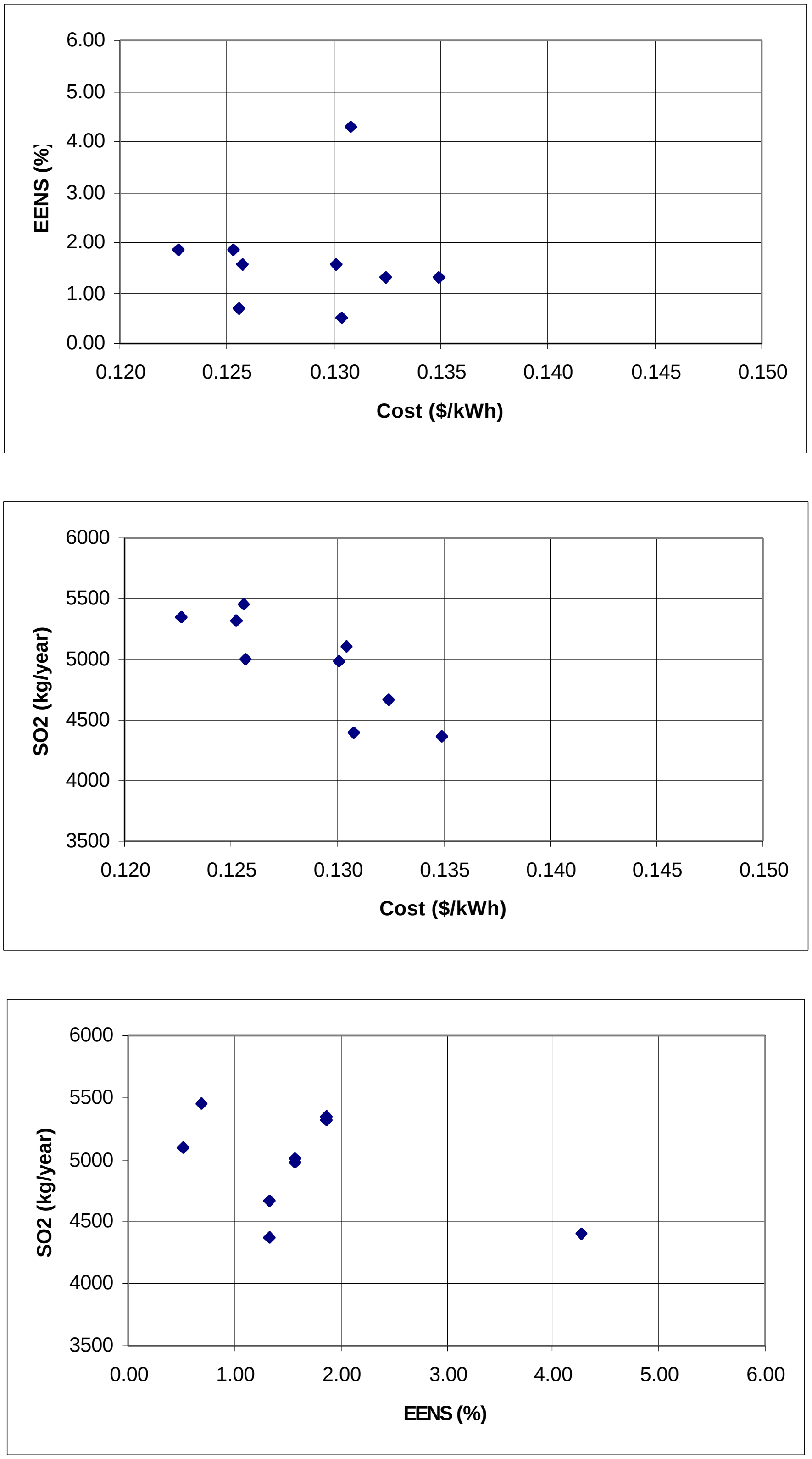
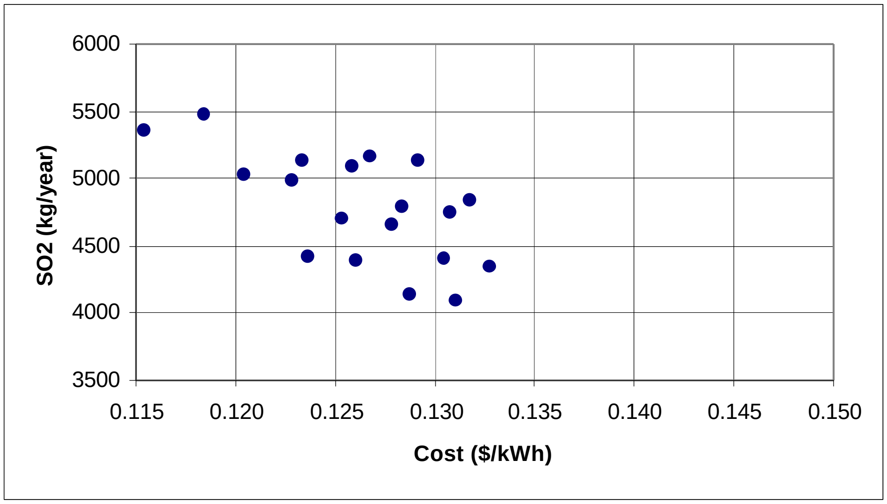
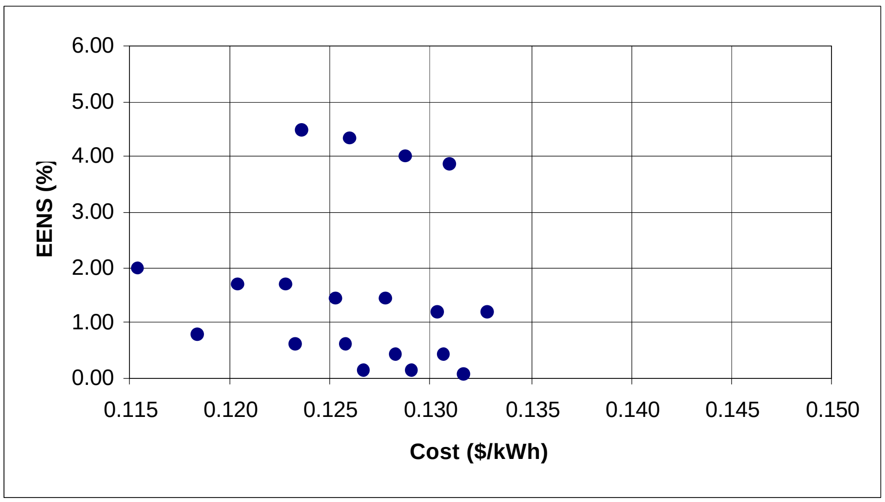


Figure C-6 Conditional Decision Set for Future C





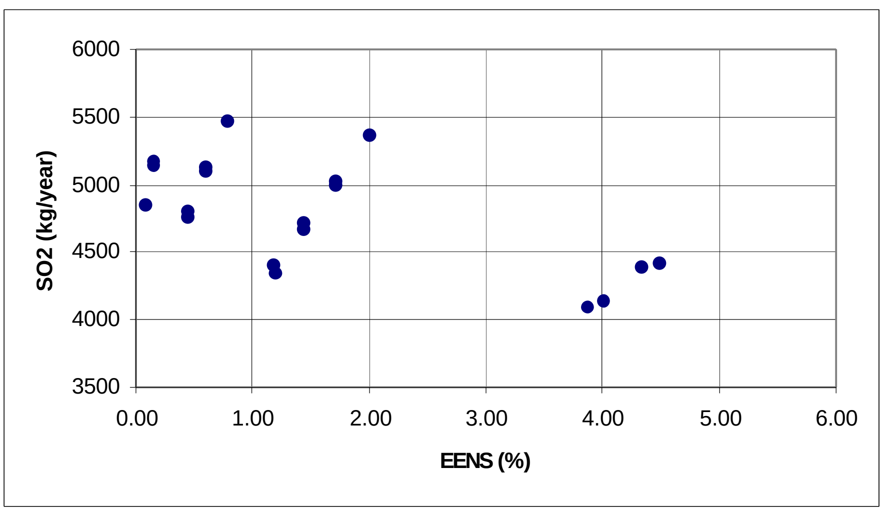
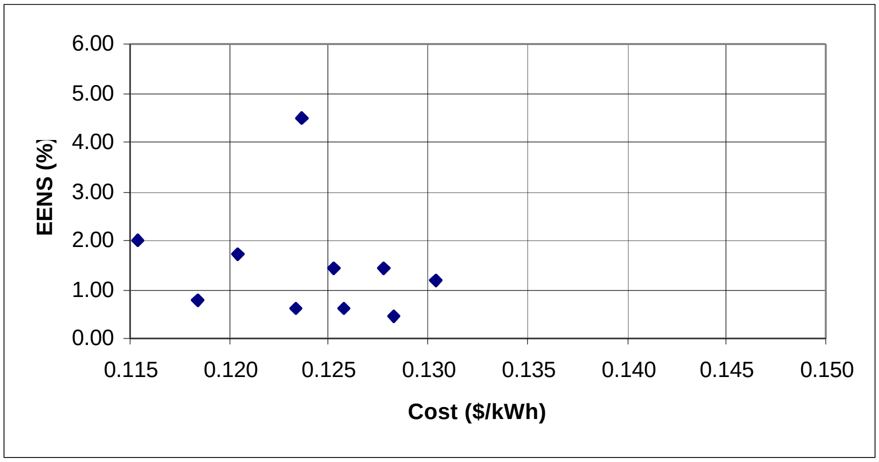
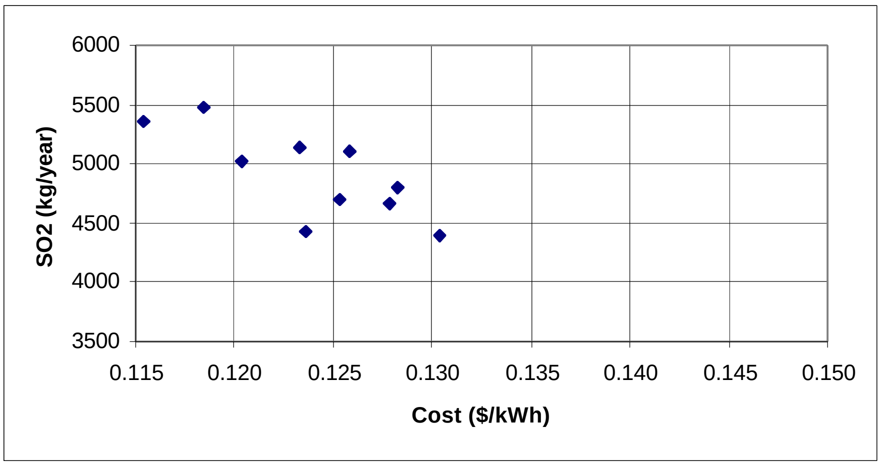


Figure C-7 Tradeoff Region or Feasible Plans for Future D





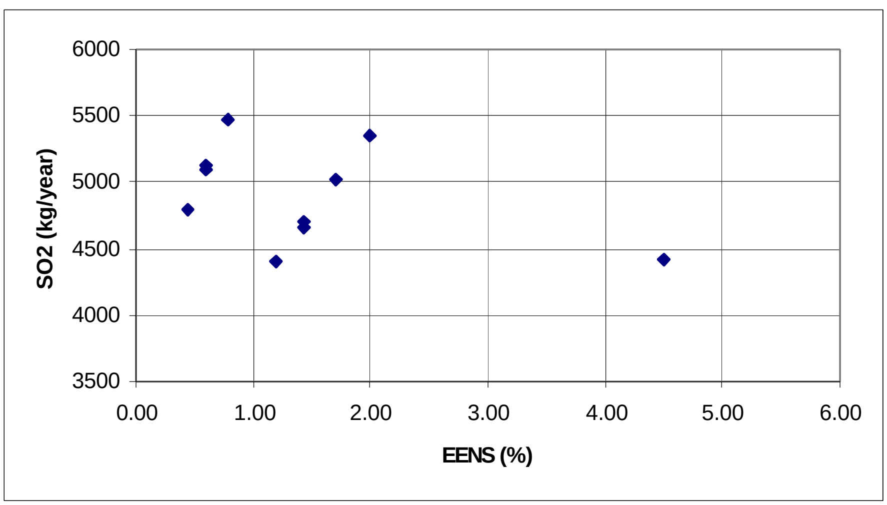


Figure C-8 Conditional Decision Set for Future D

Vita

Jiuping Pan

The author was born on May 15, 1955 in Qingdao, P. R. China. He received the B.S. and M.S. degrees in electrical engineering from Shandong University of Technology, P. R. China, in 1982 and 1990, respectively. He joined the faculty of the Department of Power Engineering of Shandong University of Technology in 1982 and was promoted to Associate Professor in 1992. From 1993 to 1995, he was a visiting scholar at the Center for Energy and Global Environment of Virginia Polytechnic Institute and State University (Virginia Tech). In August 1995, he enrolled the graduate program at Virginia Tech to pursue his Ph.D. degree. In December 1999, he successfully fulfilled the requirements for the degree of Doctor of Philosophy.

Since August 1999, he has been working with the Department of Electrical & Computer Engineering of Virginia Tech as a Research Associate. His main research interests include strategic resource planning; power system modeling and analysis; reliability evaluation; industry deregulation and transmission open access. He is a member of the Institute of Electrical and Electronics Engineers (IEEE).