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Propagation of uncertainty in a knowledge-based system to assess energy management strategies for new technologies

Chun-Yen Hsu
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**Propagation of uncertainty in a knowledge-based system to assess energy
management strategies for new technologies**

by

Chun-Yen Hsu

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Graduate Faculty in Partial Fulfillment of the
Requirements for the Degree of
DOCTOR OF PHILOSOPHY

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1995

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LIST OF SYMBOLS

η	energy efficiency
P	power
R	set of all real numbers
\in	belongs to; is an element of; is a member of
\notin	not belong to; is not an element of; is not a member of
$[a, b]$	closed interval; $x \in R, a \leq x \leq b$
U	universal set
S	sample space
$\{a, b, c\}$	set described as a list
$\{x g(x)\}$	set described by a rule
$A \cup B$	union of A and B
$A \cap B$	intersection of A and B
$\bigcup_{i=1}^n A_i$	union of A_1, A_2, \dots, A_n
$\bigcap_{i=1}^n A_i$	intersection of A_1, A_2, \dots, A_n
A^c	complement of A
\emptyset	empty set; a set with no elements
$A \subseteq B$	A is a subset of B
$A \subset B$	A is a proper subset of B

$A - B$	relative complement of B with respect to A
\vee	or
\wedge	and
\forall	for each
\exists	there exists
\oplus	combination
Σ	summation
$f : A \rightarrow B$	f is a function from A to B
(x, y)	ordered pairs
$A \times B$	Cartesian product of A and B ; $(x, y) \in A \times B$ if and only if $x \in A$ and $y \in B$
2^S	power set of S ; the collection set of all subsets of S
$2^S \times 2^S$	the set of all ordered pairs in sample space; $(A, B) \subseteq S \times S$ if and only if $A \subseteq S$ and $B \subseteq S$
$P(e)$	the probability that e will occur
$P(h e)$	conditional probability of h given e ; the probability that h will occur if e occurs
MB	measure of increased belief
MD	measure of increased disbelief
CF	certainty factor
Θ	the frame of discernment
m	basic probability assignment
Bel	belief function
Pl	plausibility function

$Ucty$	uncertainty function
μ	membership function
$V(g)$	a finite set of vertices
$A(g)$	a finite set of arcs
Z	adoption
X	rebate
PWF	pre-weighting factor
WF	weighting factor
SD	standard deviation
F	factor
CCT	percentage of customers contacted

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CHAPTER 1. INTRODUCTION

Overview of the Project

Energy efficiency of equipment can be defined as the ratio of the useful energy rate, P_{out} , to the input power, P_{in} ,

$$\eta = \frac{P_{out}}{P_{in}} \quad (1.1)$$

The input power is the sum of the useful energy rate and various internal losses, i.e.

$$P_{in} = P_{out} + P_{loss} \quad (1.2)$$

Thus, an alternative form of energy efficiency is

$$\eta = \frac{P_{in} - P_{loss}}{P_{in}} = 1 - \frac{P_{loss}}{P_{in}} \quad (1.3)$$

Since the summation of power losses are always greater than zero, the energy efficiency of any equipment will never exceed unity. However, the efficiency of this equipment can be increased by reducing the internal power losses as much as practical.

Energy efficiency has become an increasingly vital business since the oil embargo of 1973. A number of new technologies, including new lighting, electric heat pumps, motors, refrigeration systems, microwave clothes dryers, electric vehicles, more efficient gas furnaces, gas heat pumps, engine-driven chillers, absorption chillers, and

natural gas vehicles, have the potential to increase the efficiency of electric and natural gas use. Some of the technologies are commercially available and others are still under development.

To obtain the opportunities for energy savings and protect the environment, demand-side management (DSM) programs are planned and implemented. The number of utility-sponsored electrical DSM programs has increased from 134 in 1977 to about 1,300 in 1991 (Morron 1991). Approximately 21,000 megawatts (MW) of capacity and nearly \$21 billion of investment have been deferred because of these programs. By the year 2000, the deferrals are estimated to be 45,000 MW of capacity and \$45 billion of investment. The major reasons for addressing electrical DSM programs include:

1. They reduce the need to build new generating facilities that are expensive and difficult to site because of environmental concerns.
2. They reduce consumer electricity expense.
3. They reduce power plant emissions.
4. They increase utility profit in Iowa because the utilities can keep a part of the benefit generated from energy savings.

The most common electrical demand-side management programs could be classified into six groups: peak clipping, valley filling, load shifting, strategic conservation, strategic load growth, and flexible load shaping (Hayes 1989, Morron 1991). A graphical illustration of these possible DSM programs are given in Figure 1.1. Peak clipping reduces the customer peak-hour demand. Direct load control is the primary method.

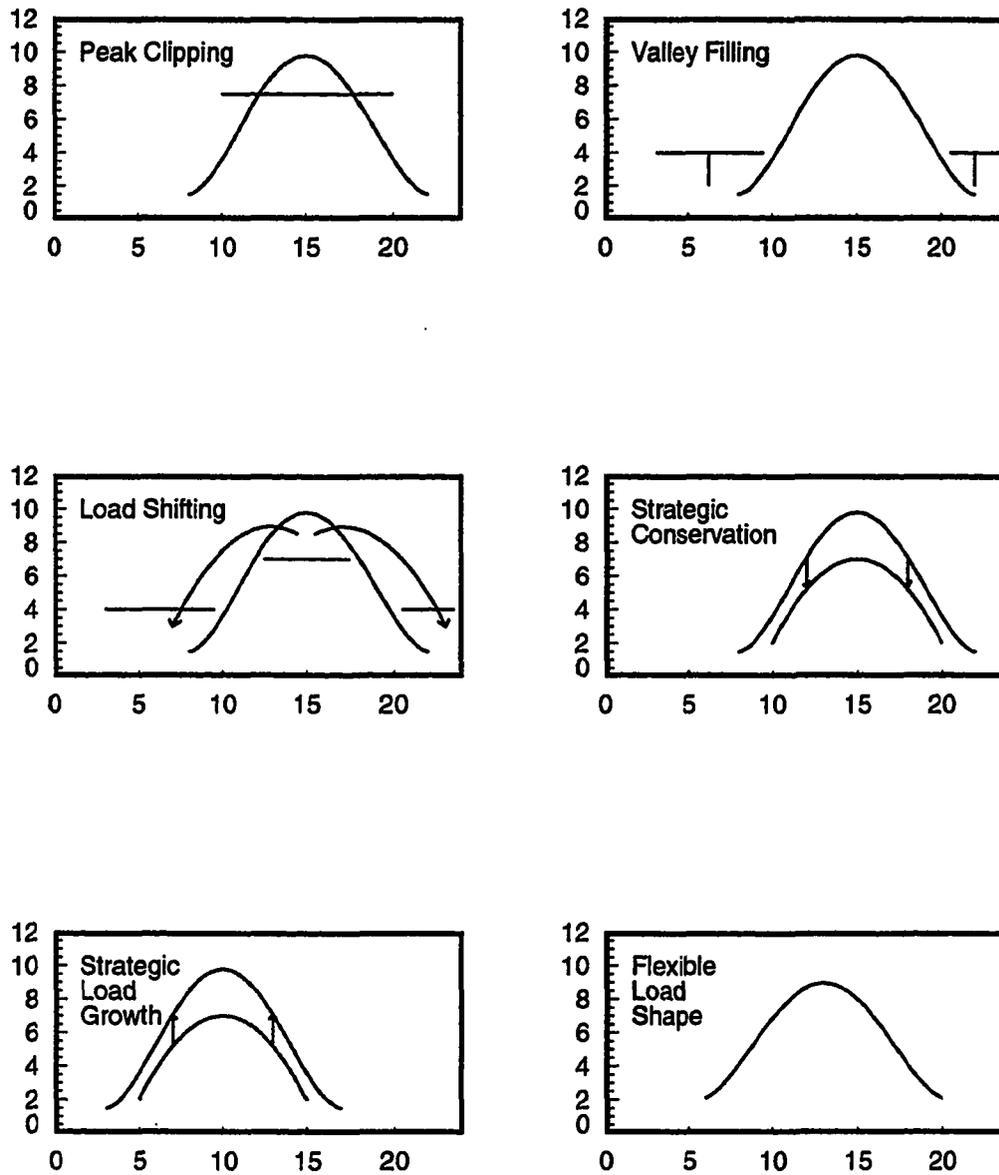


Figure 1.1: A graphical illustration of six possible demand-side management programs.

Valley filling increases demand using new technologies during off-peak hours through lower service charges. Thus, average generating costs can be reduced. Load shifting moves existing load from peak hours to off-peak hours. Thermal storage is the most common approach. Strategic conservation reduces demand by the adoption of higher efficiency equipment instead of lower efficiency equipment. Increasing the demand of existing technologies during specific seasons or off-peak hours is called strategic load growth. Lower energy cost is charged. Flexible load shaping adjusts the load shape by agreement with customers using incentive policies. The major methods for DSM programs are summarized in Table 1.1.

Table 1.1: The most common electrical demand-side management methods.

Peak clipping	reduce the peak hour demand by direct load control, load shedding, interruptible rates, etc.
Valley filling	increase off-peak hour demand using new technologies.
Load shifting	move loads from peak hours to off-peak hours.
Strategic conservation	reduce demand using higher efficiency equipment.
Strategic load growth	increase off-peak hour demand of existing technologies.
Flexible load shaping	adjust load shape by incentive policies.

Gas utilities also offer DSM programs to increase the use of more efficient gas technologies. The major part of their DSM programs are rebates and selling gas technologies at mature market price. Thus, consumers pay an equal amount of money as buying electric equipment but benefit from lower operating and maintenance costs and help level electric peak power demand.

This project will focus on conservation. We expect to lower energy demand using efficient technologies to replace inefficient technologies. Therefore, from our point of view, demand-side management means that utilities try to sell less electricity and more natural gas.

The keys to success of DSM programs are the adequacy of incentives, use of innovative techniques, and strong marketing programs. Assessing the DSM policies to conserve energy and control demand, more detailed information on the impacts of these new technologies are needed. The technologies that might be adopted when typical Iowa residential, commercial, industrial, and transportation sectors are considered. The energy efficiencies, cost savings, and anticipated usage of each new technology are evaluated according to typical Iowa conditions. The assessment of these technologies will provide very useful information to the utilities to determine what technologies ought to be emphasized in their next DSM programs.

Objective

The objective of this project is to investigate the propagation of uncertainty in a knowledge-based system that assesses energy management strategies for new gas and electric technologies that can help reduce energy consumption and demand.

Description of the Project

The major activities of the project are described as follows:

1. To compile a list of potential new technologies that will impact electrical and natural gas energy use in the residential, commercial, industrial, and trans-

portation sectors.

2. To determine the maximum potential technical energy savings of each promising new technology.
3. To assess the economic feasibility and anticipated use of each new technology.
4. To provide an overview and comparison of major uncertainty representing mechanisms.
5. To develop a knowledge-based system (KBS) that can be used by utilities to evaluate various methods of promoting some of the new energy saving technologies. Different methods for evaluating uncertainties in the given information are assessed.
6. To provide a list of references on the various technologies.
7. To define the future work.

The results from the project are:

1. The adoption of new technologies will benefit consumers, utilities, and the environment. A key issue is to increase the market penetration of these technologies through successful energy management programs.
2. From the comparison of major uncertainty representing mechanisms, we found that fuzzy logic and Dempster-Shafer theory are appropriate methods to be applied in utility prediction knowledge-based systems to estimate energy and demand impacts.

3. Human input is required to determine the shapes of the membership functions for fuzzy logic mode and basic probability assignments for Dempster-Shafer mode. Different input for these quantities will give different uncertainties in the results.
4. The report and knowledge-based system should help utilities determine which new technologies are most promising and which strategies should be emphasized in their energy management programs.

CHAPTER 2. NEW TECHNOLOGIES FOR ELECTRIC AND NATURAL GAS USE

The major potential new technologies that will impact electric and natural gas efficiencies and use are distributed throughout the residential, commercial, industrial, and transportation sectors. An overview of each of these technologies in each sector is given below.

Overview of Energy Efficiency and New Technologies

In recent years, energy efficiency has become an important topic, which occupies the central position in any serious discussion of an energy plan (Barker 1992, Faruqui *et al.* 1990, Miller 1989, Rost 1992, Schipper 1992). Significant amounts of time and money are being invested to study how to promote energy efficiency and to find better ways to gain more benefit from the energy we do use. The concept of energy efficiency doesn't just mean conservation. It means using the primary energy resources more productively and taking advantage of the most efficient technologies available. We may not need to reduce the quality of life to save energy. We could obtain high quality service and still protect the environment.

Advanced technical developments in materials, controls, lighting, motors, appliances, and a wide variety of new technologies have sped up the promotion of energy

efficiency. More than sixty energy sector leaders in the U.S. had a meeting in 1992 to explore the future possibilities in energy efficiency (Barker 1992). They concluded three major points for energy savings. The first one is that the potential savings for electricity are about 70% by using new end-use technologies. The second one is that we need to introduce the new technologies to the public immediately. The third one is that the efficient use of energy adds extra-value to our products and reduces the financial loads of producers and customers.

New electric and natural gas technologies can lead to more efficient utilization of energy. Some technologies are already available in the marketplace, some are on the way to the market, and others are just being investigated. A report by the Electric Power Research Institute (EPRI) indicates that the United States consumed about 7% more primary energy in 1991 than it did in 1973, while the gross national product (GNP) increased about 46% (Jaret *et al.* 1992). The major part of this increase is because of the wider use of electricity even though the highest conversion efficiency of primary energy resources to electricity is limited to 53%.

Electricity is a versatile and controllable form of energy. It can perform many tasks effectively and efficiently (Johansson *et al.* 1989, Gellings *et al.* 1992, Jaret *et al.* 1992). Advanced end-use electric technologies provide an opportunity to meet the world's future energy needs and lessen environmental pollution. Electricity can be controlled more accurately than other forms of energy, so a large amount of energy loss can be avoided by getting more efficient technologies adopted. New electric technologies, such as advanced heat pumps, freeze concentration¹, and electric vehicles

¹Freeze concentration is a technology to separate and remove a liquid from a mixture using electric refrigeration.

(EVs), are just some of the examples of electrical technologies that promise higher efficiencies.

The maximum technical potential (MTP) is defined as 100% adoption of the new technology. The MTP is never achieved, or even generally approached, in real situations. The following discussion presents estimates from a number of sources. Almost without exception, they are overly optimistic. A study by Faruqui *et al.* (1990) indicates that the maximum technical potential electric energy savings are distributed throughout the residential, commercial, industrial, and transportation sectors. The main results were summarized and discussed in several other articles (Lamarre *et al.* 1990, Gellings and Yau 1991, Wikler *et al.* 1993). The energy-saving technologies are classified as electricity-saving technologies² and electrification technologies³. The MTP electric energy savings in the year 2000 by electricity-saving technologies is estimated to be 24%–44% or 8,000–14,400 trillion Btu. The residential savings range from 27%–46%, the commercial savings from 23%–49%, the industrial savings from 24%–38%. Each of these three sectors accounts for approximately one third of the total electric use (35% for the residential sector, 31% for the commercial sector, and 34% for the industrial sector in 1987). Meanwhile, replacing fossil fuel with efficient electric end-use in the primary applications in the industrial and transportation sectors will result in a MTP energy savings of 363 trillion Btu in the year 2000. Forty percent of the transportation energy could be saved by electrification technologies. The MTP energy savings results from the two categories of technologies is shown in Table 2.1.

²Electricity-saving technologies replace inefficient electric equipment with more efficient electric equipment.

³Electrification technologies replace fossil-fuel equipment with electric equipment.

Table 2.1: Estimated maximum technical potential (MTP) energy savings by electricity in the U.S. in 2000.

Unit in trillion Btu ^a				
Technologies	Sector	Low MTP	Mean MTP	High MTP
Electricity-Savings Technologies	Residential	2,889	3,864	4,839
	Commercial	2,339	3,697	5,054
	Industrial	2,771	3,620	4,468
Electrification Technologies	Industrial		290.6	
	Transportation		72.7	
Total Mean MTP			11,544	

^a1 Btu = 1.0551 kJ

The mean value of the maximum technical potential energy savings in the U.S. is estimated to be 11,544 trillion Btus. The major contributors to the potential savings in the residential sector are technological advancements in space heating, water heating, and residential appliances. Many of these advancements are only used in new dwellings. Efficient electric heat pumps would reduce energy use for space and water heating. Compact fluorescent lamps with an incandescent-like color spectrum would benefit residential and commercial lighting. The biggest contributors to the potential savings in the commercial sector are space cooling, lighting, and office equipment. Smart control systems can save more energy through the integrated design of commercial building systems. To save the full potential in the industrial sector, motors with adjustable-speed drives (ASDs) should be used. Commercial and industrial applications are generally dependent on the payback period – the shorter the better. One potential for saving energy in the transportation sector is to increase the adoption of electric vehicles, which to date have only been used as metropolitan delivery vehicles.

In another report, the Rocky Mountain Institute, optimistically estimates the maximum long term potential to save electricity is about 75% (Fickett *et al.* 1990). They also say that if new end-use technologies are applied appropriately, electricity can be saved without sacrificing the quality of life. Many new devices provide even better service than the conventional equipment they replace.

According to Fickett *et al.* (1990), the biggest savings of electricity can be obtained in a few areas such as lighting, motors, and refrigeration. Lighting accounts for about 25% of the consumption of electricity in the United States, and may have the largest potential for reducing the use of electricity for all end-use technologies. Efficient lighting devices are available for most applications. New equipment provides the same amount of light as old systems, with lower glare, lower noise, more comfortable color, and no flicker. Electric motors have the second largest potential for reducing energy consumption, because they consume about 70% of all industrial electricity. Improved motor systems can save half of the electricity that is now consumed by adjustable-speed drives, high efficiency motors, improvements in the choice and maintenance, etc. Some innovations, such as electronic adjustable-speed drives, can reduce the use of electricity in pumps and fans. The consideration of new technologies should be part of a whole system design to save energy and cost.

To increase the use of more efficient end-use electric technologies, strategies are needed to influence adoption by consumers and to reduce possible barriers. The value of energy efficiency is often discounted by consumers in their purchasing decisions. The initial costs of products usually carry much more weight than the energy efficiency, even though lower operating and maintenance costs can save consumers much more money in the long run. Information for evaluating payback periods and the

benefits of the new electrical technologies should be explained to customers.

Another way to save energy and reduce environmental pollution is to use more efficient natural gas technologies. New gas technologies provide consumers greater value through convenience, ease of operation, comfort, and safety. According to an article in *Plant Engineering* (Katzel 1992), plentiful and low-price natural gas supply will continue through the year 2050. Thus, we have good opportunities to expand the use of natural gas. Promising applications for natural gas include residential gas furnaces, gas heat pumps, absorption chillers, and natural gas vehicles.

Gas cooling is a primary natural gas application (AGCC 1994). The reasons for renewed interest in gas cooling include:

1. the availability of more efficient and reliable gas cooling equipment
2. phase-out of CFCs because of environmental concerns
3. low natural gas prices
4. reduction of energy bills and peak electric demand
5. incentives from local utilities
6. increased national security since about 95% of natural gas supply is domestic

More efficient, microprocessor-controlled cooling equipment is available for residential, commercial, and industrial applications. Elimination of expensive electric demand charges is an important advantage of gas cooling technologies. On the other hand, higher initial cost is a major disadvantage.

Basis for Comparisons

The energy-saving technologies are classified as electricity-saving technologies, electrification technologies, and gas technologies. For electricity-saving technologies, the percentage of energy savings for each technology is derived from the new technology compared to the older technology based on electricity consumption. For electrification technologies, the percentage of energy savings for each technology is compared based on the primary energy resources consumption. For gas technologies, the percentage of energy savings for each technology is compared based on the consumption of natural gas except natural gas vehicles. The electricity-saving technologies include lighting, motors, and refrigerators. The electrification technologies include microwave clothes dryers, freeze concentration, electric vehicles, and light rail transit systems. Electric heat pumps are treated as an electricity-saving and electrification technology. The gas technologies include gas furnaces, gas heat pumps, engine-driven chillers, absorption chillers, and natural gas vehicles.

New Technologies in the Residential Sector

The potential technologies for saving energy in the residential sector include new lighting, electric heat pumps, electric motors, microwave clothes dryers, high-efficiency refrigerators, more efficient gas furnaces, and gas heat pumps. With the exception of lighting, most of these technologies will be installed only when the existing technology is worn out and needs replacing, or when a new dwelling is acquired.

Residential Lighting

Lighting is a significant residential electrical load, which accounts for about 10% of residential electricity use (Hendrix and Ushimaru 1992). In the United States, the electrical consumption in residential lighting is in the range 40–50 billion kWh each year. Residential lighting is dominated by incandescent lamps in spite of the more efficient compact fluorescent lamps (CFLs) that are available in the marketplace. Replacing incandescent lamps with energy-efficient compact fluorescent lamps obviously reduces demand for electricity. According to manufactures' reports, residential compact fluorescent lamps are about four times more efficient than conventional incandescent lamps and can last at least 10 times longer.

Residential high efficiency programs contain two major technologies: halogen lamps and compact fluorescent lamps (EPRI 1992b). The retail price of halogen lamps is about twice that of conventional incandescent lamps. Halogen lamps can be fitted into existing incandescent lamp fixtures. A 60-watt incandescent lamp could be replaced by a 52-watt halogen lamp, thus, saving about 13% of the energy. The compact fluorescent lamp's retail price is a little less than 20 times the price of traditional incandescent lamps. An 18-watt compact fluorescent lamp could replace a 75-watt incandescent lamp, hence, the energy savings is 76% per bulb. Overall, a high-efficiency residential lighting system can reduce residential lighting energy consumption up to 50% (Faruqui *et al.* 1990). Compact fluorescent lamps need new fixtures and other changes to fit existing lamp installations. This increases the total cost of the technology. However, the life of compact fluorescent lamps is about 13 times that of incandescent lamps. If the customers use compact fluorescent lamps to replace the inefficient incandescent lamps, a large amount of electric energy can be

saved. Referring to a paper of Nadel *et al.* (1993), published in *Energy*, the maximum technical potential energy savings of residential lighting is estimated to be 47% by the year 2010.

The cost savings of using a CFL is presented by a simple example. Consider a 75-watt incandescent lamp replaced by an 18-watt CFL that puts out the same amount of light. The life of an incandescent light bulb is 1,000 hours, and that of a compact fluorescent lamp is 13,000 hours. Assume the initial cost of an incandescent light bulb is \$1, and that of a compact fluorescent lamp is \$12. The cost of a CFL fixture is \$12, and that of incandescent lamp is zero since it is existing. The average electric energy cost is assumed to be \$0.05/kWh. The cost comparisons of replacing an incandescent lamp system with a CFL system are shown in Table 2.2 based on the life cycle of the CFL system. For 13,000 operating hours, the total cost of an incandescent lamp system is \$67.75, and that of a CFL system is \$37.14. Thus, the cost savings is 45% over existing system. We can compare the costs of a new incandescent lamp system with a CFL system if the fixture cost of an incandescent lamp is known, for example \$2. The comparisons are given in Table 2.3. The total costs of the new incandescent lamp system is \$69.75. Therefore, the cost savings becomes 47%.

An article published in the *EPRI Journal* (Lamarre *et al.* 1993) describes important information about compact fluorescent lamps. CFLs were introduced to U.S. customers about ten years ago. Up to now only a small group of people have accepted compact fluorescent lamps. The primary reasons for low acceptance are high initial cost, incompatibility with existing fixtures, incompatibility with dimming devices, and not being suitable for tasks such as reading. According to an EPRI survey

Table 2.2: Cost comparisons of replacing an incandescent lamp system with a CFL system.

Cost	Incandescent Lamp System	CFL System
Fixture	\$0 (existing)	\$12
Lamp	$\$1 \times 13 = \13	\$12
Operating	$\frac{75 \times 13,000}{1,000} \times 0.05 = \54.75	$\frac{18 \times 13,000}{1,000} \times 0.05 = \13.14
Total	\$67.75	\$37.14
Savings	$(\$67.75 - \$37.14) / \$67.75 = 45\%$	

Table 2.3: Cost comparisons of a new incandescent lamp system with a CFL system.

Cost	Incandescent Lamp System	CFL System
Fixture	\$2	\$12
Lamp	$\$1 \times 13 = \13	\$12
Operating	$\frac{75 \times 13,000}{1,000} \times 0.05 = \54.75	$\frac{18 \times 13,000}{1,000} \times 0.05 = \13.14
Total	\$69.75	\$37.14
Savings	$(\$69.75 - \$37.14) / \$69.75 = 47\%$	

(Lamarre *et al.* 1993), 43% of CFL users and 53% of nonusers would probably not purchase CFLs in the future. Approximately 25% of CFL users are willing to buy compact fluorescent products in the future because of their concern for energy savings and environmental protection. Another study funded by EPRI reveals that many customers are dissatisfied with the ability to meet manufacturers' claims for light output, life expectancy, and versatility. This results in consumers' returning to the use of inefficient incandescent lamps. Some of these problems result from lack of information and misunderstanding. A number of studies have indicated that the lack of information is one of the most important barriers to the adoption of new lighting technologies (Nadel *et al.* 1993). The manufacturers' claims may be technically ac-

curate, but some factors reduce the CFL quality. For example, if a lamp is installed in a fixture to direct the light upwards, the light output can be decreased by up to 30%. Similarly, longevity can be reduced by frequent turning on and off. The key point is that more complete information should be delivered to customers.

The use of CFLs in American houses is negligible; however CFLs supply more than 80% of Japan's residential lighting (Lamarre *et al.* 1993). Therefore, the U.S. residential sector is a potential market for efficient lighting technologies. To encourage the use of CFLs for residential lighting, several institutions, including manufactures and retailers, electric utilities, governmental bodies related to energy programs, and sales of CFLs, are involved to educate the public about applications where they can be used and design various strategies to increase customer adoption. To date, these strategies have met with limited success.

Compact fluorescent lamps are available in a wide variety of colors in addition to the most commonly used cool white (Eley 1992, Eley *et al.* 1992, Eley *et al.* 1993, Gough and Blevins 1992). Consumers are still reluctant to shift their preference from inefficient incandescent lamps to far more efficient lighting sources because of technical, economic, and social reasons. To increase consumer adoption of compact fluorescent lamps, several barriers must be overcome, such as high lamp cost (typically up to \$25 per lamp), limited availability (not available in stores where light bulbs are purchased), limited models of fixtures and lamp sizes, consumers' preference for incandescent lamp characteristics, and misconceptions about compact fluorescent lamps. Characteristics of CFLs such as energy savings, convenience, ease of control, long life, and benefit to the environment should be strongly emphasized. The utilities and government play the major roles for increasing the market penetration of

energy-efficient residential lighting devices. To enhance the adoption of new residential lighting technologies, more innovative demand-side management programs are needed. Nevertheless, effective programs depend on accurate estimates of current lamp use (Nielsen 1993) and the potential savings of energy-efficient lighting technologies (Bartlett 1993). Many estimates are currently subject to large measurement error. Therefore, a detailed structural information and data analysis of residential lighting consumption is needed.

The availability of new lighting fixtures using CFL technology in K-Mart, Wal-Mart, and furniture stores would speed the adoption of the technology.

Residential Heat Pumps

Electric heat pumps offer more efficient space heating, space cooling, and water heating in houses when compared to older equipment of the same type. They use electricity to collect and concentrate energy from the air or the ground. Electric heat pumps can deliver more energy for heating than they consume in electricity. Advanced designs of electric heat pumps have led to significant efficiency gains in recent years (Ganji 1991, Ganji and Lloyd 1991, Kesselring 1993). They could not only enhance energy efficiency and reliability for customers, but also reduce the peak power demand for the utilities. Because of their higher installed and operating costs, electric heat pumps are not always competitive with gas furnaces in cold climates. In some instances, heat pumps may not be sufficient.

The capacity of an electric heat pump depends on its application and motor/compressor combination (Chen and Freedman 1990). For example, an average

capacity of a residential heat pump is about 3 tons⁴ for a 2,000 ft² house in cold climates. The technology for residential heat pumps is typically a reciprocating compressor driven by a single-speed motor. In the quest for higher energy efficiency, several new features such as variable-speed motor control, more efficient rolling pistons, and scroll compressors, have been incorporated into the design of residential heat pumps.

Advanced, air-source heat pumps for residential use in space heating, space cooling, and water heating were proposed by EPRI (Petersen 1989). The major reasons for water heating being integrated with the residential heat pumps are: hot water can be supplied at little or no additional cost during space cooling periods, and defrosting heat can be extracted from the water tank instead of the indoor air, thus eliminating "cold blow". The new systems offer opportunities to reduce energy consumption by 20% in the northern states and by 40% in the southern states of America when compared to older single-speed heat pumps. Heat pumps are used in only a small percentage of residential dwelling in the U.S.

Reports in *Electrical Construction and Maintenance* (1989) and the *EPRI Journal* (Kesselring and Lannus 1991) reference a new generation of advanced electric heat pump called HydroTech 2000 that provides heating and cooling efficiencies 30%–40% better than conventional residential heat pumps. A variable-speed electronic compressor is used to change the pump's speed to match the desired heating or cooling temperature. The variable-speed system can deliver the expected warmer or cooler air quickly using the high speed capability and then maintain the temperature with a lower speed while using less energy. A variable-speed-drive is also used for offering

⁴A ton of refrigeration is equal to 200 Btu/min or 211 kJ/min.

maximum comfort. The indoor unit of the advanced electric heat pump makes less noise than a refrigerator. The outdoor unit is eight times quieter than traditional heat pumps. Advanced heat pumps can supply a major part of summer hot water for free from the waste heat. The key to the power of advanced electric heat pumps are electronic controls. Temperature and pressure sensors are installed at several locations in the system to reflect the conditions of the house; thus, high efficiency and maximum comfort are obtained.

Advanced electric heat pumps offer benefits not only to customers but also to the utilities (Rose *et al.* 1990). Customers can make a choice from a variety of models and configurations of electric heat pumps to fit their needs. The concerns of customers for efficiency, comfort, reliability, and safety can all be satisfied by using energy-efficient electric heat pumps. The electric utilities benefit from the revenue additions, load factor improvements, and customer satisfaction.

Residential Motors

Residential motors include the motors in home appliances and small tools. Motors in heat pumps, refrigerators, microwave clothes dryers, and furnaces are not included in this category. According to reports in *Consulting/Specifying Engineer* (Van Son 1989) and *Energy Engineering* (Hiatt 1990), 50–60% of the nation's electricity is used to drive electric motors. Integral horsepower and polyphase motors account for 80–90% of the consumption. Fractional horsepower motors share only 7% of the consumption. Another report in *EPRI Journal* (Douglas *et al.* 1992) indicates that about 67% of the electricity in the United States is used for motor drives. The distribution of motor population and motor electric use described in the report

Table 2.4: Distribution of motor population and motor electric use.

Size	Number (%)	Electric Use (%)
under 1 hp	90	8
1-5 hp	8	22
over 5 hp	2	70

is shown in Table 2.4. In all applications (residential, commercial, and industrial), only 2% of electric motors are larger than 5 horsepower (hp), however, they consume more than 70% of electricity used by electric motors. Roughly estimated, the residential motors represent about 10% of motor electric use. Using the data offered by Faruqui *et al.* (1990), we found that residential motors account for approximate 18% of residential electric use.

Electric motor manufacturers have introduced more efficient motors in response to the increasing price of electricity. A variety of electric motors are being developed for applications which range from small tools to major home appliances to drives for large industrial processes (ASHRAE 1991).

An important element in evaluating and applying energy-efficient motors is the cost of electricity. Many motors are still purchased on an initial cost basis, without regard for the potential energy-cost savings. These motors are generally an integral component of a large system. Customers need to be made more aware of these potential savings when they choose appliances with motors in them. Motor efficiency is a measure of a motor's ability to convert electrical-power input to mechanical power. The losses in a motor consists of stator-winding loss, rotor-winding loss, magnetic-core loss, friction and windage loss, and stray load loss. Each of these losses must be evaluated carefully in order to increase motor efficiencies. Optimizing design

and using active materials, such as copper-magnet wire and low-loss lamination steel, can lead to higher efficiency. Improved motor systems (including adjustable-speed drives, high efficiency motors, improvements in the choice and maintenance, etc.) can save 50% of the electricity that they consumed in 1990 (Fickett *et al.* 1990). However, because of the low annual operating hours and low percentage of full load, the savings of residential motors is limited. Thus, the methods for calculating annual cost savings and life cycle energy savings won't be described in this section. They will be discussed in the section entitled Industrial Motors.

High-Efficiency Refrigerators

Refrigerators are a major part of the residential load. They account for 20% of the U.S. residential electricity use. Development of high efficiency refrigerators will result in less consumption of electricity and lessen the additional need of power plants, each of which will benefit the customers, utilities, and the environment. The use of non-CFC working fluids will also have an impact on the efficiency of refrigerators. The mission of the Super Efficient Refrigerator Program (SERP) is to provide highly efficient and environmentally friendly refrigerators to consumers years ahead of normal market expectation (SERP 1992). The price of high-efficiency refrigerators is not expected to be higher than the price of less efficient refrigerators with comparable size and performance features.

Whirlpool Corporation was the winner of the \$30-million dollar Super Efficient Refrigeration Program (Baker 1993). The first high-efficiency SERP model was expected to be delivered to consumers in SERP utility areas in 1994. Between 1994 and 1997, Whirlpool will manufacture 250,000 of these refrigerators in a variety of

models to serve the consumers. HFC-134a will replace CFC-12 as the refrigerant, and HCFC-141b will replace CFC-11 as the foam-blowing agent. All the SERP refrigerators will be at least 25% more energy-efficient than the 1993 government energy standard. Whirlpool increased the efficiencies by using newly-designed compressors (suitable for non-CFC refrigerants), better insulation, more efficient condenser fan motors, and smart defrost controls. The real winners of the program are the customers, who will not only benefit from the high quality technology but will also help to protect the environment.

Residential Microwave Clothes Dryers

Microwave clothes dryers (MCDs) are just being developed (Kesselring 1992). Initial experimental tests show that the benefits of microwave dryers include a 20% savings in energy over traditional dryers, decreased operating cost, shorter drying time, and lower drying temperatures. Lower drying temperatures result in less shrinkage and wear on clothes. As an important feature, microwave dryers enable users to dry woolens and delicate fabrics, which used to be dry-cleaned.

The first-year development of microwave clothes dryers by major appliance manufacturers were not successful because of the problems with arcing and heating of metals (EPRI 1993). These problems caused burning holes in clothes and the possibility of dryer fires. However, the efficiency of MCDs was verified.

Microwave clothes dryers are actually more expensive than conventional dryers, but their operating savings, better service, and flexible utilization should eventually benefit consumers. The operation time for microwave dryers is 65% faster than that for conventional dryers (Lamarre *et al.* 1994). Since microwave ovens are used in

79% of U.S. households because of their rapid cooking capacities, researchers expect microwave clothes dryers will obtain similar success as prices approach conventional clothes dryers.

Residential Gas Furnaces

The Gas Research Institute (GRI) is working with Carrier Corp. and United Technologies Research Center (UTRC) to develop a new generation of residential gas furnaces that will be smaller, lighter, quieter, less expensive, and higher efficiency than conventional furnaces (GRI 1993a). The use of advanced nonmetallic materials reduces the costs of manufacturing, installation, operation, and maintenance. Higher efficiency results from the improvement of burners (with low emissions), heat exchangers, fans, motors, vents, controls, and electronic drives.

More detailed information of new gas furnaces, such as the date for market introduction and first cost, is not available at this time according to the message offered by GRI. Although older home furnaces are approximately 40% efficient, new furnaces are 90–98% efficient, so future technologies will have little room for improvement.

Gas Heat Pumps

A 3-ton gas heat pump manufactured by York International Corp. exceeds a seasonal COP (coefficient of performance) of 1.3 for heating and 1.1 for cooling (Helmut *et al.* 1992, GRI 1994a). This heating and cooling unit is called Triathlon. The Triathlon is claimed to have lower operating and maintenance costs, higher durability, and higher efficiency when compared to older systems. The cooling performance of this unit is as good as or better than the most advanced electric heat pump while

considering operating costs on the basis of national average energy price and mean climate conditions. The maintenance is easy. The only requirement is a yearly change of the oil, oil and air filters, spark plug, and spark wire. The durability has been tested to be over 15 years. Triathlon provides more heating capacity than electric heat pumps because it recovers rejected engine heat. More comfort is achieved because air is delivered 10–15°F higher than electric units. When supplemental heat is needed, an auxiliary boiler can satisfy the request. In the cooling mode, a humidity control produces a high quality comfort.

The annual operating cost savings are projected to be as high as 50% when compared to an older combination of gas furnace and electric air conditioner or a traditional electric heat pump (GRI 1994a). More than 100 local gas utilities and pipelines are assisting the market penetration of Triathlon. They have offered \$14.45 million financial support to reduce the initial cost of the first 25,000 units. The York Triathlon is commercially available and hopes to sell at least 25,000 units per year by 1997.

New Technologies in the Commercial Sector

The promising technologies for energy savings in the commercial sector include new lighting, electric heat pumps, supermarket refrigeration units, microwave clothes dryers, and gas cooling systems.

Commercial Lighting

Lighting consumes approximately 25% of the nation's electric energy (Lamarre *et al.* 1989). According to an article published in *Electrical World* (1991), about

60% of the commercial lighting electricity is utilized by retail stores, 10%–20% by schools, and 10%–30% by commercial buildings. When the extra loads on cooling systems because of heat emitted by light are included, lighting's share in electricity use rises to 40%. Because commercial lighting accounts for 25–40% of the peak demand in commercial buildings, it plays a significant role in the management of electrical capacity (Busch 1993, Capehart 1989, Energy Information Administration 1986, Energy Information Administration 1991, Geissler 1991, Piette *et al.* 1989, Thumann 1992).

The potential for energy savings by adopting efficient commercial lighting technologies is estimated to be 39%–55% by the year 2000 (Lamarre *et al.* 1989). The commercial lighting savings accounts for approximately 65% of the total lighting savings through the nation. Lawrence Berkeley Laboratory estimates that 50% of the lighting electricity could be saved if we replaced the existing lighting with more efficient systems. Faruqui *et al.* (1990) indicated that overall energy savings for commercial lighting ranges from 30% to 60%. Another report in *Energy* (Nadel *et al.* 1993) estimated the technical potential energy savings for commercial lighting is 66% in the year 2010 under the vital contributions of reduced-wattage fluorescent lamps, electronic ballasts, efficient fixtures, and smart control units. Electronic ballasts make the biggest contribution. They reduce energy consumption, reduce ballast losses, and increase lamp efficiency (Yarnell 1993).

It is a challenge to convince business that energy-efficient lighting can maintain and improve their environment. Utilities often give commercial customers special rates, low-interest loans, and other incentives to upgrade their lighting systems. However, more effort is still required to increase the market penetration of efficient

lighting devices.

Daylight compensators, infrared motion detectors, power reducers, and excess light turn-off systems are just some of the fluorescent lighting energy savings opportunities. The potential cost and energy savings are extremely important. The challenge is to identify which products are applicable to a particular situation and to evaluate the potential savings.

Determining how to achieve the potential savings is more important than determining the magnitude of these savings (EPRI 1991). Many efficient lighting products are available now and new technologies are regularly entering the marketplace. The new systems supply the same, or even greater, amount of light as the old systems. Nevertheless, several obvious barriers to their implementation still exist. The significant barriers are high initial cost, long payback periods, customer reluctance to accept new efficient lighting products and "why fix something that is not broken". In order to enhance the market penetration of high-efficiency technologies, the utilities have been requested (by regulators) to provide various demand-side management strategies to increase consumer adoption of advanced lighting technologies. The general DSM programs include information service, audits, and economic incentives such as rebates, loans, installation, leasing, and design assistance. Rebates are the most common type of commercial lighting program, which represent 70% of the lighting programs. With electric utility deregulation under way, demand-side management programs may be a thing of the past, unless they become energy savings service programs for the customers.

Efficient commercial lighting includes quality lighting devices and careful system design. The satisfaction of customers is the key to the success of a demand-side

management program. High-efficiency lighting technologies offer significant savings; nevertheless, those savings are ignored if the customers feel discomfort with the new lighting products. Proper re-education of the utility technicians regarding new lighting technologies and design can make sure that high quality lighting is delivered to the customers.

Commercial Heat Pumps

A variety of efficient electric heat pumps can be applied to different commercial buildings (Blatt and Khattar 1992, Bunting and Gerber 1991, Kavanaugh 1992, Kesselring *et al.* 1990, Oshinski 1988). The electric heat pump capacity for small commercial applications ranges from 10 to 30 tons (2,000–6,000 Btu/min), where motor-driven multicylinder reciprocating compressors or screw compressors are commonly used. The capacities for large commercial applications are greater than 200 tons (40,000 Btu/min), where centrifugal chillers are usually selected. Advanced electric heat pump systems optimize the temperature distribution of large commercial buildings by removing the heat from the sunny side of the building or from a room full of machines and transferring it to where it is needed. HydroTech 2000 is a new generation of electric heat pump that is 30–40% more energy-efficient than previously available models. It's suitable for small commercial and residential customers. The advantages of this model have already been presented in the section Residential Heat Pumps.

The retrofit and replacement market for electric heat pumps will continue to grow significantly (Blatt and Pietsch 1992). It is estimated that there will be an increase of about 70% from the present 3.5 million tons (700 million Btu/min) to 6

million tons (1,200 million Btu/min) installed by the year 2000. The primary factors suggested for this rapid growth include the need to improve air quality in buildings, the aging of installed HVAC (heating, ventilating, and air conditioning) devices, and the trend to replace aged, but functioning systems with more efficient and cleaner devices. Pietsch (1994) offers a significant amount of information on alternatives for heat pumps. Usually, the best replacement is determined by the characteristics of the existing system.

To show the application of a replacement, a commercial building with a cooling capacity of 300 tons (60,000 Btu/min) is considered as an example. We will assume that the additional initial cost of a more efficient electric heat pump is \$20,000, the COP of the old system is 2.75, and the COP of the new system is 3.75. Since 1 ton = 211 kJ/min, we can calculate the following data:

System	COP	kW/ton
old	2.75	1.28
new	3.75	0.94

The cooling season is about 4 months per year in Iowa. The annual operating hours are assumed to be 12 hrs/day \times 120 days/yr = 1,440 hrs/yr. The electric energy cost is \$0.05/kWh. Thus, the annual cost savings is computed to be

$$300 \times (1.28 - 0.94) \times 1,440 \times 0.05 = \$7,344/\text{yr}$$

The simple payback period is calculated as

$$\text{Payback period} = \frac{\$20,000}{\$7,344} = 2.72 \text{ years}$$

The actual payback period might be shorter if the financial incentives provided by local utilities are involved.

Many models of efficient heat pumps can be selected for different commercial buildings, such as all electric commercial unitary heat pumps, dual fuel heat pumps, water source heat pumps, packaged terminal heat pumps, etc. Heat pumps are easy to fit into most commercial buildings, because a variety of sizes are available which provide flexibility in installation and space configuration.

The utilities usually provide education and rebates to encourage customers to retrofit electric heat pumps. The rudimentary and intriguing part of educational materials is to present the advantages of using new the technologies to the customers, such as lower cooling and heating energy costs and reduced maintenance costs. Regardless of the improvements in efficiency, first cost is still a major factor in adoption.

Supermarket Refrigeration

In a modern supermarket, refrigeration systems consume more than 50% of the energy (Walker 1992). Many supermarkets employ traditional refrigeration systems using single-compressor units with fixed-head pressure control, no subcooling, and electric defrost. If the old units are replaced with high-efficiency refrigeration systems using multiple compressors with common suction and discharge, floating head control, ambient and mechanical subcooling, hot gas defrost, and evaporatively cooled condensers, significant energy savings can be achieved.

According to an EPRI investigation (Walker 1992), nearly 25% of the energy consumed by supermarket refrigeration and 30% of the peak electric demand for refrigeration could be reduced if we replaced the inefficient systems with more efficient units. Efficient multiple compressors would account for 29.5% of the savings, evaporative condensers would contribute 20.5%, and floating head pressure control,

subcooling, and hot gas defrost would co-contribute the remaining 50% savings. An earlier EPRI report (Faruqui *et al.* 1990) estimated that the electric energy savings for commercial refrigerators ranges from 20% to 40%.

Commercial Microwave Clothes Dryers

The technology of microwave clothes dryers can be applied to the commercial sector as well as the residential sector.

Commercial Gas Cooling

Air conditioning accounts for 40% of peak electric demand, and 25% of this peak is for commercial cooling (Drugan 1994). In Japan, more than 50% of commercial cooling is served by gas technologies. However, in the U.S., the gas market accounted for only 1–2% of commercial cooling in 1985. Gas sales are lower in the summer than in the winter. In order to reduce the peak electric demand and build gas load to receive revenue, many utilities are offering incentives to encourage the installation of gas cooling equipment. Approximately 65,000 commercial electric centrifugal chillers will be replaced by the year 2000 because of aging, refrigerant unavailability, low efficiency, or high operating costs (Drugan 1993). The Gas Research Institute expects that new gas technologies can increase gas cooling equipment sales from 180,000 tons (36 million Btu/min) in 1992 to 800,000 tons (160 million Btu/min) by 2000. Gas technologies cool the air in three basic types—engine-driven, absorption, and desiccant. The initial costs of gas cooling systems investigated by Itteilag (1994) are reviewed in Table 2.5. When refrigeration tonnage (RT) is larger, the initial cost per ton is lower. A comparison of gas cooling systems with advanced electric heat pump

Table 2.5: Initial costs of gas cooling equipment.

Equipment Type	RT ^a (tons)	Initial Costs ^b
Engine-Driven Systems		
	150	\$500-\$600/ton
with heat recovery	150	\$600-\$800/ton
	230-460	\$450-\$600/ton
	30	\$800-\$850/ton
	300	\$530-\$560/ton
with heat recovery	300	\$560-\$660/ton
DX ^c Rooftop	15	\$1,170/ton
DX Rooftop	20	\$780/ton
Absorption Systems		
double-effect	20-50	\$900-\$1,300/ton
double-effect	60-100	\$720-\$1,000/ton
double-effect	100-300	\$357-\$700/ton
double-effect	300-500	\$400-\$500/ton
double-effect	1,000-1,500	\$350-\$400/ton
Desiccant Systems		
	40	\$700-\$1,300/ton
	60-80	\$900-\$1,100/ton

^aRefrigeration tonnage.

^bInstallation costs range from 20% to 100% of initial costs.

^cDirect expansion.

systems is not currently available.

Engine-Driven Systems A gas-engine-driven system uses a gas engine to drive the compressor in the cooling system. The initial cost of an engine-driven system is higher than an electric motor-driven unit, but the lower operating cost will payback the initial cost premium in about two years. Various new gas-engine-driven systems are available on the market ranging from 15 tons to 6,000 tons, such as Alturdyne engine-driven chiller systems, Thermo King 15-ton rooftop units, and Carrier 25-ton rooftop units. The available packaged engine-driven systems are shown in Table 2.6 (AGCC 1994).

A Carrier gas rooftop package, called GAS-COOL, claims the features of significant operating cost savings, easy installation and maintenance, and flexibility (Drugan 1994, GRI 1994b). It reduces electric demand charge and power consumption more than 75% in the cooling mode. The cooling costs can be reduced by as much as 50% when compared to a conventional 25-ton rooftop system. Since the gas-driven engine can operate over a wide range of speeds, the cooling output is variable. Thus, a high seasonal cooling efficiency is obtained. The major advantages of GAS-COOL are natural gas as primary fuel, high part-load performance, and low electric consumption. Therefore, this product could be a least-cost energy option for many commercial customers.

Absorption Systems An absorption system is driven by a heat source instead of an electric compressor to produce the cooling effect. They shared 40% of the commercial cooling equipment market in the 1960s, but they were replaced by electric-driven machines that were easier to use and maintain in the early 1970s (Katzel

Table 2.6: Available gas engine-driven cooling systems.

Engine-Driven Systems	COP	RT (tons)
Standard Engine Chillers		
Alturdyne Engine-Driven Chiller Systems	1.25-1.87	25-1,100
EnChill EDC Systems	1.13-2.24	50-6,000
Sierra Power-SRS Engine-Driven Refrigeration Systems	1.00-2.00	50-4,000
TECOCHILL Air-Cooled Gas Engine-Driven Chillers	0.82-0.95	60-120
TECOCHILL Gas Engine-Driven Chillers	1.20-1.30	75-170
TECOCHILL Gas Engine-Driven Chillers	1.2	340
TECOCHILL Gas Engine-Driven Chillers	1.6	500-725
Packaged DX Systems		
Carrier Engine-Driven Rooftop Air Conditioner	1.0	25
Thermo King Rooftop DX Air Conditioning And Heating System	0.8	15
Thermo King Split System Air Conditioning System	1.0	15
Gas Heating & Cooling System		
York Triathlon Gas Heating and Cooling System	0.9	3-4

1992). Older single-stage absorption systems were very inefficient because of rather low COPs, in the range 0.6–0.7 (Sun 1991). During the past few years, absorption cooling technologies have been improved significantly. The initial costs of absorption systems are higher. The price premium of an absorption system is about \$200 per ton for sizes over 250 tons (Drugan 1993). Nevertheless, because of much lower operating and maintenance costs, the payback period of the initial cost premium is 2–5 years. With rebates, some absorption systems are obtained at the same price as electric units. Energy cost savings of absorption systems can be up to 50% depending on local utility rates.

The single-effect absorption systems have a COP of about 0.8 running on 15 psig steam or hot water 180–270°F (Dotiwalla 1992). The COP of double-effect absorption systems is about 1.15. Double-effect machines operate with 100–150 psig steam or hot water in the range 550–1500°F. A triple-effect absorption chiller that uses the input energy three times is, basically, a cascade of two single-effect chillers (GRI 1993c); one chiller operates at regular chiller temperatures (100–200°F) and the other one at higher temperatures (200–450°F). Approximately 40% of the cooling is provided by the higher-temperature cycle. A number of absorption systems that use non-CFC working fluids are commercially available or soon will be, including Trane Thermachill gas-fired absorption chillers, York direct-gas-fired absorption chiller/heaters⁵, and Trane triple-effect absorption chillers. A list of new absorption equipment is given in Table 2.7 (AGCC 1994). The cooling capacities of absorption systems range from 3 to 1,700 tons (600–340,000 Btu/min). The indirect-fired systems are powered by

⁵Chiller/heaters do not have a reversible refrigeration cycle. Heating is operated by an internal boiler.

Table 2.7: Available gas absorption cooling systems.

Absorption Systems	COP	RT (tons)
Direct-Fired		
Yazaki Gas-Fired Double-Effect Chiller/Heater	0.95–1.00	30–100
Carrier Direct-Fired Double-Effect Absorption Chiller/Heater	0.97	135–1,000
Robur Direct-Fired Single-Effect Chiller/Heater	0.48–0.62	3–5
Robur Direct-Fired Single-Effect Chiller	0.48–0.62	3–25
McQuay/Sanyo Double-Effect Direct-Fired Modular Chiller/Heater	0.95	20–80
McQuay/Sanyo Double-Effect Direct-Fired Absorption Chiller	1.00	100–1,500
Trane Thermachill Direct-Fired Double-Effect Absorption Chiller	0.97–1.04	100–1,100
York ParaFlow Direct-Fired Two-Stage Absorption Chiller/Heater	0.92–1.00	120–1,500
Indirect-Fired^a		
Yazaki Water-Driven Single-Effect Chiller	0.60–0.70	5–10
Carrier Double-Effect Steam Absorption Chiller	1.20	100–1,700
Carrier Single-Effect Absorption Chiller	0.70	100–680
McQuay/Sanyo Double-Effect Steam-Fired Absorption Chiller	1.20	100–1,500
Trane Two-Stage Absorption Chiller	1.21	385–1,060
Trane Single-Stage Absorption Chiller	0.68	112–1,660
York ParaFlow Two-Stage Steam Absorption Chiller	1.19	250–1,500
York Single-Effect Absorption Chiller	0.69	120–1,377

^apowered by steam, hot water, or waste heat.

steam, hot water, or waste heat. Higher reliability and lower maintenance are the advantages of absorption systems over engine-driven systems.

The Thermachill absorption chillers are designed for commercial buildings with capacities 100–1100 tons (GRI 1994c). A successful example of cost savings by using Thermachill is the Caldor Department Store in New York. They replaced a 600-ton electric unit with a 500-ton Thermachill absorption chiller/heater manufactured by Trane. The equipment cost premium was \$160,000 and the installation cost premium was \$450,000. At the same time, they obtained a \$35,000 efficiency rebate and a \$240,000 equipment rebate. The maintenance cost savings is computed to be \$130,000/yr and the electric demand charge savings is \$100,600/yr. With rebates, the payback period was 1.5 years; without rebates, the payback period would be 2.6 years.

The ParaFlow direct-fired two-stage absorption chillers are in capacities 120–1500 tons (GRI 1993b). The technology was bought back from Japan. York developed several components, including advanced microprocessor controls, better burner train, and low-maintenance pumps, to improve it. In the double-effect design, heat is recovered from the condenser and used again in the absorption cycle.

A cost-effective triple-effect absorption chiller, originated at Oak Ridge National Laboratory, is being developed by the Gas Research Institute and Trane (Drugan 1993, GRI 1993c). It uses input heat three times to provide 50% more efficiently than a direct-fired, double-effect chiller/heater at a 25% cost premium. Product introduction is scheduled during 1996–97.

The sales of gas absorption systems have doubled for two successive years. The use of water and simple salt compounds as working fluids is a big advantage over

conventional chillers since CFC refrigerants will be phased out in 1996. Another opportunity to increase the adoption of gas cooling technologies is the high demand charge during peak hours because of constrained electric supply. The major advantages of absorption systems over electric systems can be summarized as lower operating costs, low maintenance, CFCs or HCFCs free, quieter operation, and high reliability.

Desiccant Cooling Systems Most air conditioning systems reduce the humidity of an air stream and lower its temperature. However, desiccant systems attract moisture from the air without subcooling it. A desiccant cooling system does not use refrigerants, compressors, or absorption cycles. Desiccant materials that can be either liquid or solid are placed on a rotating wheel. Desiccants remove moisture from the air because of the vapor pressure difference between air and desiccant materials through one half of the wheel and release it through the opposite half. Gas desiccant cooling systems are particularly useful for businesses such as supermarkets and hotels. A number of available desiccant systems, such as Munters DryCool SuperAire Systems, Seasons 4 Desiccant Systems, and SEMCO Desiccant-Based Air Conditioners, are shown in Table 2.8 (AGCC 1994).

New Technologies in the Industrial Sector

New lighting, electric motors, freeze concentration, and gas cooling systems are the primary technologies for saving energy in the industrial sector.

Table 2.8: Available gas desiccant cooling systems.

Desiccant Systems	Capacity (cfm ^a)
ICC DESI/AIR	4,000–20,000
Munters DryCool SuperAire System	5,000–10,000
Munters DryCool IceAire System	5,000–10,000
Munters DryCool MedAire System	5,000–10,000
Seasons 4 Desiccant System	5,000–10,000
SEMCO Desiccant-Based Air Conditioner	5,000–30,000
SEMCO Desiccant-Based Dehumidifier	5,000–30,000

^acubic feet per minute.

Industrial Lighting

Lighting is a productivity tool that can help companies to optimize production, maintain high quality, and control operating costs. Well-planned and well-designed industrial lighting has been proven to promote performance, productivity, and safety. Lighting matched to the needs of the environment can result in significant savings in energy and maintenance costs.

Referring to an EPRI report (Faruqui *et al.* 1990), lighting consumes 10% of industrial electricity. Certainly, it can be a significant contributor to savings. A report in *Plant Engineering* (1991a) indicates that electricity represents 86% of the total installation-and-operating cost of a lighting system, lamps account for only 3% of the total cost and the rest is labor cost. The primary savings can be achieved through energy-cost reductions. Energy-efficient light sources available today make it possible to obtain an equal amount of light with less energy use and lower total cost. The potential savings estimated by Faruqui *et al.* (1990) is 37–50% in the year 2000. According to another study of Nadel *et al.* (1993), the technical potential energy

savings of industrial lighting is 38% in 2010. The major contributors are reduced-wattage fluorescent lamps, electronic ballasts, metal halide lamps, and high pressure sodium lamps. Suitable regulation and utility programs can effectively promote the adoption of energy saving technologies.

Industrial Motors

The study of Faruqui *et al.* (1990) estimated that electric motors account for two thirds of the electricity consumption in the industrial sector. Another publication in *Plant Engineering* (Hirzel 1992) revealed that a limited number of motors in continuous-duty service consume 75% of industrial electricity. Their estimations are not the same, but we can accept 67–75% as a reasonable range for the percentage of industrial electricity consumed by motors. Just a small increase in motor efficiency would produce significant reductions in electric usage and costs. Thus, a wide range of high efficiency induction motors are being designed and tested for different industrial requirements (Smith 1992, Umans 1992a, Umans 1992b).

For many different reasons, most motors are running inefficiently. Usually, motors are oversized and operating when not required. Broadly speaking, there are three common methods to make motor systems more efficient: good housekeeping, high-efficiency motors, and variable speed drives (IEEE 1993). Good housekeeping means turning off idling motors using appropriate switches. Currently, a variety of high-efficiency motors are available for different applications. The main idea of high-efficiency motors is to reduce losses. The distribution of motor losses is shown in Table 2.9 (Hirzel 1992). The resistance loss in the stator can be reduced using increased slot sizes with extra copper in the windings. The hysteresis and eddy-current

Table 2.9: Distribution of motor losses.

Types of Losses		Amount of Losses (%)
Non-Load Losses	Windage and Friction	14
	Core	16
Load Losses	Stator	33
	Rotor	15
	Stray Load	22

losses also can be reduced using low-loss steel in the stator and rotor for operating at a lower flux density. Since the losses are reduced, the heat generation is decreased and the cooling fans can be smaller. However, the most efficient method is to use a variable-speed drive to adjust the motor speed. For centrifugal fans and pumps, the power input is proportional to the cube of speed and the flow is proportional to the speed. Therefore, a reduction to 80% of maximum speed will save about 50% of the power consumption.

Motor elements, such as motor drives and power transmissions, need to be evaluated carefully. Electronic controls, such as solid-state reduced voltage starters, adjustable speed drives (ASDs), and power-factor correction devices, can reduce energy consumption (Patzler 1992, Sen 1989). The overall possible energy efficiency improvement for motor systems is estimated by Faruqui *et al.* (1990) to be 35–50%.

The cost of electricity plays a very important role when evaluating and applying energy-efficient motors. Before selecting a motor for a system, an economic payback analysis should be performed. Simple payback analysis and total energy savings analysis are the common methods used for evaluating savings (Andreas 1990, Hirzel 1992, Lobodovsky *et al.* 1989). When applying the simple payback analysis method, annual cost savings with motors of different efficiencies, under the same load, can be

calculated as:

$$S = 0.746 \times HP \times L \times C \times N \times \left(\frac{100}{E_L} - \frac{100}{E_H} \right) \quad (2.1)$$

where

C = electric energy cost, \$/kWh

E_L = lower motor efficiency, %

E_H = higher motor efficiency, %

HP = rated horsepower, hp

L = percentage motor load/100, % of rated horsepower

N = annual hours of operation, hr/yr

S = annual cost savings, \$/yr

U.S. manufacturers and most foreign manufacturers have standardized the determination of motor efficiency on Institute of Electrical and Electronics Engineers (IEEE) 112B test methods (Van Son 1989, Hiatt 1990), so it is reasonable to compare the efficiencies of different motors by nameplates. The rated horsepower chosen for a specific application should be as close to the load requirement as possible. The payback period can be determined by

$$\text{Payback years} = (\text{Cost difference}) / (\text{Annual cost savings}) \quad (2.2)$$

For example, consider the situation of a 50 hp motor operating at 100% load with 8760 annual hours of operation (continuous-duty service). The energy cost is assumed to be \$0.05/kWh. The lower motor efficiency is 91.5% and the higher motor efficiency is 94%. The cost difference is \$500. Substituting the appropriate values into Equation 2.1, we can acquire the magnitude of annual cost savings.

$$S = 0.746 \times 50 \times 1 \times \$0.05 \times 8,760 \times \left(\frac{100}{91.5} - \frac{100}{94} \right)$$

$$= \$475/\text{yr}$$

Thus, the payback period is calculated to be 1.05 years.

The simple payback analysis is an approximation. It is generally assumed to be acceptable if the first investment can be recovered in less than 3 years (Andreas 1990). Simple payback analysis usually only considers energy charge savings. The other savings such as demand charge and power factor penalty savings are not usually included.

When annual cost savings analysis confirms the replacement of lower efficiency motor with higher efficiency motor, a total energy saving analysis should be undertaken to determine the total benefit. Before using the total energy savings analysis, an efficiency factor as defined by (Andreas 1990, Hirzel 1992, Lobodovsky *et al.* 1989) could be used:

$$EF = C \times N \times n \quad (2.3)$$

where

C = average electric energy cost during the evaluation period, \$/kWh

EF = efficiency factor, \$/kW

N = annual hours of operation, hr/yr

n = evaluation period, yr

Using the data given in the previous example with evaluation period $n = 10$ years, we have

$$EF = \$0.05 \times 8,760 \times 10 = \$4,380/\text{kW}$$

The total energy savings (TES) can be calculated as

$$TES = 0.746 \times HP \times EF \times \left(\frac{100}{E_L} - \frac{100}{E_H} \right) \quad (2.4)$$

Savings in demand charges and power factor penalties are also not usually considered in total energy savings analysis.

$$\begin{aligned} TES &= 0.746 \times 50 \times 1 \times 4,380 \times \left(\frac{100}{91.5} - \frac{100}{94} \right) \\ &= \$4,750 \end{aligned}$$

The correct specification of the desired motors for any given application can reduce operational expenses and make significant contributions to energy savings. In order to obtain the best energy savings in motor use, both motor efficiency and operating system efficiency must be considered (Andreas 1990, Hiatt 1990, Hirzel 1992, Lobodovsky *et al.* 1989). If a number of devices are connected in series, the system efficiency is the product of individual efficiencies.

$$\text{System Efficiency} = E_1 \times E_2 \times \cdots \times E_n \quad (2.5)$$

Since new energy sources are harder to find or more expensive to develop, saving energy is a good resource that must be explored with the careful application of new technologies and modern electronics. Many utilities offer incentives and rebates to their customers to increase efficiency. The facilities receive the funds to buy the efficient motors they want and the utilities reduce their kW demand. This can benefit utilities more than expanding power production capacities.

Freeze Concentration

New freeze concentration technologies have been developed that separate and remove a liquid from a mixture at a substantial savings in cost and energy over the

conventional evaporation methods. Based on the theory of electric refrigeration, these technologies offer a wide range of applications. These technologies have been applied in processing of fruit juices, beer, wine, vinegar, and coffee. Some other potential applications include preparation of food, treatment of wastewater, and desalination of seawater.

Using electric freeze concentration techniques instead of conventional evaporation methods can produce a higher quality product at a lower cost and lower energy use, especially in the dairy industry (Douglas and Amarnath 1889, Rosen 1990, Jaret *et al.* 1992). For example, consider extracting a pound of water from a milk product. This typically takes 700 Btu per pound by evaporation methods; however, it requires only 114 Btu per pound using freeze concentration. Freezing water requires approximately 16% of the energy that boiling it off needs. The real energy savings for milk concentration is 50% based on primary energy resources. Frozen concentrated milk has a longer shelf life and can be reconstituted conveniently. The most important point is that it has the taste of fresh milk. Another significant impact of freeze concentration techniques is on the treatment of wastewater. Freeze concentration for wastewater treatment is 87% more energy-efficient than conventional methods. A list of energy saving applications of freeze concentration versus conventional methods is given in Table 2.10 (Jaret *et al.* 1992). These techniques offer other advantages in addition to lower energy use. A system can be constructed with less expensive materials because of lower temperatures. Useful by-products can be easily purified.

Table 2.10: Energy saving applications of freeze concentration versus conventional methods.

Application	Maximum Savings (%)
Alcohol Refining	41.2
Beet Sugar Production	83.1
Black Liquor Concentration	61.5
B-T-X Fractionation	58.3
Cane Sugar Production	65.5
Caustic Soda Concentration	97.5
Milk Concentration	50.0
Naphtha Fractionation	86.8
Wastewater Treatment	87.0
Wet Corn Milling	83.3

Industrial Gas Cooling

Most of the gas cooling technologies can be applied not only to commercial buildings and institutions as discussed previously, but also to industrial facilities.

New Technologies in the Transportation Sector

The use of electric vehicles, light rail transit systems, and natural gas vehicles has potential for energy and/or cost savings in the transportation sector.

Electric Vehicles

The transportation sector consumes 26% of the total nation's end-use energy and 65% of the petroleum (Wang and DeLuchi 1992). The adoption of electric vehicles (EVs) can reduce both energy consumption and petroleum use. Imported petroleum accounted for 42% of total petroleum use in 1989, and is estimated to be about 60% in 2010.

Electric vehicles may provide several advantages to the electric utility industry in addition to energy savings (EPRI 1992a). For some applications, electric vehicles may reduce environmental pollution comparing power plant emissions to gasoline-powered vehicles. Also, the major part of the electricity requirement to serve electric vehicles can be generated at off-peak periods, so generating capacity can be utilized more effectively and efficiently, assuming a limited percentage of electric vehicles. The greater use of electricity will promote energy security for the United States since only 4% of the electricity will be generated from petroleum. In most areas, the use of electric vehicles may reduce per-mile petroleum consumption by 90%, because the majority of electricity is generated from non-petroleum fuels. In some areas where a significant portion of electricity is generated from petroleum, the use of electric vehicles may still reduce per-mile petroleum consumption (Wang and DeLuchi 1992).

Wang and DeLuchi's study (1992) reports that the use of electric vehicles, based on 1980's models, could increase energy consumption by 13-30%. Nevertheless, the adoption of more efficient EVs, which are expected to be available in the future, could lead to a reduction in energy consumption of 7-33% or more.

So far, two models of new electric vehicles, the G-Van and the TEVan, are being developed according to a special publication of EPRI (1992a). Their features are shown in Table 2.11. The G-Van is the first commercial product of EV technology, representing a bright beginning for the EV industry. The G-Van offers a top urban driving range of 60 miles and a top speed of 52 mph. Market investigation has shown that many vehicles in large fleets, such as delivery fleets, never go beyond 60 miles a day, so the G-Van has a very good chance of penetrating the market if first costs can be reduced. The TEVan provides a top range of more than 100 miles and a top speed

Table 2.11: Features of modern electric vehicles.

Model	Driving range (miles)	Top speed (mph)
G-Van	60	52
TEVan	100	65

of 65 mph. This range allows the TEVan to perform the tasks of most conventional gasoline-powered vehicles.

It is difficult to compare the overall energy savings of electric vehicles with gasoline-powered vehicles of similar function since their operating features are not the same. However, an example is given when considering the urban driving conditions (Jaret *et al.* 1992). The consumption of primary energy for gasoline-powered fleet driving is about 14,400 Btu per mile, and the consumption for the G-Van is 10,800 Btu per mile. The primary energy use for a Chrysler's gasoline-powered mini-van is 9,000 Btu per mile and that for the TEVan (based on energy energy used at a power plant) is 5,400 Btu per mile. The primary energy savings for the G-Van is 25%, and for TEVan is 40%. The next generation of electric vans are estimated to provide 60% more energy-efficiency than their gasoline-powered counterparts. This estimation is much higher than the study of Wang and DeLuchi (1992) because of the significant improvement in batteries.

First cost is a major drawback of EVs; some sources indicate a first cost of as much as 8 times the cost of gasoline-powered vehicles. Costs would probably decrease as production increases.

A major challenge for electric vehicles are batteries. The disadvantages of conventional EV lead-acid batteries include: weight, low power, limited storage capacity, long recharge times, and high cost. According to Moore and Guy (1994), a near-term

high-performance EV lead-acid battery has been developed, which is expected to be commercially available in 1995. It delivers 50–80% more specific energy and 2–3 times more power than conventional units. The new battery is rechargeable to 50% of capacity in 8 minutes and to 99% in half hour. It can be recharged 1,000 times or up to 80,000 miles of maintenance-free use. The price of a new EV battery pack is about \$3,000, which is much lower than the conventional units. Other more powerful mid-term and long-term EV batteries are being continuously developed by the United States Advanced Battery Consortium (USABC), but they won't be available in the market before the year 2000.

The successful progress of the G-Van, the TEVan, and EV batteries has created a promising future for electric vehicles. These systems not only prove the feasibility of EV technology but also provide the catalyst for important legislative mandates and an increasing impulse for EV research and development. For example, a mandate of the California Air Resources Board requires zero-emission vehicles to account for 2% of new car sales in 1998, and 10% of new car sales in 2003 (EPRI 1992a, Philipson 1993). Large automakers are continuously dedicating significant resources to expand their EV programs. Meanwhile, utilities are also developing facilities to serve the growth of EV demand. The cooperation of government, automakers, and utilities has set the stage for a revolution in transportation.

Light Rail Transit

Light rail transit (LRT) is another promising possibility in the transportation sector (Mora 1991, Murray 1992, National Academy Press 1992, Stone 1993). There are three light rail transit modes: transit from suburban residential areas to central

business districts, feeder service to rapid transit, and local area transit. The overuse of automobiles causes strain on our environmental system. Using light rail transit is a good way to reduce the number of automobiles.

Light rail transit systems have negligible pollution at the point of use and can make use of a variety of energy resources. They offer 50% energy savings per passenger mile compared to conventional gasoline-powered vehicles (Jaret *et al.* 1992). This transport mode became unpopular after the World War II, but now there is renewed interest and many cities are planning to rebuild light rail systems (Ware and Jones 1992). The developments in LRT technologies have lowered energy consumption and maintenance costs. Many electronic advancements have been integrated into light rail transit systems to provide better services and promote energy efficiency. Increased use of computing power in maintenance, monitoring and control, scheduling, and management have enhanced the quality of LRT.

A number of existing LRT systems have been upgraded and several new systems have gone into operation or are currently in the planning stages (Schumann 1989). Completely LRT systems have proven their worth in the marketplace. The ability to perform a variety of services is the major advantage of light rail transit systems, which combine some of the characteristics of rapid transit systems and buses. Light rail transit systems can reach the speed of rapid transit, while they also offer ease of access. Therefore, an expansion of LRT systems can be expected.

Natural Gas Vehicles

The initial investment in natural gas vehicles (NGVs) began in the early 1970s because of drastically increasing gasoline prices (Plant Engineering 1991b). Today,

environmental concerns are also important incentives. Exhaust emissions from gasoline vehicles and emissions during vehicle fueling account for half of total volatile organic compound emissions and two-thirds of total carbon monoxide emissions. These two emissions are the major components of urban smog. Natural gas vehicles are much more environmentally safe than gasoline vehicles. An EPA investigation that compared a natural gas vehicle with a gasoline vehicle, found that 83%–90% of volatile organic compound emissions and 90% of carbon monoxide emissions could be reduced when using the NGV.

Natural gas vehicles are safe (Plant Engineering 1991b), because natural gas has a higher ignition temperature of 1,200°F compared with 600°F for gasoline and a narrower range of flammability. Concentrations of natural gas below 5% and above 15% will not burn. High-ignition temperatures and a narrow range of flammability make accidental ignition or combustion almost impossible. If the natural gas should leak, it would dissipate quickly into the air.

A disadvantage of natural gas vehicles is their high initial cost. According to Schaedel (1993), the cost premium is \$3,000 to \$4,000 for a light-duty van compared to traditional gasoline vehicles. NGV cylinders, which are large and heavy, are the most significant factor in the high price. However, mass production of standardized cylinders should lower the costs. New designs are packing more gas into cylinders at a higher pressure to save space. Space requirements for gas storage in the vehicles as well as the general availability of natural gas stations are other disadvantages.

A recently released study by the American Gas Association (1993) compares the operation of natural gas vehicles with reformulated gasoline vehicles. In order to meet the federal and California low-emission standards, an electrically heated catalyst is

added to the reformulated gasoline vehicles. The electrically heated catalyst adds about \$500 to the initial cost of a vehicle. Meanwhile, the reformulated gasoline will cost an additional 19 cents per gallon relative to conventional gasoline. On the other hand, the natural gas vehicles not only meet the identical standards, but also have lower toxic and cold start emissions, no evaporative and running losses, less control equipment and equipment degradation, and less greenhouse emissions. The cost of natural gas is estimated to be 70 cents per-gallon-equivalent of gasoline. The current price of gasoline in Iowa ranges from \$1.00 to \$1.20. Thus, the operating cost savings is 40-50%.

Several recent actions taken by the federal government, state legislatures, and major businesses will speed up the development of natural gas vehicles (Plant Engineering 1990, Environmental Health 1993), because natural gas is domestic, available, abundant, economical, efficient, and clean. In 1990, 93% of the required natural gas was domestic, and the other 7% was imported from Canada. New federal tax deductions make it more economical than ever to purchase natural gas vehicles. Natural gas vehicles and refueling equipment were eligible for the new deductions after July 1, 1993. State legislatures in Texas, Colorado, Louisiana, and Oklahoma, among others, have approved legislation to promote the use of natural gas vehicles.

A U.S. auto maker has initiated volume production of a tested natural gas vehicle. The production is sponsored by natural gas companies in Texas, California, and Colorado, which have opened the first compressed gas station to serve natural gas vehicles. A delivery company has announced a 2,700 natural gas vehicle program. As the developments indicate, the use of natural gas vehicles will expand rapidly across the country which should reduce the U.S. dependence on imported oil.

Table 2.12: Sector contribution of nation's actual electric use in 1987 and estimated electric use in 2000.

Sector	Use in 1987 (%)	Use in 2000 (%)
Residential	35	33
Commercial	31	31
Industrial	34	36
Transportation	0	less than 1

Table 2.13: Technical potential lighting energy savings and achievable potential lighting energy savings in 2010.

Sector	TPLES (%)	APLES (%)	Total Lighting Use (%)
Residential	47	—	23
Commercial	66	—	57
Industrial	38	—	17
Other ^a	—	—	3
Total	57	35-46	100

^astreet and roadway lighting.

Discussion and Summary

The distribution of the nation's actual electric use in 1987 and the estimated electric use in 2000 studied by Faruqui *et al.* (1990) are shown in Table 2.12. Each of the first three sectors (residential, commercial, and industrial sectors) accounts for about one third of the U.S. electric use. The transportation sector consumes less than 1% of the total electric generation even assuming optimistic impacts of electric vehicles.

The technical potential lighting energy savings (TPLES) and achievable potential lighting energy savings (APLES) in the year 2010 estimated by Nadel *et al.* (1993) are shown in Table 2.13. The technical saving potential is 57%. The achievable sav-

ing potential is 35–46%. About 70–80% of the technical saving potential could be achieved in 2010 by appropriate demand side management and regulation programs. Residential lighting accounts for 23% of lighting electric consumption. Commercial and industrial lighting consume 57% and 17% of lighting electricity, respectively. Roughly speaking, the relation of electric consumption of residential lighting, commercial lighting, and industrial lighting is 1:3:1, which is very close to EPRI estimations (Faruqui *et al.* 1990, Hendrix and Ushimaru 1992).

The potential contributors to significant electrical energy savings in the residential, commercial, and industrial sectors are summarized in Tables 2.14, 2.15, and 2.16. New lighting, heat pumps, and industrial motor systems are the vital elements for electric energy savings. The data of sector use for residential and commercial heat pump use include all the current consumption for space heating, space cooling, and water heating. Residential motors account for approximately 18% of sector electric use; however, the opportunity for savings is limited because of low annual operating hours and low percentage of rated horsepower. Microwave clothes dryers and freeze concentration are classified as electrification technologies. In evaluating the energy savings of these two technologies, the conversion efficiencies of energy from primary energy resources to electricity are assessed. Microwave clothes dryers are still under development, thus the percentage of sector use cannot be determined at this time.

Lighting, HVAC, and supermarket refrigeration account for about 80% of the commercial energy consumption. According to a report in the ASHRAE Journal (Miro and Cox 1994), the savings of other commercial energy use is up to 50%. A program was commissioned by the U.S. Department of Energy (DOE) to study the current consumption and estimate the maximum savings.

Table 2.14: Maximum potential energy savings for electric use of new versus current systems in the residential sector and current sector use.

Technology	Maximum Savings (%)	Sector Use (%)
Residential Lighting	50	10
Residential Heat Pumps	20-40	40 ^a
Residential Motors	limited ^b	18
Refrigerators	25-30	20
Microwave Clothes Dryers ^c	20	-

^aincludes all the current consumption for space heating, space cooling, and water heating.

^bbecause of low annual operating hours and low percentage of full load.

^cunder development, compared to current gas use.

Table 2.15: Maximum potential energy savings for electric use of new versus current systems in the commercial sector and current sector use.

Technology	Maximum Savings (%)	Sector Use (%)
Commercial Lighting	30-60	30
Commercial Heat Pumps	20-40	40
Supermarket Refrigeration	25	10
Microwave Clothes Dryers	20	-
Other	50	20

Table 2.16: Maximum potential energy savings for electric use of new versus current systems in the industrial sector and sector use.

Technology	Maximum Savings (%)	Sector Use (%)
Industrial Lighting	37-50	10
Industrial Motors	35-50	67-75
Freeze Concentration	varied ^a	-

^adepends on individual application.

The technology of freeze concentration is continuously creating a number of new applications. The energy savings of individual applications are varied (Jaret *et al.* 1992). For example, the savings for milk concentration is 50%, the savings for wastewater treatment is 87%, and the savings for caustic soda concentration can be as high as 97.5%.

The overall estimate of potential energy savings for electricity-saving technologies in the year 2000 investigated by Faruqi *et al.* (1990) is shown in Table 2.17. Only available technologies in 1990 and their technical potential were evaluated in the study. A long-term potential for savings should be higher than the given estimates because new technologies are continuously getting into the market. A report by Barker (1992) indicated that the potential savings for electricity is 70%. The Rocky Mountain Institute estimated a higher long-term potential savings of 75% (Fickett *et al.* 1990).

The contributors to primary fuel energy savings by using electricity in the transportation sector are summarized in Table 2.18. An estimate of energy savings for EVs ranges from 25% to 40%. The expected savings of the next generation of EVs is projected to be 60%. Initial costs, however, are high.

An estimate of potential sector contribution to energy savings is given in Table 2.19. The transportation sector is a less significant contributor to energy savings, however, the importance of this sector is under the consideration of environmental protection.

The potential contributors to energy and cost savings for natural gas use are shown in Table 2.20. The new generation of residential gas furnaces will be more convenient, quieter, cheaper, and more efficient than older furnaces. York Triathlon

Table 2.17: Overall estimate of potential energy savings by electricity-saving technologies in 2000.

Sector	Maximum Savings (%)	Total Use (%)
Residential	27-46	33
Commercial	23-49	31
Industrial	24-38	36
Total	24-44	100

Table 2.18: Maximum potential energy savings for electric use of new versus current technologies in the transportation sector.

Technology	Maximum Savings (%)
Electric Vehicles	60
Light Rail Transit	50

Table 2.19: Potential sector contribution to energy savings by electricity in the year 2000.

Sector	Contribution (%)
Residential	33
Commercial	32
Industrial	34
Transportation	1
Total	100

Table 2.20: Potential energy and cost savings for natural gas use.

Technology	Maximum Energy Savings (%)	Maximum Energy Cost Savings (%)
Gas Furnaces	-	-
Gas Heat Pumps	-	50
Engine-Driven Chillers	50	50
Absorption Chillers		
Double-Effect	50	50
Triple-Effect	75	75
Natural Gas Vehicles	-	40-50

gas heat pumps can be installed in household or small commercial stores. Engine-driven chillers and absorption chillers are suitable for large commercial buildings. Double-effect absorption systems are 50% more energy efficient than the gas chillers used 20 years ago. An advanced triple-effect unit is being developed, which will provide an additional 50% hike in efficiency when compared to double-effect units. The operating costs of natural gas vehicles is 40-50% lower than for conventional automobiles.

More efficient technologies for electricity and natural gas are continuously being made commercially available. The adoption of these new technologies will benefit consumers, utilities, and the environment. A key issue is to increase the market penetration of these technologies. Successful utility-sponsored customer energy management programs are necessary. First cost and early replacement are the two factors that will determine how accurate the forecasted estimates are. The information in this chapter will be used to develop a computer code to help local utilities assess their energy management strategies.

CHAPTER 3. UNCERTAINTY

The description of a complex system may be simplified by allowing some degree of uncertainty. The information loss in reducing the complexity of a system to a manageable level is represented by uncertainty. The proper application of uncertainty always offers an effective and efficient representation of knowledge. Uncertainty representing mechanisms that could be used in the computer code are reviewed and compared in the following sections.

Overview of Uncertainty

Uncertainty is not a homogeneous notion, but there are several possible sources (Bench-Capon 1990). The first source may result from incomplete information or data. A major reason for incompleteness is that some events have not yet occurred. A second source of uncertainty may be some vagueness or ambiguity in the predicate itself. We may know a man with \$500,000 to be wealthy, but we might be unsure whether the predicate can be applied to a man with \$480,000 or not. The third source of uncertainty may be an element of irreducible uncertainty. For example, when we judge the honesty of a person, uncertainty is naturally existing.

There are several methods that can be used to handle uncertainty such as probability theory, certainty factors, Dempster-Shafer theory, possibility theory, rough

sets, and non-numerical methods. For a long time, probability theory has been the primary numerical approach for representation and inference with uncertainty. Certainty factors, Dempster-Shafer theory, and possibility theory are significant models extended from probability theory during the past two decades. Rough sets is a model for data analysis and knowledge discovery from disorganized and incomplete data. People also attempt to manage the problem of incomplete information using classical logic. The well-known approaches are non-monotonic logic and the theory of endorsements. Application of these theories to rule-based systems enables us to represent uncertainty in production rules. Uncertainty can be propagated through the rules and combined to give the uncertainty in the conclusions.

Basic symbols and operations of set theory are summarized in Appendix A to provide the necessary background for uncertainty investigation.

Probability Theory

Probability theory (Barr and Zehna 1983, Feldman and Fox 1991) was one of the earliest methods used to manage uncertainty. It is based on the theory of conditional probability. Before we discuss the theory, let's have a short review of the notation and terminology of probability.

All possible outcomes of an experiment is called the sample space for that experiment, denoted by " S ". A subset " e " of the sample space of a selected experiment is called an event. If an experiment is performed and the outcome is in e , we say the event e has occurred. When the event e has not occurred, the notation " e^c " is used to represent it. The notation e^c is called the complement of event e . An event that occurs if and only if both events e_1 and e_2 occur is called the intersection of e_1 and

e_2 , denoted by " $e_1 \cap e_2$ ". An event that occurs if at least one of e_1 and e_2 occurs is called the union of e_1 and e_2 , denoted by " $e_1 \cup e_2$ ". The intersection and union of n events are represented by $\bigcap_{i=1}^n e_i$ and $\bigcup_{i=1}^n e_i$, respectively. The events e_1, e_2, \dots, e_n contained in the sample space are called mutually exclusive if and only if $e_i \cap e_j = \emptyset$ (empty set) for $i \neq j, 1 \leq i, j \leq n$.

A function P mapping from a set 2^S to $[0, 1]$ is denoted by $P : 2^S \rightarrow [0, 1]$, and has the properties:

1. $P(e) \geq 0$
2. $P(S) = 1$
3. $P(\bigcup_{i=1}^n e_i) = \sum_{i=1}^n P(e_i)$ if e_1, e_2, \dots, e_n , are mutually exclusive,

then the function P is called a probability function on the sample space S and $P(e)$ represents the probability that event e will occur. The probability relation between event e and its complement e^c is represented as

$$P(e^c) = 1 - P(e) \quad (3.1)$$

A special case $P(\emptyset) = 1 - P(S) = 0$ is observed, since the empty set is the complement of sample space S .

Usually, we have interest only in the outcomes that are in a given non-empty subset e . Let " h " be the event we are interested in, i.e. the hypothesis. Conditional probability of h given e is the probability that h will occur if e occurs, denoted by $P(h|e)$. According to conventional probability theory, we have

$$P(h|e) = \frac{P(h \cap e)}{P(e)} \quad (3.2)$$

The event e is fixed and $P(e) > 0$. If $P(e) = 0$, then $P(h|e)$ is not defined. The event e can be any event over the sample space. Rearranging Equation 3.2, we obtain

$$P(h \cap e) = P(h|e)P(e) \quad (3.3)$$

Similarly,

$$P(e \cap h) = P(e|h)P(h) \quad (3.4)$$

Since the probability of two events is the same regardless of the order in which they are written, $P(h \cap e) = P(e \cap h)$. Thus, the right-hand-side of Equation 3.3 is equal to the right-hand-side of Equation 3.4, so we have

$$P(h|e)P(e) = P(e|h)P(h) \quad (3.5)$$

Dividing both sides by $P(e)$, we have a fantastic relationship

$$P(h|e) = \frac{P(e|h)P(h)}{P(e)} \quad (3.6)$$

This is the simplest form of Bayes' Theorem, which allows us to compute the value of $P(h|e)$, if $P(h)$, $P(e|h)$, and $P(e)$ are given. $P(h)$ is often called a prior probability because it is the probability prior to the discovery of e . $P(h|e)$ is the posterior probability because it is the probability once information about e is available. Bayes' theorem is an useful tool to calculate probabilities $P(h|e)$, because in practice the probabilities $P(h|e)$ are always difficult to find. However, the probabilities $P(e|h)$ are often easier to determine. Sometimes, Equation 3.6 is called the inversion formula since it defines $P(h|e)$ in terms of $P(e|h)$.

The conditional probability function given an event e over the sample space S satisfies the following properties:

1. $P(h|e) \geq 0$
2. $P(S|e) = 1$
3. $P(\bigcup_{i=1}^n h_i|e) = \sum_{i=1}^n P(h_i|e)$ if h_1, h_2, \dots, h_n are mutually exclusive.

The more general form of Bayes' theorem is

$$P(h|e_1 \cap e_2 \cap \dots \cap e_k) = \frac{P(e_1 \cap e_2 \cap \dots \cap e_k|h)P(h)}{P(e_1 \cap e_2 \cap \dots \cap e_k)} \quad (3.7)$$

The denominator can be expanded using general multiplication rule:

$$\begin{aligned} P(e_1 \cap e_2 \cap \dots \cap e_k) \\ = P(e_1)P(e_2|e_1)P(e_3|e_1 \cap e_2) \dots P(e_k|e_1 \cap e_2 \cap \dots \cap e_{k-1}) \end{aligned} \quad (3.8)$$

We can simplify the system if certain events are assumed to be independent of each other. For example, if any pair of events e_i and e_j are independent, we have

$$P(e_i) = P(e_i|e_j) \quad (3.9)$$

It means the assignment of probability to the occurrence of e_i is not affected by the information that e_j occurs. If $P(e_i|e_j) = P(e_i)$ and by definition

$$P(e_i|e_j) = \frac{P(e_i \cap e_j)}{P(e_j)} \quad (3.10)$$

then we have

$$P(e_i \cap e_j) = P(e_i)P(e_j) \quad (3.11)$$

If all the events are mutually independent, no more information is needed for multiple event cases than the single event cases. The general multiplication rule can be simplified as

$$P(e_1 \cap e_2 \cap \dots \cap e_k) = P(e_1)P(e_2) \dots P(e_k) \quad (3.12)$$

for $1 \leq k \leq n$. On the other hand, the events e_1, e_2, \dots, e_n are conditionally independent given an event h over S , if

$$P(e_1 \cap e_2 \cap \dots \cap e_k | h) = P(e_1 | h)P(e_2 | h) \dots P(e_k | h) \quad (3.13)$$

is satisfied. The probability of the hypothesis (i.e. conclusion) being true can then be calculated for the simplified system by substituting Equations 3.12 and 3.13 into Equation 3.7. Thus, we have a new form of Bayes' theorem as follows:

$$P(h | e_1 \cap e_2 \cap \dots \cap e_k) = \frac{P(e_1 | h)P(e_2 | h) \dots P(e_k | h)P(h)}{P(e_1)P(e_2) \dots P(e_k)} \quad (3.14)$$

In practice, we usually have more than one hypothesis for the problem. Let $H = \{h_1, h_2, \dots, h_m\}$ be a set of m possible hypotheses and $E = \{e_1, e_2, \dots, e_n\}$ be a set of n pieces of evidence. To simplify the system, we assume the hypotheses in H are mutually exclusive and collectively exhaustive, i.e. $\bigcup_{i=1}^m h_i = S$. Under this assumption, we have to consider only the m hypotheses separately. Probability $P(e)$ can be written as

$$P(e) = P\left(\left(\bigcup_{j=1}^m h_j\right) \cap e\right) \quad (3.15)$$

$$= P\left(\bigcup_{j=1}^m (h_j \cap e)\right) \quad (3.16)$$

$$= \sum_{j=1}^m P(h_j \cap e) \quad (3.17)$$

$$= \sum_{j=1}^m P(e | h_j)P(h_j) \quad (3.18)$$

Therefore, the Bayes' theorem for any hypothesis $h_i \in H$ is expressed as

$$P(h_i | e) = \frac{P(e | h_i)P(h_i)}{\sum_{j=1}^m P(e | h_j)P(h_j)} \quad (3.19)$$

for $1 \leq i \leq m$. Another assumption used to simplify the system is that all pieces of evidence $e_i \in E$ are conditionally independent given any hypothesis $h_i \in H$. According to this assumption, the expression of general Bayes' theorem is

$$P(h_i | e_1 \cap e_2 \cap \dots \cap e_k) = \frac{P(e_1 | h_i) P(e_2 | h_i) \dots P(e_k | h_i) P(h_i)}{\sum_{j=1}^m P(e_1 | h_j) P(e_2 | h_j) \dots P(e_k | h_j) P(h_j)} \quad (3.20)$$

for $1 \leq k \leq n$, $1 \leq i \leq m$. Using Bayes' theorem we can compute the combined influence of the pieces of evidence e_1, e_2, \dots, e_k given the hypothesis h_i . However, $(m \times n)^k + m$ of probabilities are required. Even for a modest value of k , it is still a big number.

A number of reasons indicate that probability theory is not a suitable uncertainty handling mechanism (Jackson 1990, Reichgelt 1991):

1. Probability theory can't exactly represent linguistic variables such as "few", "modest", and "most".
2. It is imperative that the application of probability theory needs many numbers, but the acquisition of these numbers is very difficult because of the unavailability of sufficient information.

Certainty Factor Model

The certainty factor model is another approach for handling uncertainty, developed by Shortliffe and Buchanan (1975) in the MYCIN system¹. Certainty factors reflect the degree of increased belief MB (measure of increased belief) and the degree of increased disbelief MD (measure of increased disbelief). The measure of increased

¹MYCIN is a medical expert system.

belief expresses the degree to which an observed piece of evidence e increases the belief in a hypothesis h . The measure of increased disbelief expresses the degree to which an observed piece of evidence decreases the belief in a hypothesis.

We have to understand the definitions and meanings of MB and MD before we can start the other part of work regarding certainty factor model. Let P be a probability function defined on a sample space S . According to probability theory, $P(h)$ represents the belief in h , and $1 - P(h)$ is the representation of disbelief regarding the truth of h . If $P(h|e)$ is greater than $P(h)$, the evidence e increases the belief in h and decreases the disbelief regarding the truth of h . The ratio of decrease in disbelief is expressed as

$$\frac{P(h|e) - P(h)}{1 - P(h)}$$

This ratio is called the measure of increased belief in h resulting from the evidence of e . On the other hand, if $P(h|e)$ is less than $P(h)$, the evidence e decreases the belief in h and increases the disbelief regarding the truth of h . The ratio of decrease in belief is

$$\frac{P(h) - P(h|e)}{P(h)}$$

We called this ratio the measure of increased disbelief resulting from the evidence of e . Since one piece of evidence cannot support and disfavor a single hypothesis, when $MB(h, e) > 0$, then $MD(h, e) = 0$, and when $MD(h, e) > 0$, then $MB(h, e) = 0$. When an evidence is independent of the hypothesis [i.e. $P(h|e) = P(h)$], we have $MB(h, e) = MD(h, e) = 0$. Therefore, the measure of increased belief can be expressed in terms of conditional and priori probabilities, which is a function MB:

$2^S \times 2^S \rightarrow [0, 1]$, such that

$$\text{MB}(h, e) = \begin{cases} 1 & \text{if } P(h) = 1 \\ \text{Max} \left(0, \frac{P(h|e) - P(h)}{1 - P(h)} \right) & \text{if } P(h) \neq 1 \end{cases} \quad (3.21)$$

and the measure of increased disbelief is expressed as a function MD: $2^S \times 2^S \rightarrow [0, 1]$, such that

$$\text{MD}(h, e) = \begin{cases} 1 & \text{if } P(h) = 0 \\ \text{Max} \left(0, \frac{P(h) - P(h|e)}{P(h)} \right) & \text{if } P(h) \neq 0 \end{cases} \quad (3.22)$$

Both $\text{MB}(h, e)$ and $\text{MD}(h, e)$ range from 0 to 1. For example, if $\text{MB}(h, e) = 0.75$, the number 0.75 reflects the extent to which the belief that h is true is increased by the information that e is true. $\text{MD}(h, e) = 0$ for this case, which means there is no reason to increase disbelief in h based on the evidence e .

In order to compute the MB and MD for combinations of pieces of evidence, we rewrite the expressions of MB and MD. By probability relations

$$P(h) + P(h^c) = 1 \quad (3.23)$$

$$P(h|e) + P(h^c|e) = 1 \quad (3.24)$$

$$\frac{P(h|e)}{P(h)} = \frac{P(e|h)}{P(e)} \quad (3.25)$$

we have

$$\begin{aligned} \text{MB}(h, e) &= \frac{P(h|e) - P(h)}{1 - P(h)} \\ &= \frac{[1 - P(h^c|e)] - [1 - P(h^c)]}{P(h^c)} \end{aligned}$$

$$\begin{aligned}
&= \frac{P(h^c) - P(h^c|e)}{P(h^c)} \\
&= 1 - \frac{P(h^c|e)}{P(h^c)} \\
&= 1 - \frac{P(e|h^c)}{P(e)}
\end{aligned}$$

Rearranging the result, we have a new correlation

$$\frac{P(e|h^c)}{P(e)} = 1 - \text{MB}(h, e) \quad (3.26)$$

The combination of two pieces of evidence for the measure of belief can be derived from the assumption of simple Bayes' theorem with e_1 and e_2 being mutually exclusive.

$$\frac{P(e_1 \cap e_2|h^c)}{P(e_1 \cap e_2)} = \frac{P(e_1|h^c)}{P(e_1)} \cdot \frac{P(e_2|h^c)}{P(e_2)} \quad (3.27)$$

Applying the relationship of Equation 3.26 into Equation 3.27, we have

$$1 - \text{MB}(h, e_1 \cap e_2) = [1 - \text{MB}(h, e_1)][1 - \text{MB}(h, e_2)] \quad (3.28)$$

From the definition of MD and by Eq 3.25, we have

$$\begin{aligned}
\text{MD}(h, e) &= 1 - \frac{P(h|e)}{P(h)} \\
&= 1 - \frac{P(e|h)}{P(e)}
\end{aligned}$$

Rearranging the result given above, we obtain

$$\frac{P(e|h)}{P(e)} = 1 - \text{MD}(h, e) \quad (3.29)$$

The combination of two pieces of evidence for the measure of disbelief can be derived from the right-hand-side of Bayes' theorem of general and simplified forms. It's a special case for simplifying from Equation 3.7 to Equation 3.14:

$$\frac{P(e_1 \cap e_2|h)}{P(e_1 \cap e_2)} = \frac{P(e_1|h)}{P(e_1)} \cdot \frac{P(e_2|h)}{P(e_2)} \quad (3.30)$$

After applying the relationship of Equation 3.29 into Equation 3.30, we acquire the following correlation:

$$1 - MD(h, e_1 \cap e_2) = [1 - MD(h, e_1)][1 - MD(h, e_2)] \quad (3.31)$$

Let's rewrite the combination functions for co-evidence in a straightforward manner in the following:

$$\begin{aligned} & MB(h, e_1 \cap e_2) \\ &= \begin{cases} 0 & \text{if } MD(h, e_1 \cap e_2) = 1 \\ MB(h, e_1) + MB(h, e_2)(1 - MB(h, e_1)) & \text{otherwise} \end{cases} \end{aligned} \quad (3.32)$$

$$\begin{aligned} & MD(h, e_1 \cap e_2) \\ &= \begin{cases} 0 & \text{if } MB(h, e_1 \cap e_2) = 1 \\ MD(h, e_1) + MD(h, e_2)(1 - MD(h, e_1)) & \text{otherwise} \end{cases} \end{aligned} \quad (3.33)$$

The computations of the measure of belief and the measure of disbelief for combinations of pieces of hypotheses defined by Shortliffe and Buchanan are stated in the following:

$$MB(h_1 \cap h_2, e) = \text{Min}\{MB(h_1, e), MB(h_2, e)\} \quad (3.34)$$

$$MD(h_1 \cap h_2, e) = \text{Max}\{MD(h_1, e), MD(h_2, e)\} \quad (3.35)$$

$$MB(h_1 \cup h_2, e) = \text{Max}\{MB(h_1, e), MB(h_2, e)\} \quad (3.36)$$

$$MD(h_1 \cup h_2, e) = \text{Min}\{MD(h_1, e), MD(h_2, e)\} \quad (3.37)$$

The first argument of the combination function given above are communicative² and associative³. For a special condition if h_1 and h_2 are mutually exclusive, $h_1 \cap h_2 = \emptyset$, the assumptions on the conjunction of hypotheses are unreasonable.

²Communicative: $MB(h_1 \cap h_2, e) = MB(h_2 \cap h_1, e)$

³Associative: $MB[(h_1 \cap h_2) \cap h_3, e] = MB[h_1 \cap (h_2 \cap h_3), e]$

The certainty factor is denoted by CF, subtracting MD from MB.

$$CF(h, e) = MB(h, e) - MD(h, e) \quad (3.38)$$

Therefore, CF is a real number between -1 and 1 . As evidence is accumulated, MB and MD will change and result in increasing or decreasing CF. A positive value of CF indicates that the conditions are supporting evidence for the conclusion, while a negative value of CF indicates that the conditions are evidence against the conclusion. $CF = -1$ means the conclusion is certain to be false if the conditions are fully satisfied. $CF = 1$ means the conclusion is certain to be true if the conditions are completely satisfied. When the priori belief in a hypothesis is small (i.e. $P(h) \rightarrow 0$), the CF of a hypothesis confirmed by evidence is approximated to the conditional probability.

$$\begin{aligned} CF(h, e) &= MB(h, e) - MD(h, e) \\ &= \frac{P(h|e) - P(h)}{1 - P(h)} - 0 \\ &\approx P(h|e) \end{aligned}$$

Similarly, as $P(h) \rightarrow 0$, $CF(h^c, e) \approx -P(h|e)$.

If $P(h|e) = 1$, then $MB(h, e) = 1$, $MD(h, e) = 0$, and $CF(h, e) = 1$. On the other hand, if $P(h^c|e) = 1$, then $MB(h, e) = 0$, $MD(h, e) = 1$, and $CF(h, e) = -1$. When $MB(h, e) = 0$, we say h is not confirmed by e . When $MD(h, e) = 0$, we say h is not disconfirmed by e . When $CF(h, e) = 0$, we say h is not confirmed or disconfirmed by e . It can be shown that

$$CF(h, e) + CF(h^c, e) = 0 \quad (3.39)$$

since the evidence supports a hypothesis and disfavors the complement of the hypothesis to an equal extent. Let's prove this statement under the assumption that h

is confirmed by e (i.e. h^c is not confirmed by e).

$$\begin{aligned} CF(h, e) &= MB(h, e) - MD(h, e) \\ &= \frac{P(h|e) - P(h)}{1 - P(h)} - 0 \\ &= \frac{P(h|e) - P(h)}{1 - P(h)} \end{aligned}$$

$$\begin{aligned} CF(h^c, e) &= MB(h^c, e) - MD(h^c, e) \\ &= 0 - \frac{P(h^c) - P(h^c|e)}{P(h^c)} \\ &= -\frac{[1 - P(h)] - [1 - P(h|e)]}{1 - P(h)} \\ &= \frac{P(h) - P(h|e)}{1 - P(h)} \end{aligned}$$

Therefore,

$$CF(h, e) + CF(h^c, e) = \frac{P(h|e) - P(h)}{1 - P(h)} + \frac{P(h) - P(h|e)}{1 - P(h)} = 0$$

The combination functions of certainty factor for two hypotheses are defined by

$$CF(h_1 \cap h_2, e) = \text{Min}\{CF(h_1, e), CF(h_2, e)\} \quad (3.40)$$

$$CF(h_1 \cup h_2, e) = \text{Max}\{CF(h_1, e), CF(h_2, e)\} \quad (3.41)$$

The co-evidence combination function of certainty factor (Lucas and van der Gaag 1991) is expressed as follows:

$$CF(h, e_1 \cap e_2) = \begin{cases} CF(h, e_1) + CF(h, e_2)(1 - CF(h, e_1)) & \text{if } CF(h, e_i) > 0, i = 1, 2 \\ \frac{CF(h, e_1) + CF(h, e_2)}{1 - \text{Min}\{|CF(h, e_1)|, |CF(h, e_2)|\}} & \text{if } -1 < CF(h, e_1) \cdot CF(h, e_2) \leq 0 \\ CF(h, e_1) + CF(h, e_2)(1 + CF(h, e_1)) & \text{if } CF(h, e_i) < 0, i = 1, 2 \end{cases} \quad (3.42)$$

The certainty factor model is not well-founded from the mathematical point of view even though it has been successfully employed in many rule-based expert systems. This model seems to be very *ad hoc*. It provides a specific solution to a problem, not a principled solution to the problem. A couple of criticisms have been addressed (Adams 1984, Lucas and van der Gaag 1991):

1. It doesn't have a strong theoretical support.
2. The certainty factor model is loosely based on probability theory, but under some circumstances the results are different from the ones derived from probability theory.

According to Adams' study (Adams 1984), the empirical success of MYCIN and other systems with similar characteristics might result from the short reasoning chains and simple hypotheses. The application of CF model to general systems is difficult.

Dempster-Shafer Theory

Dempster-Shafer theory (Shafer 1976, Lucas and van der Gaag 1991, Tessem 1993) is an extension of probability theory, also called evidence theory. It supplies a framework for computing uncertain information. If we have several pieces of independent evidence and we can make inferences for each piece of evidence, the Dempster-Shafer theory allows us to combine all the evidence and obtain a more complete assessment. Traditional probability theory cannot distinguish between uncertainty and ignorance, but Dempster-Shafer theory can.

The initial set of all hypotheses in Dempster-Shafer theory is called the frame of discernment, denoted by Θ . The set of all possible subsets of Θ is denoted by 2^Θ ,

since there are 2^n subsets of a set with n elements. A subset of Θ is called a focal element. The individual hypotheses are assumed to be disjunctive. The impact of a piece of evidence on the confidence or belief in a certain subset of a given frame of discernment is described by a function called the basic probability assignment (bpa). The basic probability assignment value is based on a probability mass function. The function represents the total mass of the belief in evidence according to a particular hypothesis set. As a kind of probability, bpa ranges from 0 to 1. Any focal element A is a subset of Θ , expressed as $A \subseteq \Theta$. Let m be a basic probability assignment mapping from each subset $A \subseteq \Theta$ to inclusive range $[0,1]$, such that

1. $m(A) \geq 0$.
2. $m(\emptyset) = 0$. [\emptyset is the null set]
3. $\sum_{A \subseteq \Theta} m(A) = 1$.

for each subset $A \subseteq \Theta$. The number $m(A)$ is called the basic probability number of A over Θ .

A basic probability assignment number $m(A)$ expresses the measure of the confidence or belief committed to exactly the set A . It does not express any belief in subsets of A . However, the total confidence in A is not only dependent on the confidence in A itself, but also on the confidence of all subsets of A . Therefore, a belief function is used to describe the cumulative belief in a set of hypotheses. The belief function corresponding with m in the function $Bel : 2^\Theta \rightarrow [0, 1]$

$$Bel(A) = \sum_{B \subseteq A} m(B) \quad (3.43)$$

for each $A \subseteq \Theta$. The properties of belief function are:

1. $Bel(\Theta) = 1$ since $\sum_{B \subseteq \Theta} m(B) = 1$.
2. For each $A \subseteq \Theta$ with only one element, we have $Bel(A) = m(A)$.
3. For each $A \subseteq \Theta$, we have $Bel(A) + Bel(A^c) \leq 1$
since

$$\begin{aligned} Bel(\Theta) &= Bel(A \cup A^c) \\ &= Bel(A) + Bel(A^c) + \sum_{\substack{A \cap B \neq \emptyset \\ A^c \cap B \neq \emptyset}} m(B) = 1 \end{aligned}$$

where A^c is the complement of A .

4. $Bel(A) + Bel(B) \leq Bel(A \cup B)$ for each $A, B \subseteq \Theta$.

In addition to the belief function, the Dempster-Shafer theory defines another function corresponding with m called plausibility function (Barbett 1991). Plausibility function $Pl : 2^\Theta \rightarrow [0, 1]$ defined by

$$Pl(A) = \sum_{A \cap B \neq \emptyset} m(B) \quad (3.44)$$

for each $A \subseteq \Theta$. It indicates the degree to which the evidence is consistent with A . In other words, a function value of $Pl(A)$ represents the total confidence not assigned to A^c . Therefore,

$$Pl(A) = 1 - Bel(A^c) \quad (3.45)$$

for each $A \subseteq \Theta$. A belief function provides for each focal element A the lower bound; a plausibility function provides an upper bound. The difference $Pl(A) - Bel(A)$ indicates the confidence in the sets B for which $A \subseteq B$, and expresses the uncertainty

with respect to a given hypothesis A .

$$Ucty(A) = Pl(A) - Bel(A) \quad (3.46)$$

For each $A \subseteq \Theta$, the closed interval $[Bel(A), Pl(A)]$ is called the belief interval of focal element A . The inferences are more uncertain with a wider belief interval. If we have $[Bel(A), Pl(A)] = [0, 1]$, there is no available information about A . If we have $[Bel(A), Pl(A)] = [1, 1]$, the focal element A is fully confirmed. If we have $Pl(A) - Bel(A) = 0$, we are back to traditional probability theory. In such a situation, the belief function is called a Bayesian belief function.

In order to clarify the definitions of basic probability assignment, belief function, plausibility, and uncertainty, let's consider an example. Assume the initial set of hypothesis space is $\Theta = \{\alpha, \beta, \gamma\}$. Then, all possible subsets of this frame of discernment are $2^\Theta = \{\{\alpha\}, \{\beta\}, \{\gamma\}, \{\alpha\beta\}, \{\alpha\gamma\}, \{\beta\gamma\}, \{\alpha\beta\gamma\}\}$. We assign basic probability numbers to each member of 2^Θ . The summation of these numbers is exactly equal to one. Thus, we can compute the values of Bel , Pl , and $Ucty$, as shown in Table 3.1. There is no direct evidence to support the proposition in focal element $\{\beta\gamma\}$, however, the values of belief function and plausibility are not zero, because the bpa values of other focal elements are non-zero.

Dempster's rule of combination provides a function for computing a new basic probability assignment from two belief functions based on two different evidences. Let Bel_1 and Bel_2 denote two belief functions with basic probability assignments of m_1 and m_2 . The rule computes a new bpa $m_1 \oplus m_2$ describing the combined effect of m_1 and m_2 .

1. $m_1 \oplus m_2(\emptyset) = 0$

Table 3.1: An example for calculating the magnitudes of belief, plausibility, and uncertainty functions.

A	m	Bel	Pl	$Ucty$
α	0.15	0.15	0.65	0.50
β	0.10	0.10	0.30	0.20
γ	0.25	0.25	0.70	0.45
$\alpha\beta$	0.05	0.30	0.75	0.45
$\alpha\gamma$	0.30	0.70	0.90	0.20
$\beta\gamma$	0	0.35	0.85	0.50
$\alpha\beta\gamma$	0.15	1.00	1.00	0
Σ	1.00			

$$2. m_1 \oplus m_2(A) = \frac{\sum_{X \cap Y = A} m_1(X)m_2(Y)}{1 - \sum_{X \cap Y = \emptyset} m_1(X)m_2(Y)} \quad \text{for all } A \neq \emptyset.$$

Commutativity of multiplication ensures that Dempster's rule gives the same result regardless of the order of evidence is combined. Then, a new belief function $Bel_1 \oplus Bel_2$ is obtained based on the definition of Equation 3.43. $Bel_1 \oplus Bel_2 : 2^\Theta \rightarrow [0, 1]$ defined by

$$Bel_1 \oplus Bel_2(A) = \sum_{B \subseteq A} m_1 \oplus m_2(A) \quad (3.47)$$

We illustrate the usage of Dempster's rule of combination through an example of vegetable classification, in which the frame of discernment is {broccoli, celery, lettuce}. We denote B for broccoli, C for celery, and L for lettuce, i.e. $\Theta = \{B, C, L\}$. Assume the first piece of evidence gives m_1 and the second piece of evidence gives m_2 .

$$m_1(A) = \begin{cases} 0.7 & \text{if } A = \{B, C, L\} \\ 0.3 & \text{if } A = \{B, C\} \\ 0 & \text{otherwise} \end{cases}$$

Table 3.2: Intersection tableau of m_1 and m_2 .

$m_1 \downarrow m_2 \rightarrow$...	CL (0.8)	...	BCL (0.2)
⋮				
BC (0.3)		C (0.24)		BC (0.06)
⋮				
BCL (0.7)		CL (0.56)		BCL (0.14)

$$m_2(A) = \begin{cases} 0.2 & \text{if } A = \{B, C, L\} \\ 0.8 & \text{if } A = \{C, L\} \\ 0 & \text{otherwise} \end{cases}$$

Applying Dempster's rule of combination, we acquire a new basic probability assignment $m_1 \oplus m_2$. The processing tableau is shown in Table 3.2. The first column corresponds to one set of basic probability assignment, the first row to the other. The tableau shows only the focal elements with non-zero bpa. The crossing of a row and a column (called a cell) represents the intersection of the row and the column, associated with a new basic probability assignment by multiplying the corresponding numbers.

After summing the basic probability numbers that belong to the same subset of hypothesis space for each subset, a set of new basic probability assignment is obtained.

$$m_1 \oplus m_2(A) = \begin{cases} 0.14 & \text{if } A = \{B, C, L\} \\ 0.24 & \text{if } A = \{C\} \\ 0.06 & \text{if } A = \{B, C\} \\ 0.56 & \text{if } A = \{C, L\} \\ 0 & \text{otherwise} \end{cases}$$

A problem happens, when one cell is empty. Let's consider one more piece of

Table 3.3: First-step intersection tableau of m_1 and m_3 .

$m_1 \downarrow m_3 \rightarrow$...	L (0.4)	...	BCL (0.6)
⋮				
BC (0.3)		\emptyset (0.12)		BC (0.18)
⋮				
BCL (0.7)		L (0.28)		BCL (0.42)

evidence which gives m_3 .

$$m_3(A) = \begin{cases} 0.6 & \text{if } A = \{B, C, L\} \\ 0.4 & \text{if } A = \{L\} \\ 0 & \text{otherwise} \end{cases}$$

The intersection of m_1 and m_3 following the previous procedure is shown in Table 3.3. In the tableau, the empty set is assigned a basic probability assignment that is greater than zero, i.e. $m_1 \oplus m_3(\emptyset) = 0.12$. This violates the first axiom of Dempster's rule of combination. Modifying it by Dempster's rule of combination, we set $m_1 \oplus m_3(\emptyset) = 0$. In this way, another rule is violated since $\sum_{A \subseteq \Theta} m_1 \oplus m_3(A)$ is less than 1. To overcome this problem, the second axiom of Dempster's rule of combination shows to divide the remaining numbers by the scaling factor

$$1 - \sum_{X \cap Y = \emptyset} m_1(X)m_2(Y) = \sum_{X \cap Y \neq \emptyset} m_1(X)m_2(Y).$$

In this example, the scaling factor is 0.88. The correct (second-step) intersection tableau of m_1 and m_3 is given in Table 3.4.

Dempster-Shafer theory of evidence include many features of certainty factor model, but with a firm mathematical foundation. Nevertheless, Lucas and van der Gaag (1991) indicated that Dempster-Shafer theory can't be applied directly to ex-

Table 3.4: Correct (second-step) intersection tableau of m_1 and m_3 .

$m_1 \downarrow m_3 \rightarrow$...	L (0.4)	...	BCL (0.6)
⋮				
BC (0.3)		∅ (0)		BC (0.20)
⋮				
BCL (0.7)		L (0.32)		BCL (0.48)

pert systems for inexact reasoning without modification. The difficulties are located at its complexity of computation and lack of several combination functions.

Possibility Theory

Possibility theory (Zadeh 1978, Dubois and Prade 1988, Dubois and Prade 1992) is another approach for uncertainty management based on fuzzy set theory (Zadeh 1965). This theory deals with situations in which both the question proposed and the relevant knowledge possessed contain vague concepts. Classical set theory is a two-valued logic, while fuzzy set theory is a many-valued logic.

A fuzzy set is a membership function, μ , from an appropriate domain in the interval $[0, 1]$ to express the grade of membership.

$$\mu_A(x) \rightarrow [0, 1]$$

means the degree of membership of the element $x \in U$ in the fuzzy set A ranges from 0 to 1, in which U is an universal set. $\mu_A(x) = 0$ denotes that x is not a member in fuzzy set A , while $\mu_A(x) = 1$ means x has full membership in fuzzy set A . Membership grades are not probabilities. The summation of probabilities must be one, but this is not necessary for membership grades.

Let B be another fuzzy set in U with membership function μ_B . The elementary fuzzy set operation for handling the interaction between fuzzy propositions are summarized in the following (Dubois and Prade 1988, Klir and Folger 1988):

1. Inclusion: If the membership grade of each $x \in U$ in fuzzy set A is less than or equal to its membership grade in fuzzy set B , then A is a subset of B .

$$\mu_A(x) \leq \mu_B(x) \quad \Longrightarrow \quad A \subseteq B \quad (3.48)$$

for all $x \in U$.

2. Equality: If the membership grades of each $x \in U$ are equal in fuzzy sets A and B , then $A = B$.

$$\mu_A(x) = \mu_B(x) \quad \Longrightarrow \quad A = B \quad (3.49)$$

for every $x \in U$.

3. Complementation: The complement of a fuzzy set A with respect to the universal set U is denoted by A^c . The relation of membership grades is defined as

$$\mu_{A^c}(x) = 1 - \mu_A(x) \quad (3.50)$$

for every $x \in U$.

4. Intersection: The intersection of two fuzzy sets A and B is a fuzzy set $A \cap B$. For all $x \in U$, we have

$$\mu_{A \cap B}(x) = \text{Min}\{\mu_A(x), \mu_B(x)\} \quad (3.51)$$

5. Union: The union of fuzzy sets A and B is a fuzzy set $A \cup B$. For all $x \in U$, there is

$$\mu_{A \cup B}(x) = \text{Max}\{\mu_A(x), \mu_B(x)\} \quad (3.52)$$

For example, if we assume $\mu_A(x) = 0.3$ and $\mu_B(x) = 0.6$, then we have $\mu_{A^c}(x) = 0.7$, $\mu_{A \cap B}(x) = 0.3$, $\mu_{A \cap A^c}(x) = 0.3$, $\mu_{A \cup B}(x) = 0.6$, and $\mu_{A \cup A^c}(x) = 0.7$

The operators of intersection and union are commutative, associative, and distributive. They obey the rule of compositionality, which means the magnitude of a compound expression is calculated from the values of its component expressions only.

Fuzzy sets can be employed to represent linguistic variables such as “very”, “medium”, and “few”. The use of linguistic variables is easier for humans to interpret than the original membership functions. Consider the annual income of a family is characterized by a linguistic variable, it could be a term of {low, moderate, high, ...}. We might interpret “low” as an income of less than about \$20,000, “moderate” as an income between \$30,000 and \$60,000, and “high” as an income more than about \$70,000. A possible representation of these linguistic variables and their membership functions are shown in Figure 3.1.

Rough Sets

Rough set theory (Pawlak 1982, Pawlak 1991) is a method for data analysis and knowledge discovery from imprecise and ambiguous data. The basic idea of a rough set is to approximate a set by a pair of sets, the lower and the upper approximation of this set. It does not need any preliminary information about data. We express knowledge using rough set rules to make it easier to understand, although this sometimes makes the knowledge representation less precise. Specifically, rough set theory

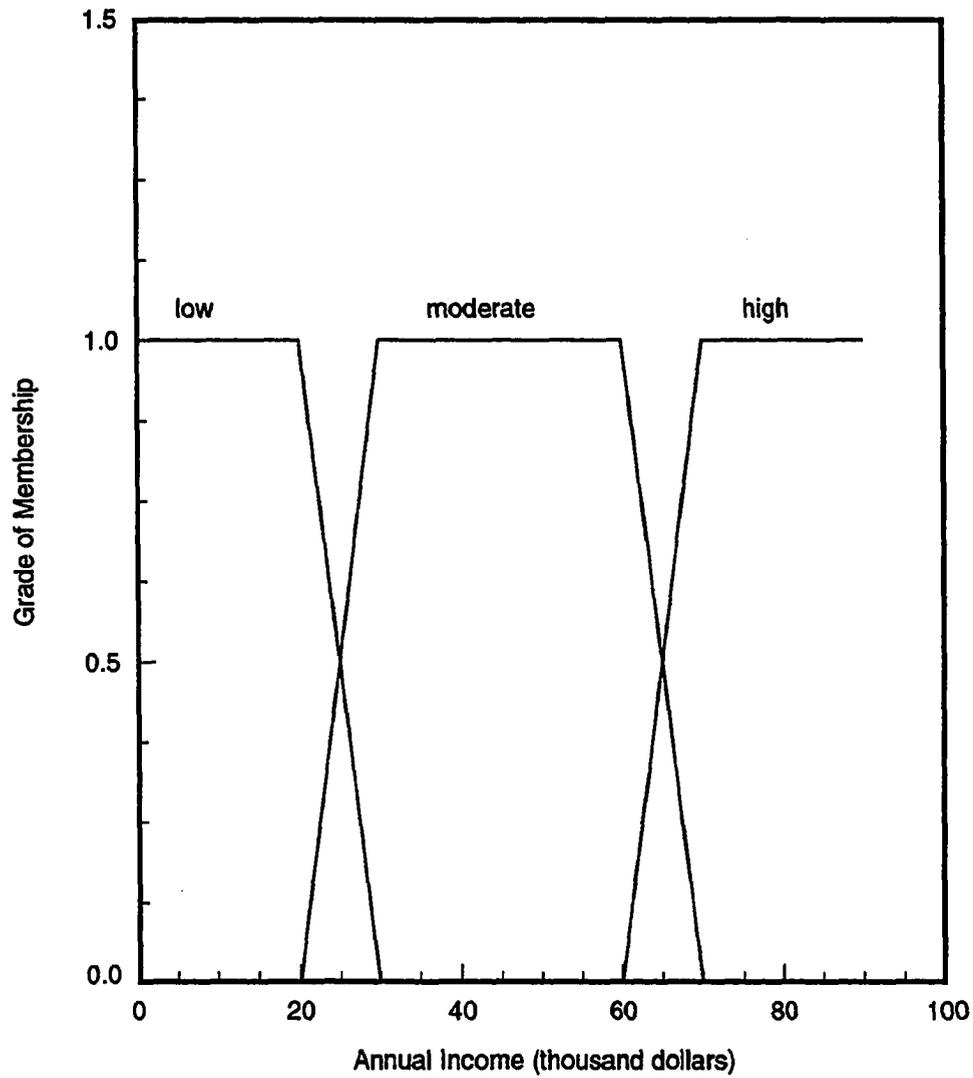


Figure 3.1: Linguistic representations of family annual income and their membership functions.

is based on the premise of lowering the degree of precision in data, thus to make data patterns more visible.

In rough set theory, knowledge is classified as objects belonging to the domain of interest. The classification process usually involves obtaining the values of attributes of the objects and classifying the objects into categories based on the information expressed in the attributes. For complicated classifications, more comprehensive knowledge may be required. The knowledge could be acquired from experienced domain experts or directly from data. In other words, the success of applying rough set to a system depends on the related knowledge and the ability of an user to classify data through observation and measurement. A number of promising applications have been found in areas such as voice recognition, approximate classification, predictive modeling, decision support, and expert system building.

Both fuzzy sets and rough sets are tools for the management of imperfect knowledge. Fuzzy sets are used for handling the vagueness of information, whereas rough sets are used for handling imprecision and ambiguity. Fuzzy sets express intensity of membership within the same class. Rough sets describe partitions that make the classes indiscernible objects. Therefore, rough sets are quite different from fuzzy sets. Fuzzy sets and rough sets complement each other in dealing with vagueness and coarseness.

Non-numerical Methods

The most famous non-numerical methods are the use of non-monotonic logic and the theory of endorsements (Bhatnagar and Kanal 1986). In non-monotonic logic (Moore 1985), there are n variables over the sample space. Each variable has a

specific value at any time based on the available evidence. A significant characteristic of non-monotonic logic is that a system cannot exist with inconsistent information. If the evidence points to more than one possible values for a variable, this ambiguity must be resolved immediately and a value must be assigned to the variable. If there is no information available for a variable, some assumption must be made about its value. There is only one description and all the uncertainties must be resolved before the representation is fixed. An uncertainty model can be set up only if predicates with certain interpretations are used. Each value assigned to a variable can have an associated belief, that is revised when new information is received.

In the theory of endorsements (Cohen 1985), a body of endorsements is associated with each hypothesis based on the evidence. There is no general rule for weighting two different bodies of endorsements. However, they can be pairwise ranked to each other individually. This way provides partial order, but it does little help for comparison when the bodies of endorsements are large.

The primary difference between numerical and non-numerical methods is that the premises of numerical methods may be partially believed, and inferences may have a high degree of confidence. However, the premises of non-numerical methods are fully believed or disbelieved, and the confidence in the inferences depends on the assumptions.

Network Model Theory

Network model theory (Pearl 1988, Neapolitan 1990, Charniak 1991) is a new theory for uncertainty representation in knowledge systems. It has various names in a number of literatures, like belief networks, Bayesian networks, knowledge maps, and

probabilistic casual networks. The methods summarized in the proceeding sections use production rules for knowledge representation, while network model theory uses a belief network. Graphical representation is the starting point of a belief network. A belief network includes the statistical variables over a problem domain and their probabilistic relations. The relationship among variables are quantified using local probabilities and a total probability function on the variables.

A belief network includes a qualitative representation of the problem domain and an associated quantitative representation. The qualitative representation is an acyclic directed graph $G = (V(g), A(g))$ where $V(g)$ is a finite set of vertices $V(g) = \{V_i, i = 1, 2, \dots, n\}$ and $A(g)$ is a finite set of arcs (V_i, V_j) which connects vertices V_i and V_j , $V_i, V_j \in V(g)$. Each vertex represents a statistical variable and each arc represents a direct relationship between two vertices. When a directed arc $(V_i, V_j) \in A(g)$ is constructed, V_j is called the successor of V_i and V_i is called the predecessor of V_j . (V_i, V_j) means V_i influences V_j directly. Absence of an arc between two vertices means the corresponding variables do not affect each other directly. For each variable (or vertex) V_i in a belief network, the magnitude of the variable is the association of the conditional probabilities of V_i to all its predecessors. If the vertex V_i has m incoming arcs, we have to assess 2^m probabilities; if V_i has no predecessor, only one probability needed to be concerned, i.e. $P(V_i)$. Since the computational complexity of belief networks is exponential in the number of variables, this model should not be applied to larger systems.

Discussion

A number of well-known numeric, non-numeric, and graphical methods have been reviewed and compared.

Probability theory can not define linguistic variables clearly and the values of probabilities can not be properly assigned because of insufficient information result in the difficulty in applying probability theory to manage uncertainty propagation.

The certainty factor model is an empirical approach. It is based on probability theory. However, for some cases, the results of the CF model are different from the results obtained by probability theory.

Dempster-Shafer theory is viewed as a generalization of probability theory. It contains the major features of the CF model coupled with a firm theoretical support. The difficulties in adopting Dempster-Shafer theory to a knowledge-based system are its complexity of computation and the insufficiency of combination functions. Basically, it cannot be applied directly to a knowledge-based system. We can use a FORTRAN program to implement some of the calculations and input the results to the knowledge base, thus simplifying the computation in the knowledge base. Because the combination functions are not sufficient, some limitations may exist when applying Dempster-Shafer theory.

Fuzzy logic can use linguistic variables to represent uncertainty and offers advanced logical operations. The powerful ability of compositionality of logical operators is the most significant advantage of fuzzy logic.

The fundamental procedure of rough sets is to lower the degree of precision of given data to make data patterns easier to discern. It is not suitable for this project, since our goal is to derive more knowledge from partial information.

The most important characteristic of non-numerical methods is their crispness, that is the conclusion is absolutely believed or disbelieved. These methods are not suitable because too many assumptions are needed.

Network model theory is a graphical mechanism associated with quantitative variables for uncertainty representation, which is not considered because production rules can not be used.

From the descriptions and comparisons of the major processing mechanisms for uncertainty, we found that the applications of Dempster-Shafer theory and fuzzy logic are more appropriate for this study. Fuzzy logic is the first choice because of its advanced logical operators.

CHAPTER 4. DEVELOPMENT OF A KNOWLEDGE-BASED SYSTEM FOR UTILITY PREDICTIONS

A knowledge-based system (or expert system) is a heuristic computer program that can make decisions or support decision making under a complex environment. Based on the information given in previous chapters and the following sections, a knowledge-based system is developed to help utilities assess their energy management strategies.

Overview of Knowledge-Based Systems

Knowledge-based systems (KBS) provide powerful and flexible tools to obtain the solutions to a variety of complicated problems. Usually, these problems can not be solved by conventional programming approaches. The knowledge for solving a problem often has a certain degree of uncertainty, and the available information to solve the problem may be imprecise or incomplete. To be useful using insufficient and imprecise information, a knowledge-based system must capture not only the expert knowledge, but also the uncertainties that go with the knowledge. Specifically, two common and intriguing characteristics of knowledge-based expert systems are their ability to deal with uncertain and partial data.

Ignizio (1991) indicated that typical knowledge-based systems have a number of

significant advantages over human experts:

1. Knowledge-based systems are always available and perform the task at the same level of expertise.
2. Knowledge-based systems can access the necessary databases without human experts' limited, biased, and imperfect recollections.
3. Knowledge-based systems are logical, objective, and consistent, but human experts might be emotional.
4. Knowledge-based systems do not make mathematical errors or forget anything.
5. Knowledge-based systems are accessible by all divisions of the company, but human experts' access are limited.
6. Knowledge-based systems make decisions only for company's benefit, but human experts might incorporate personal promotions and pay raises in their decisions.
7. Knowledge-based systems are permanent property of the company, but human experts may quit.
8. Knowledge-based systems make decisions with being able to list all of the factors used in the decisions and the weights of the factors, but human experts may not.

Of course, knowledge-based systems are not perfect, either. KBSs have some limitations when compared to human experts (Ignizio 1991). The major disadvantages are:

1. Human experts understand cultural factors, but knowledge-based systems usually do not.
2. Human experts know the limits of their knowledge, but knowledge-based systems do not.
3. Human experts exhibit creativity, but knowledge-based systems are limited to the knowledge base they have.
4. Human experts are more flexible than knowledge-based systems.
5. In some situations, people just want to consult with other people (human experts), not computer systems.

The most important part of a knowledge-based system is its knowledge base, transferred from human experts, that consists of facts and rules. The rules (or heuristic rules, or production rules) are developed through intuition, experience, and judgment. Basically, each rule has an IF statement (premise, or antecedent, or condition) and a THEN statement (conclusion, or consequent, or action). In some cases, the IF-THEN format is extended to IF-THEN-ELSE format.

Propositions may be linked together with various logical operators such as AND, OR, and NOT. If two clauses are connected by AND, both must be true for the compound statement to be true. If two clauses are connected by OR, the compound statement is true as long as at least one clause is true. The premise clauses may be connected by AND as well as OR; however, the conclusion clauses may only be connected by AND.

If the premise statement of a rule is true, the rule is triggered. If a rule is fired, the action described by the conclusion statement is implemented. A rule must be

triggered before it can be fired. One should never build a rule base such that the correct conclusion can only be reached when the production rules are arranged in a specific order.

Similar to human experts, when applying a knowledge-based expert system, we are often looking for a good solution instead of the optimal solution. We don't usually try to replace human experts with knowledge-based systems. The primary contribution of a knowledge-based system is to improve decision making, allowing human experts to increase productivity and address other more important problems.

Computer Languages for Knowledge-Based Systems

The computer languages for the development of knowledge-based systems (or expert systems) are classified as AI (Artificial Intelligence) languages, such as LISP (LISt Processing), PROLOG (PROgramming in LOGic), and OPS5 (Official Production System, Version 5), and non-AI languages, such as FORTRAN, BASIC, PL/1, PASCAL, C, C++, and Assembly language (Ignizio 1991, Bose 1994). Both LISP and PROLOG are symbolic processing languages. The LISP or its variety of dialects are very popular in the United States; however, PROLOG is widely used in Europe and Japan. Referring to Ignizio (1991), the primary advantages of PROLOG over LISP are that it is less expensive and more friendly. OPS5 is a rule-based language, which is the most popular language in production systems (Brownston *et al.* 1985).

Constructing a whole knowledge-based system using AI languages provides control of the system operation. Any portion can be modified or revised as we wish. Nevertheless, it may be very difficult to build a good user interface and include other capabilities as efficiently as available commercial shells.

Expert System Shells

An expert system shell consists of all the components included in a knowledge-based system except the knowledge base that is the heart of a knowledge-based system. A generic architecture of a knowledge-based system includes inference engine, knowledge base¹, working memory, and knowledge base adjuster, as shown in Figure 4.1. Using an expert system shell, a knowledge engineer² may develop the knowledge base and insert this knowledge base into the structure to form a complete knowledge-based system. Through the use of an expert system shell, a knowledge engineer can avoid setting up the supporting components repeatedly, and thus can concentrate on programming the knowledge base.

A number of expert system shells are available, such as EMYCIN (essential MYCIN or empty MYCIN) and LEVEL5 OBJECT (Information Builders 1990a). There is not a complete list of all existing expert system shells up-to-date; rather, we can find partial information in several places (Heath 1994, Waterman 1986, Harmon and King 1985, Mettrey 1991). The significant features of commercial expert system shells (Ignizio 1991) are:

1. They can be developed and implemented on a wide variety of computer platforms.
2. They may construct a rule base with a few hundred rules, or even many thousand rules.

¹A knowledge base includes rules, facts, and algorithms.

²A knowledge engineer is a person who can specify appropriate applications of knowledge-based systems and perform the development and implementation of knowledge-based systems.

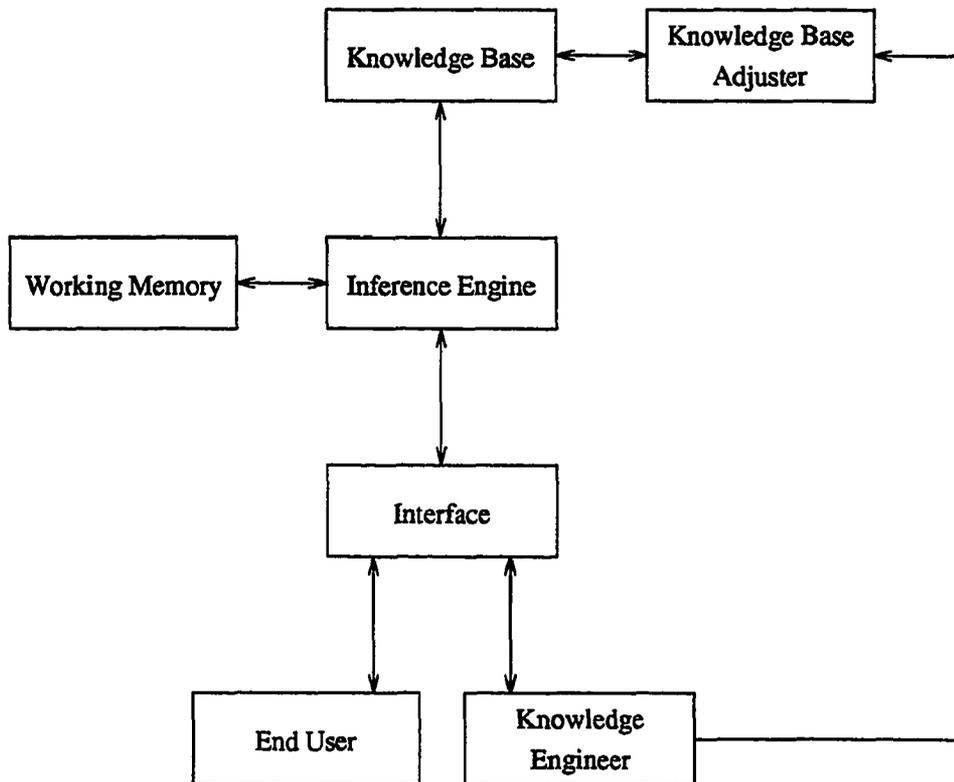


Figure 4.1: A generic knowledge-based system.

3. They provide good, or even better, computational speed when compared to conventional tools created by AI languages.
4. They allow forward chaining, backward chaining, or mixed chaining.
5. They have the capability of accessing external databases and/or programs.

Expert system shells are not general-purpose tools. Selecting an appropriate expert system shell for a specific problem is important. However, it is very difficult to recommend what shell should be used for a given problem. In the February 1989 issue of *Expert Systems* (Vedder 1989), a comparison of several popular shells applied to a specified problem is given. We were advised to talk with other users of a shell before we decide to use it.

According to Ignizio (1991), the major advantages of expert system shells include:

1. The transparent mode of knowledge representation enables users to modify and verify knowledge easily.
2. They are inexpensive (from several hundred dollars to several thousand dollars).
3. There are plenty of options to be run on inexpensive personal computers (PCs).
4. They are easy to use.
5. They allow knowledge engineers to focus on knowledge representation and acquisition.

6. They mimic most features of frame-based representation³.

The primary disadvantage of shells is that control of the inference engine (rule selector) is restricted since we can not access the source code. Also, some shells may not include all the features that a user may desire, but this is becoming less important because more powerful tools continue to become commercially available.

Knowledge-based systems with 200 or fewer rules are increasing rapidly because of the rapid development of commercial shells.

The Beginning of Programming

LEVEL5 OBJECT (LEVEL5) of Information Builders was chosen as the expert system shell to develop a knowledge-based system for utility predictions. According to comparisons, the performance of this shell is better than others based on ease of use, reasoning mechanism, and costs (initial cost and implementation cost).

Architecture

In a LEVEL5 knowledge base, information is structured as objects. An object has a structure called a class and instances, in which a class contains attributes and the instances hold the actual data of attributes. There are two kinds of objects: user-defined objects and system-defined objects. User-defined objects are created during development and are different from one another for each application. System-defined objects are created by LEVEL5 for every application.

³A frame consists of an object plus slots for all information pertinent to the object. Such slots may contain attributes, values of attributes, default values, pointers to other frames, rules, and procedures to be implemented. The use of frames is an extremely robust approach to represent knowledge.

Table 4.1: Classification of user-defined objects.

Classification	Objects
Basic	residential lighting, commercial lighting, industrial lighting, residential heat pump, commercial heat pump, residential motor, industrial motor, residential refrigerator, commercial refrigerator, residential microwave dryer, commercial microwave dryer, freeze concentration.
Technology	lighting, heat pump, motor, refrigerator, microwave dryer.
Sector	residential, commercial, industrial.
Summation	united.
Calculating	solver.

A single and pre-defined instance of the domain class is created automatically; thus, we can build an application without defining explicit classes by ourselves. Class names must be unique, but attribute names do not need to be exclusive. Different classes might have attributes using the same name. While considering inheritance, a child class can not inherit from parent classes with the same attribute names. Editing inherited attributes within a child class are not permitted.

The user-defined objects in this study were classified as basic, technology, sector, summation, and calculating objects, as shown in Table 4.1. The calculating object, solver, is inherited by each of the basic objects.

The attributes of the basic user-defined objects are the same for each object. The primary attributes are:

- **Maximum savings:** The maximum expected energy reduction of the new technology when applied, in percent of current usage per application. The maximum energy savings of the new technology is obtained from the available literature.

- **Expected savings:** The expected energy reduction of the new technology when applied, in percent of current usage per application.
- **Rebate:** The percentage of the initial cost of the new technology that is paid to the customers.
- **Customer adoption:** The percentage of current usage for which customers will utilize the new technology.
- **Useful life:** How long an equipment of the technology can be used, in years.
- **Annual adoption:** Customer adoption is modified by useful life because in practice an equipment will not be replaced until it breaks down. According to Midwest Power Systems, the maximum annual adoption is about 15% for most new technologies except lighting.
- **Peak use:** The percentage of the equipment for the technology that is used during peak hours, in %.
- **Energy:** The total annual energy consumed by the current technology, in MWh.
- **Demand:** The power peak demand of the current technology, in MW.
- **Energy reduction:** The annual energy savings if the current technology is replaced with an energy-efficient new technology, in MWh.
- **Demand reduction:** The power demand reduction if the current technology is replaced with an energy-efficient new technology, in MW.
- **Customers contacted:** The percentage of customers that are contacted by utilities about the new technology, in %.

Table 4.2: An assignment of initial cost factors.

$\$_{\text{initial}}$	F_{ic}
$0 \leq \$ \leq 100$	1.0
$100 < \$ \leq 500$	0.8
$500 < \$ \leq 2000$	0.5
$2000 < \$$	0.2

- Initial cost: The first or replacement cost to set up the equipment for the new technology, in \$.
- F_{ic} : Initial cost factor, $0 \leq F_{ic} \leq 1$. F_{ic} is decreasing with the increase of initial cost. The initial cost, from 0 to ∞ , is divided into several sections and thus each section has a F_{ic} , as shown in Table 4.2.
- Consumer confidence: Confidence that the consumers have that the new technology will meet their expectations, in %.
- Modified adoption: Annual adoption as modified according to other variables, including percent of customers contacted, initial cost, and consumer confidence, in %.

Correlations

The correlation of rebate, expected savings (savings), and customer adoption (adoption) is a basic relationship in this study. The method of least squares was used to curve fit the available data points. A correlation of expected savings in terms of rebate and customer adoption

$$\text{savings} = f(\text{rebate}, \text{adoption}) \quad (4.1)$$

is given in Figure 4.2. For a specified expected savings, the customer adoption will increase if rebate increases. Under a fixed rebate, customer adoption will increase if expected savings increases. Consider a 25% rebate a 50% expected savings, for example, the customer adoption, is 40%. The correlation of customer adoption in terms of rebate and expected savings

$$\text{adoption} = f(\text{rebate}, \text{savings}) \quad (4.2)$$

is given in Figure 4.3. For a specific customer adoption, the rebate can be reduced if expected savings increases. All three parameters are expressed in percentages.

Strictly speaking, each technology should have its own correlation in each sector. Since the focus of this project is on methodology investigation, we employ the same correlation for each technology's application with minor modifications of adoption according to useful life if necessary.

The standard form of the second-order curve fitting equation of possible customer adoption is

$$\begin{aligned} \text{adoption} = & c_1 + c_2 \left(\frac{\text{savings} - y_0}{r_y} \right) + c_3 \left(\frac{\text{savings} - y_0}{r_y} \right)^2 \\ & + \left(\frac{\text{rebate} - x_0}{r_x} \right) \left[c_4 + c_5 \left(\frac{\text{savings} - y_0}{r_y} \right) \right. \\ & \quad \left. + c_6 \left(\frac{\text{savings} - y_0}{r_y} \right)^2 \right] \\ & + \left(\frac{\text{rebate} - x_0}{r_x} \right)^2 \left[c_7 + c_8 \left(\frac{\text{savings} - y_0}{r_y} \right) \right. \\ & \quad \left. + c_9 \left(\frac{\text{savings} - y_0}{r_y} \right)^2 \right] \end{aligned} \quad (4.3)$$

where x_0 , y_0 , r_x , and r_y are constants for transformation of variables to avoid ill-

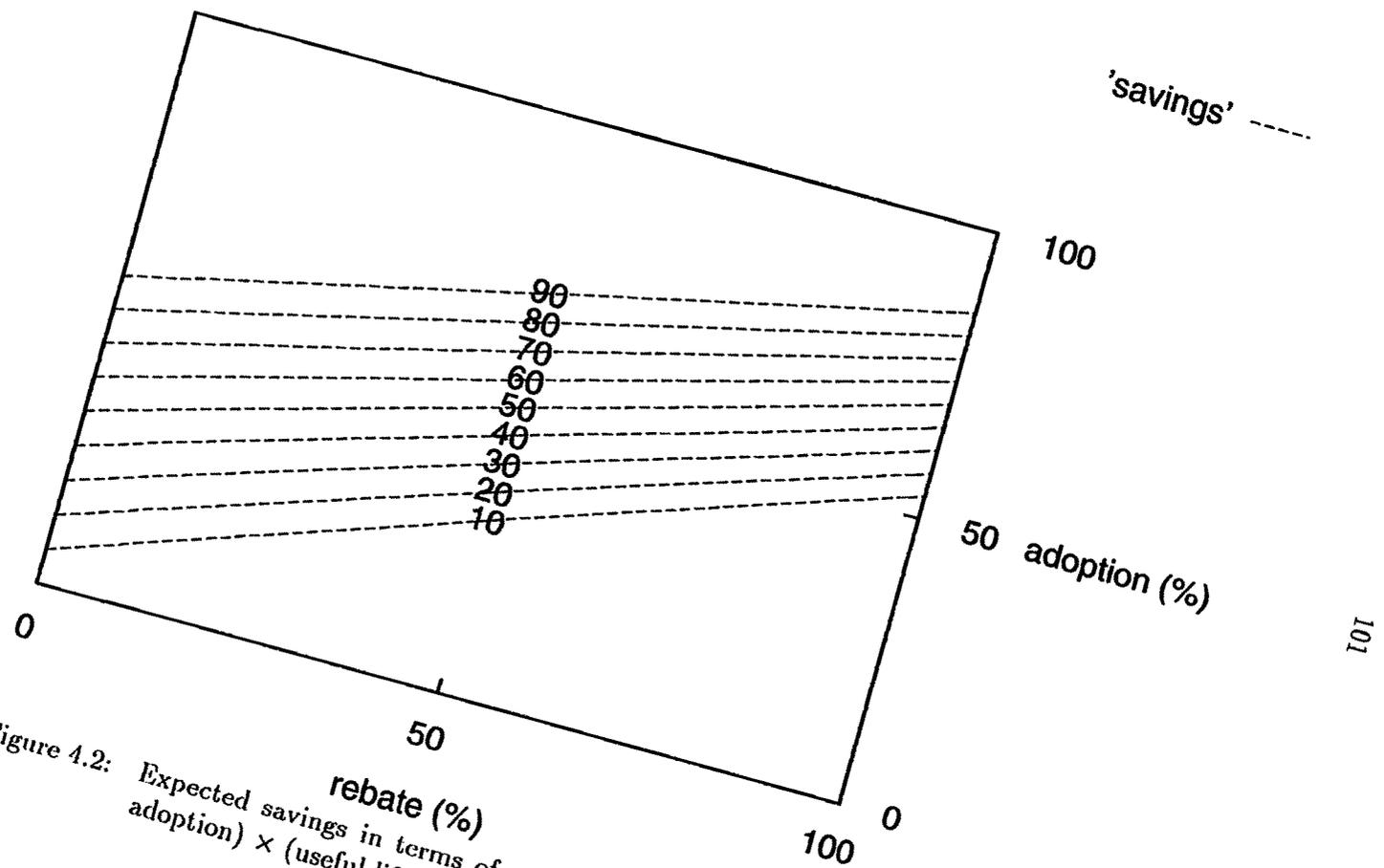


Figure 4.2: Expected savings in terms of rebate and customer adoption [(annual adoption) \times (useful life)].

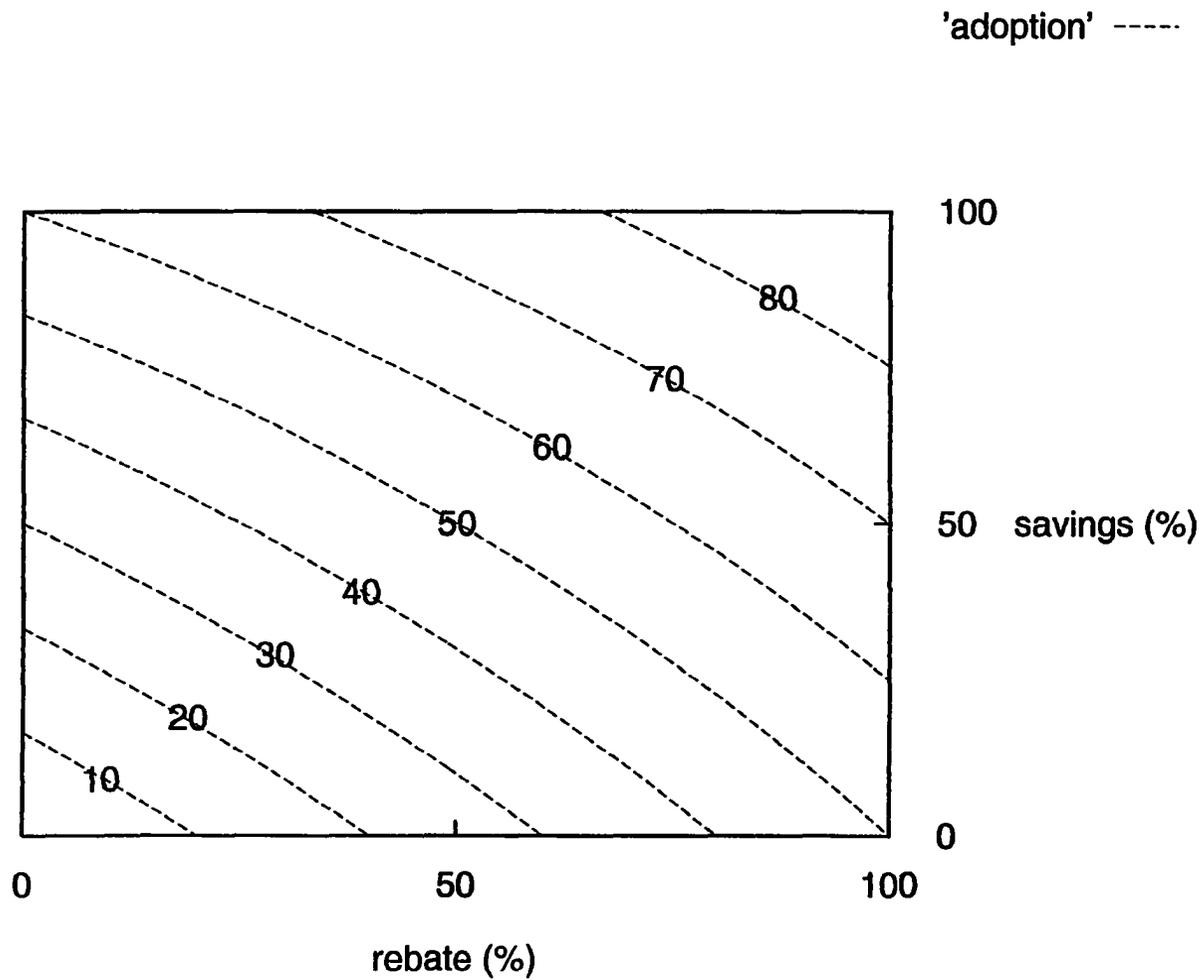


Figure 4.3: Customer adoption [(annual adoption) × (useful life)] in terms of rebate and expected savings.

conditioned matrix⁴ calculations, and c_1, c_2, \dots, c_9 are curve fitting coefficients.

Similarly, the second-order curve fitting equation of suggested rebate is

$$\begin{aligned} \text{rebate} = & d_1 + d_2 \left(\frac{\text{savings} - y_0}{r_y} \right) + d_3 \left(\frac{\text{savings} - y_0}{r_y} \right)^2 \\ & + \left(\frac{\text{adoption} - z_0}{r_z} \right) \left[d_4 + d_5 \left(\frac{\text{savings} - y_0}{r_y} \right) \right. \\ & \qquad \qquad \qquad \left. + d_6 \left(\frac{\text{savings} - y_0}{r_y} \right)^2 \right] \\ & + \left(\frac{\text{adoption} - z_0}{r_z} \right)^2 \left[d_7 + d_8 \left(\frac{\text{savings} - y_0}{r_y} \right) \right. \\ & \qquad \qquad \qquad \left. + d_9 \left(\frac{\text{savings} - y_0}{r_y} \right)^2 \right] \end{aligned} \quad (4.4)$$

where $y_0, z_0, r_y,$ and r_z are constants for the transformation of variables, and d_1, d_2, \dots, d_9 are curve fitting coefficients.

Usually, the equipment of a technology will not be replaced until it breaks down.

Thus, the practical annual adoption could be calculated using

$$\text{annual adoption} = (\text{adoption}) / (\text{useful life}) \quad (4.5)$$

This is the so-called minor modification of adoption. When the useful life is one year, the annual adoption of a technology, such as residential lighting, is the same as the adoption. If the useful life of an equipment is not one year, the adoption must be taken care by

$$\text{adoption} = (\text{annual adoption}) \times (\text{useful life}) \quad (4.6)$$

before we use Equation 4.4.

⁴For an ill-conditioned matrix, the solution of a system $Ax = b$ may be very sensitive to small changes in b .

Reasoning Mechanism

LEVEL5 allows three types of reasoning mechanisms: forward chaining, backward chaining, and mixed chaining (combination of forward and backward chaining).

Backward chaining is typically used for classification problems, while forward chaining is usually applied for construction problems. Backward chaining is the mechanism of obtaining the conditions and data to conclude a goal or prove a hypothesis. The mechanism starts with a selected goal or hypothesis and proceeds backward along a chain of reasoning process to find the evidence to support the goal or hypothesis. Backward chaining is useful for applications where the possible solutions are known but the specific conditions are not known. The objective of an application is to determine what information could be used to verify or conclude one of the possible solutions. Thus, backward chaining is a goal-driven reasoning.

Forward chaining starts with known facts or data and infers new knowledge based on the given information. The deduction processes continue until no further conclusions can be reached. It is also called data-driven or event-driven reasoning since the process is triggered by the initial event set. More specifically, if we have a few premises and many conclusions, forward chaining is the better choice. Otherwise, if we have many premises and a few conclusions, backward chaining should be employed. For some problems, mixed chaining is better than a single type of chaining.

Forward chaining is selected to be the primary reasoning mechanism because the project is designed to be data-driven. For example, if the useful life, expected savings, and rebate of residential lighting are specified, we can figure out the possible annual adoption, energy reduction, and demand reduction from initial or changed data through forward chaining.

Programming and Uncertainty Propagation with Different Modes

The rule base of Mode I is deterministic, i.e., there is no uncertainty in the facts and rules. In Modes II and III, fuzzy logic with linguistic variables and Dempster-Shafer theory with basic probability assignments are applied to the rule base, respectively.

Mode I: Without Uncertainty

Since everything is deterministic in this mode, Equation 4.3 coupled with Equation 4.5 can be used for annual adoption calculations if expected savings and rebate are specified, and Equations 4.4 coupled with 4.6 for rebate evaluations if expected savings and annual adoption are specified.

The magnitude of energy reduction for each new technology in each sector can be calculated by

$$\begin{aligned} \text{energy reduction} &= (\text{annual adoption}) \times (\text{expected savings}) \\ &\times (\text{energy}) \end{aligned} \quad (4.7)$$

where energy reduction and energy are in MWh. The demand reduction of each new technology in each sector can be computed using

$$\begin{aligned} \text{demand reduction} &= (\text{peak use}) \times (\text{annual adoption}) \\ &\times (\text{expected savings}) \times (\text{demand}) \end{aligned} \quad (4.8)$$

where the unit of demand reduction and demand is MW; peak use is the percentage of the equipment of a new technology operated at the peak hours to be investigated.

Consider residential lighting as an example to present the calculation. A set of data are selected as:

expected savings = 40%

rebate = 30%

useful life = 1 year

peak use = 45%

energy = 600 MWh

demand = 150 MW

The possible customer adoption is 36.6%, which was determined from Figure 4.2, Figure 4.3, or Equation 4.3 with proper coefficients and constants. The energy and demand reductions calculated using Equations 4.7 and 4.8 are.

$$\begin{aligned}\text{energy reduction} &= (36.6\%) \times (40\%) \times (600 \text{ MWh}) \\ &= 87.8 \text{ MWh}\end{aligned}$$

$$\begin{aligned}\text{demand reduction} &= (45\%) \times (36.6\%) \times (40\%) \times (150 \text{ MW}) \\ &= 9.8 \text{ MW}\end{aligned}$$

A number of other factors, such as percent of customers contacted, initial cost, and consumer confidence, might also influence adoption. The annual adoption can be modified using

$$\begin{aligned}\text{modified adoption} &= (\text{annual adoption}) \times (\text{customers contacted}) \\ &\quad \times (F_{ic}) \times (\text{consumer confidence})\end{aligned}\tag{4.9}$$

where F_{ic} is the factor of initial cost. An assignment of the factors is given in Table 4.2. $F_{ic} = 0.8$, for example, if initial cost is between a hundred and five hundred dollars.

Since the adoption number is modified, the energy and demand reduction should be adjusted by

$$\begin{aligned} \text{modified energy reduction} &= (\text{modified adoption}) \times (\text{expected savings}) \\ &\times (\text{energy}) \end{aligned} \quad (4.10)$$

$$\begin{aligned} \text{modified demand reduction} &= (\text{peak use}) \times (\text{modified adoption}) \\ &\times (\text{expected savings}) \times (\text{demand}) \end{aligned} \quad (4.11)$$

The total energy, demand, energy reduction, and demand reduction of each technology or sector are the sum of their members' values. The total consumptions and savings can be summed from the sector or technology objects.

Mode II: Fuzzy Logic

In this mode, fuzzy logic is used to represent uncertainty with linguistic variables, which are terms, such as “low”, “high”, etc., that are not precise. The membership functions for rebate, expected savings (savings), and customer adoption (adoption) are defined in Figure 4.4, distributed from “very low”, “low”, “medium”, “high”, to “very high” according to information in previous chapters, experience, and judgment. The fuzzy customer adoption and fuzzy rebate will be investigated, respectively.

For the first case, if the fuzzy expected savings and fuzzy rebate of a new technology are selected, the possible fuzzy customer adoption can be determined by

$$Z_f = \sum_i W F_i \times Z D_i \quad (4.12)$$

where Z_f is the fuzzy customer adoption, $W F$ is the weighting factor derived from fuzzy rebate and fuzzy expected savings, and $Z D$ is the mean division customer

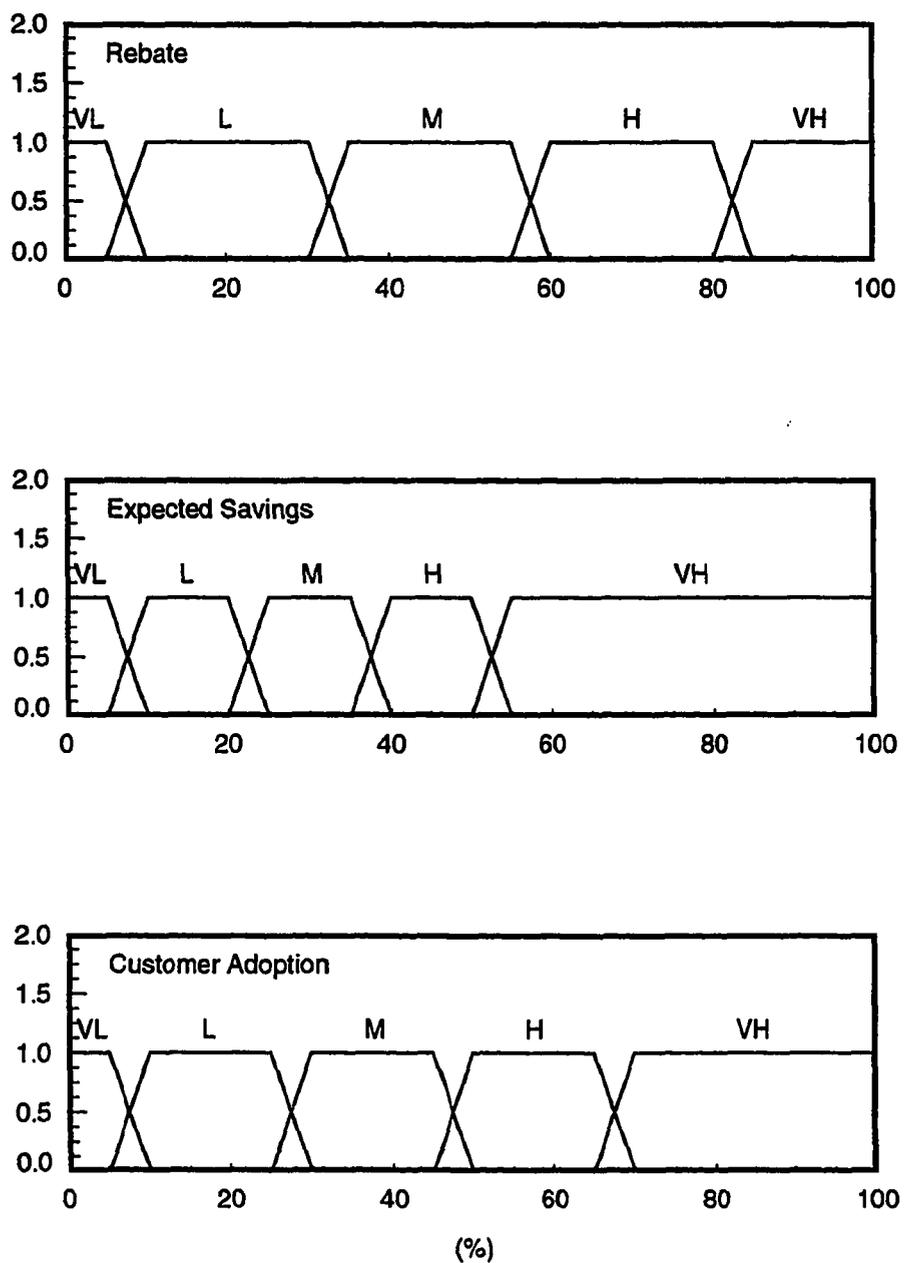


Figure 4.4: An assignment of membership functions for rebate, expected savings, and customer adoption.

adoption that is not fuzzy. The unfuzzy customer adoption is a function of rebate and expected savings, i.e.

$$\text{adoption} = f(\text{rebate}, \text{savings}) \quad (4.13)$$

The sum of the weighting factors must be unity.

$$\sum_{i=1}^n WF_i = 1 \quad (4.14)$$

The determination of weighting factors is the fundamental. According to Figure 4.5, we know the weighting factor of each division is a function of area and the factor of that area, i.e.

$$WF = f(A, F_a) \quad (4.15)$$

where A is the area of a division and F_a is the factor of that area. Since summation of the first-step weighting factors may not be one, we assign the first-step weighting factors as pre-weighting-factors (PWF), calculated using

$$PWF_i = A_i \times F_{a,i} \quad (4.16)$$

Normalization is necessary to make sure the sum of the actual weighting factors is unity.

$$WF_i = PWF_i \times \frac{1}{SPWF} \quad (4.17)$$

where $SPWF$ is the sum of pre-weighting-factors.

$$SPWF = \sum_{i=1}^9 PWF_i \quad (4.18)$$

The pre-weighting-factors and weighting factors, referring to Figure 4.5 where the shape on the x-axis is “low” rebate and on the y-axis is “low” expected savings,

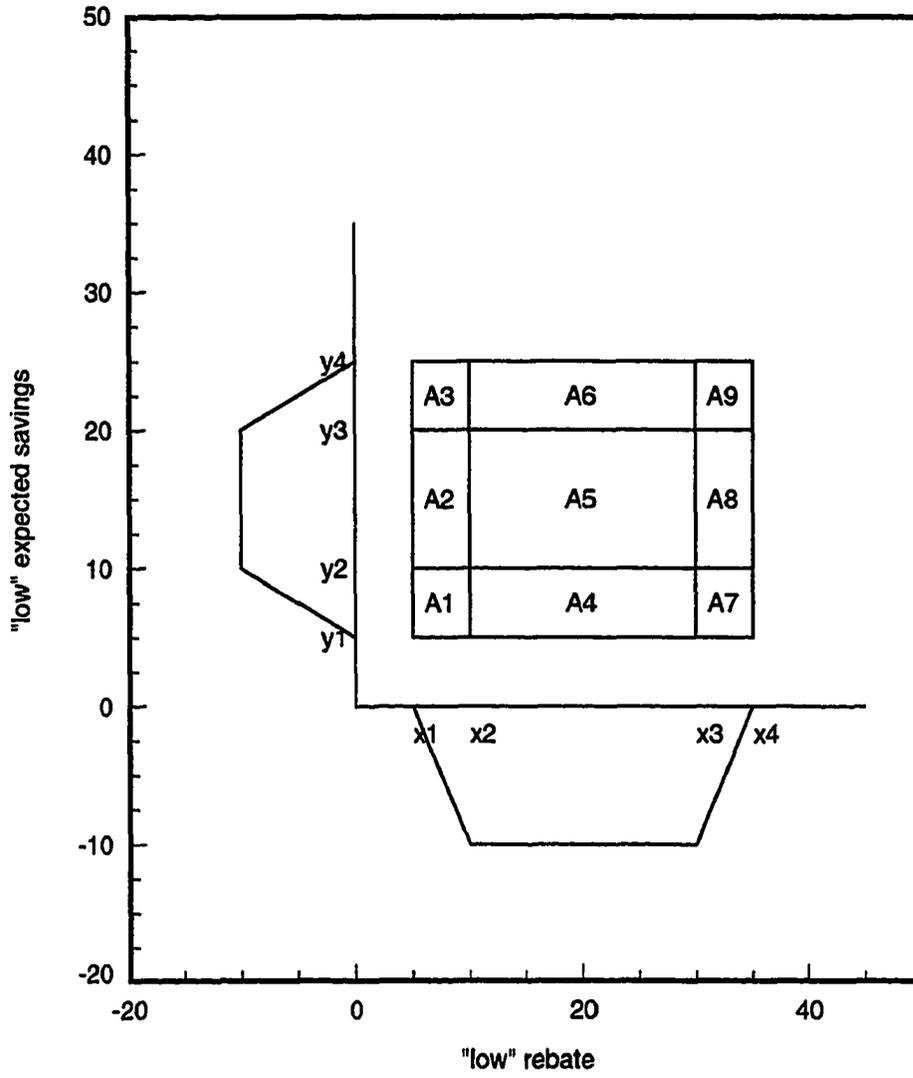


Figure 4.5: An illustration of the determination for weighting factors.

are shown in Tables 4.3 and 4.4. The sum of pre-weighting-factors is 0.0375. Thus, for example, $WF_3 = 0.00625/0.0375 = 0.0167$.

After the value for a fuzzy customer adoption is obtained, we can compare it with the membership function in Figure 4.4 to assign it as “very high”, “high”, “medium”, “low”, or “very low” using union operation of fuzzy logic. All of the possible situations of fuzzy customer adoption derived from fuzzy rebate and fuzzy expected savings are listed in Table 4.5. If expected savings is “medium” and rebate is “high”, for example, customer adoption is “high”.

The fuzzy adoption number is not certain. There is some deviation with it. The standard deviation for N measures with the same weighting factors is defined as

$$SD = \left[\sum_{i=1}^N (Z_{mean} - Z_i)^2 \times \frac{1}{N} \right]^{1/2} \quad (4.19)$$

where Z_{mean} is the mean measure. For this study, Equation 4.19 is modified to

$$SD_a = \left[\sum_{i=1}^9 (Z_f - ZD_i)^2 \times WF_i \right]^{1/2} \quad (4.20)$$

for adoption deviation because the weighting factors are not the same for all divisions.

The percent of customers contacted, initial cost, and consumer confidence are some factors that might influence the customer adoption. Usually, the percent of customers contacted is not 100%. Common sense tells us that higher initial cost and lower consumer confidence will reduce the adoption of a new technology. The fuzzy customer adoption number could be modified to a more reasonable magnitude using

$$Z_m = Z_f \times CCT \times F_{ic} \times F_{cc} \quad (4.21)$$

where Z_m is the modified fuzzy customer adoption, CCT is the percent of customers contacted, F_{ic} is the initial cost factor, and F_{cc} is the consumer confidence factor.

Table 4.3: An example of pre-weighting-factors (first-step weighting factors).

$PWF_3 = .000625$	$PWF_6 = .005000$	$PWF_9 = .000625$
$PWF_2 = .002500$	$PWF_5 = .020000$	$PWF_8 = .002500$
$PWF_1 = .000625$	$PWF_4 = .005000$	$PWF_7 = .000625$

Table 4.4: An example of normalized weighting factors.

$WF_3 = .0167$	$WF_6 = .1333$	$WF_9 = .0167$
$WF_2 = .0667$	$WF_5 = .5333$	$WF_8 = .0667$
$WF_1 = .0167$	$WF_4 = .1333$	$WF_7 = .0167$

Table 4.5: Exhaustive situations of fuzzy customer adoption.

very high	medium	high	high	very high	very high
high	medium	medium	medium	high	high
medium	low	low	medium	high	high
low	low	low	medium	medium	high
very low	very low	low	low	medium	medium
savings ↑ rebate →	very low	low	medium	high	very high

An assignment of initial cost factors has been given in Table 4.2. The consumer confidence factors for programming are assigned in Table 4.6. For example, $F_{cc} = 0.5$ if customer confidence is “medium”.

Consider an example that fuzzy adoption is $(55 \pm 5)\%$ that is assigned to “high”, customers contacted is 95%, initial cost is \$250, and consumer confidence is “high”, to illustrate the calculation of modified fuzzy customer adoption. From the given information, we have

$$Z_f = (50 \pm 5)\%$$

$$CCT = 95\%$$

$$F_{ic} = 0.8$$

$$F_{cc} = 0.9$$

Table 4.6: An assignment of consumer confidence factors.

Consumer Confidence	F_{cc}
very high	1.0
high	0.9
medium	0.5
low	0.1
very low	0.01

Substituting the numbers into Equation 4.21, a new number is acquired by

$$\begin{aligned} Z_m &= (50 \pm 5)\% \times 95\% \times 0.8 \times 0.9 \\ &= (34.2 \pm 3.4)\% \end{aligned}$$

The modified fuzzy customer adoption number is $(34.2 \pm 3.4)\%$ that would be assigned to “medium”. If other significant parameters are found to affect the fuzzy customer adoption value, as, for example, percent of customers contacted, they could be added to Equation 4.21.

The energy reduction and energy reduction deviation can be computed using

$$\begin{aligned} \text{energy reduction} &= (\text{fuzzy adoption}) \times (\text{mean savings}) \\ &\quad \times (\text{energy}) \end{aligned} \tag{4.22}$$

and

energy reduction deviation

$$\begin{aligned} &\approx [(\text{adoption deviation}) \times (\text{mean savings}) \\ &\quad + (\text{fuzzy adoption}) \times (\text{savings deviation})] \times (\text{energy}) \end{aligned} \tag{4.23}$$

where energy reduction and energy reduction deviation are in MWh. Mean savings and savings deviation are referring to Figure 4.4. The demand reduction and demand reduction deviation are calculated by

$$\begin{aligned} \text{demand reduction} &= (\text{peak use}) \times (\text{fuzzy adoption}) \\ &\quad \times (\text{mean savings}) \times (\text{demand}) \end{aligned} \tag{4.24}$$

and

demand reduction deviation

$$\begin{aligned} &\approx (\text{peak use}) \times [(\text{adoption deviation}) \times (\text{mean savings}) \\ &+ (\text{fuzzy adoption}) \times (\text{savings deviation})] \times (\text{demand}) \end{aligned} \quad (4.25)$$

in which the unit of demand reduction and demand reduction deviation is MW.

Similar procedures can be employed to evaluate suggested fuzzy rebates when the fuzzy expected savings and fuzzy customer adoption of a new technology are specified, i.e.

$$X_f = \sum_i W F_i \times X D_i \quad (4.26)$$

where X_f is the fuzzy rebate, $W F$ is the weighting factor derived from fuzzy customer adoption and fuzzy expected savings, and $X D$ is the mean division rebate that is not fuzzy. The unfuzzy rebate is a function of expected savings and customer adoption, i.e.

$$\text{rebate} = f(\text{savings}, \text{adoption}) \quad (4.27)$$

The division rebates could be negative in some situations. For practical purposes, they are set to zero. The rebate deviation can be calculated using

$$S D_r = \left[\sum_{i=1}^9 (X_f - X D_i)^2 \times W F_i \right]^{1/2} \quad (4.28)$$

All the possible fuzzy rebates derived from fuzzy expected savings and fuzzy customer adoption are shown in Table 4.7. For example, if expected savings is “low” and customer adoption is “high”, rebate is “very high”.

These results can also be modified for customers contacted, consumer confidence, and initial cost. The reductions and reduction deviations for energy use and power demand are evaluated using the same equations as for the first case, Equations 4.22 to 4.25.

Table 4.7: Exhaustive situations of fuzzy rebates.

very high	very low	very low	very low	low	very high
high	very low	very low	low	high	very high
medium	very low	very low	medium	very high	very high
low	very low	low	high	very high	very high
very low	very low	medium	high	very high	very high
savings ↑ adoption →	very low	low	medium	high	very high

Mode III: Dempster-Shafer Theory

Dempster-Shafer theory is another mechanism used to represent uncertainty propagation. We can define a frame of discernment as

$$\Theta = \{a_1, a_2, a_3, \dots, a_{20}\} \quad (4.29)$$

where

$$a_1 = \{x \mid 0\% \leq x \leq 5\%\},$$

$$a_2 = \{x \mid 5\% < x \leq 10\%\},$$

$$a_3 = \{x \mid 10\% < x \leq 15\%\},$$

...

$$a_{20} = \{x \mid 95\% < x \leq 100\%\}$$

The description of basic probability assignments (bpa) for a set of expected savings is shown in Figure 4.6. The basic idea is the area under the curve is unity. In practice, we take four subsets of which the accumulation of basic probability assignments is exact or close to one. If the summation is not one, normalization is implemented to make it one. Referring to Figure 4.6, the focal elements with non-zero bpa are $\{a_1, a_2, a_3, a_4, a_5, a_6, a_7, a_8\}$ at $\text{bpa} = 0.4$, $\{a_3, a_4, a_5, a_6, a_7, a_8\}$ at $\text{bpa} = 0.3$, $\{a_5, a_6, a_7, a_8\}$ at $\text{pba} = 0.2$, and $\{a_6, a_7\}$ at $\text{bpa} = 0.1$.

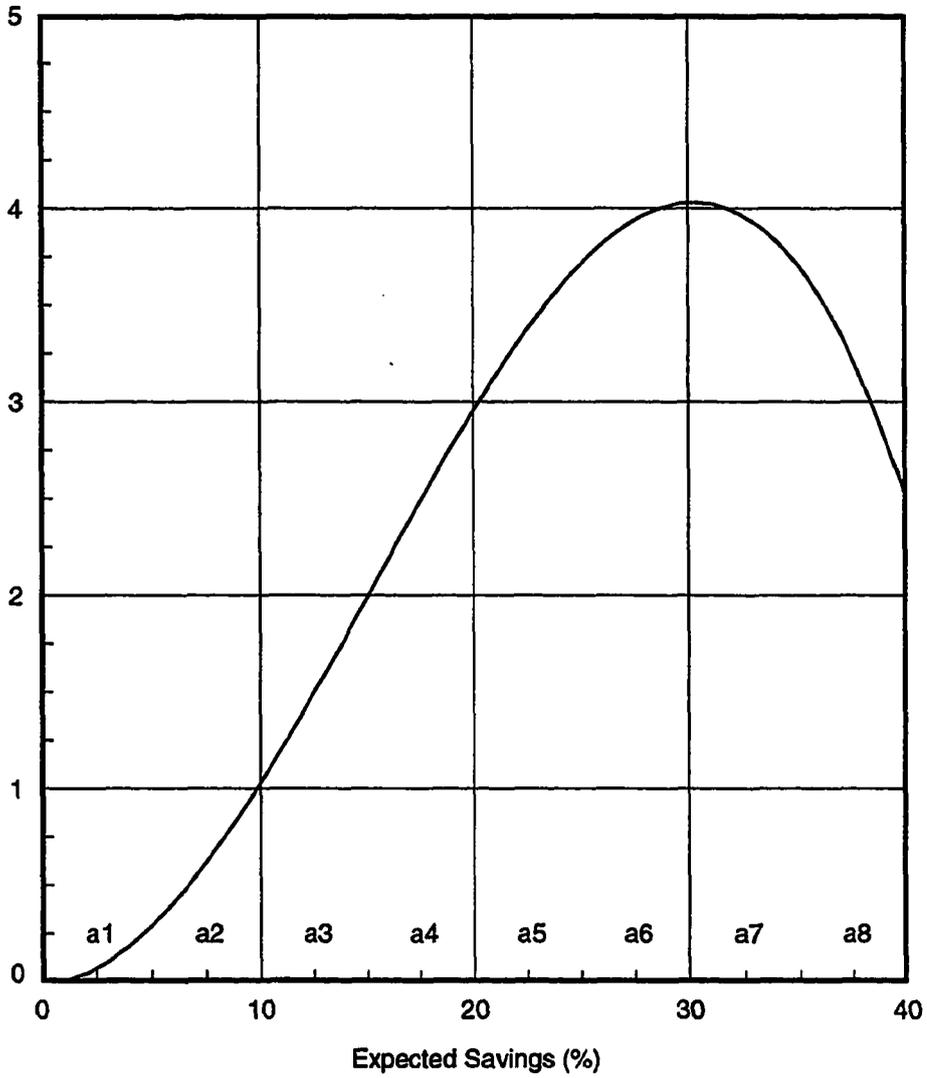


Figure 4.6: An example of basic probability assignments for expected savings.

Dempster's rule of combination is employed to compute the weighting factors for customer adoption when the maximum savings and rebate are specified. The specified rebate is a point that belongs to one of the single element subsets of Θ . A basic probability assignment number $m(A)$ expresses the measure of the confidence or belief committed to the set A . Assume the basic probability assignment for rebate is m_r and for expected savings is m_s . The combination rule computes a new basic probability assignment $m_r \oplus m_s$ describing the combined effect of m_r and m_s according to

1. $m_r \oplus m_s(\emptyset) = 0$
2. $m_r \oplus m_s(A) = \frac{\sum_{X \cap Y = A} m_r(X)m_s(Y)}{1 - \sum_{X \cap Y = \emptyset} m_r(X)m_s(Y)}$ for all $A \neq \emptyset$.

For example, consider the basic probability assignments of expected savings derived from Figure 4.6 and the value of a rebate located in $\{a_5\}$. The first-step and normalized intersections of m_s and m_r are shown in Tables 4.8 and 4.9. Because the sum of the first-step new basic probability assignments is not unity, normalization is necessary.

The new basic probability assignments are the weighting factors for customer adoption subsets. Thus, the Dempster customer adoption and adoption deviation can be calculated by

$$Z_{ds} = \sum_i WF_i \times ZSUB_i \quad (4.30)$$

and

$$SD_a = \left[\sum_i (Z_{ds} - ZSUB_i)^2 \times WF_i \right]^{1/2} \quad (4.31)$$

where Z_{ds} is the Dempster customer adoption, WF is the weighting factor, $ZSUB$ is the subset customer adoption, and SD_a is the adoption deviation.

Table 4.8: The first-step intersection tableau of m_s and m_r .

$m_s \downarrow m_r \rightarrow$	\dots	$a_5(1)$	\dots
\vdots			
a_6a_7 (0.1)		\emptyset	
\vdots			
$a_5a_6a_7a_8$ (0.2)		$a_5(0.2)$	
\vdots			
$a_3a_4a_5a_6a_7a_8$ (0.3)		$a_5(0.3)$	
\vdots			
$a_1a_2a_3a_4a_5a_6a_7a_8$ (0.4)		$a_5(0.4)$	
\vdots			

Table 4.9: The normalized intersection tableau of m_s and m_r .

$m_s \downarrow m_r \rightarrow$	\dots	$a_5(1)$	\dots
\vdots			
a_6a_7 (0.1)		\emptyset	
\vdots			
$a_5a_6a_7a_8$ (0.2)		$a_5(0.222)$	
\vdots			
$a_3a_4a_5a_6a_7a_8$ (0.3)		$a_5(0.333)$	
\vdots			
$a_1a_2a_3a_4a_5a_6a_7a_8$ (0.4)		$a_5(0.444)$	
\vdots			

Table 4.10: An inappropriate input for rebate.

$m_s \downarrow m_r \rightarrow$	\dots	$a_{10}(1)$	\dots
\vdots			
$a_6 a_7 (0.1)$		\emptyset	
\vdots			
$a_5 a_6 a_7 a_8 (0.2)$		\emptyset	
\vdots			
$a_3 a_4 a_5 a_6 a_7 a_8 (0.3)$		\emptyset	
\vdots			
$a_1 a_2 a_3 a_4 a_5 a_6 a_7 a_8 (0.4)$		\emptyset	
\vdots			

The limitation of this Dempster-Shafer application is that the value of each input rebate must be less than or equal to the value of maximum savings, i.e.

$$|\text{maximum savings}| \geq |\text{rebate}| \quad \text{for input} \quad (4.32)$$

If the input value of a rebate is greater than the maximum savings, the intersection of each expected savings subset and the rebate is an empty set. An inappropriate rebate input example is shown in Table 4.10. The sum of the new basic probability assignments is zero, which violates the third definition of Dempster-Shafer theory. Therefore, the requirement of this application is that at least one intersection is a non-empty set. The evaluated value of Dempster customer adoption could be a number greater than maximum savings, however.

Similarly, a Dempster rebate and rebate deviation can be calculated using

$$X_{ds} = \sum_i W F_i \times X S U B_i \quad (4.33)$$

and

$$SD_r = \left[\sum_i (X_{ds} - XSUB_i)^2 \times WF_i \right]^{1/2} \quad (4.34)$$

where X_{ds} is the Dempster rebate, WF is the weighting factor, $XSUB$ is the subset rebate, and SD_r is the rebate deviation.

For this case, the input value of customer adoption can not exceed maximum savings, i.e.

$$|\text{maximum savings}| \geq |\text{customer adoption}| \quad \text{for input} \quad (4.35)$$

For some situations, the subset rebates could be negative. They are set to zero for practical purposes. The evaluated Dempster rebate could be a number ranging from 0% to more than 100%. If the maximum savings is high enough and the customer adoption is low enough, for example, the Dempster rebate could be 0%. On the other hand, if the savings is low and utilities desire high customer adoption, they could offer a rebate greater than 100%, although this would be unlikely.

Annual adoption can be modified according to customers contacted, initial cost, and consumer confidence. The energy and demand reductions and reduction deviations are evaluated, basically, using the same equations as for fuzzy logic mode. Mean savings and savings deviation for this mode are computed by

$$\text{mean savings} = \sum_{i=1}^4 WF_i \times (\text{savings})_i \quad (4.36)$$

and

$$SD_s = \left\{ \sum_{i=1}^4 [(\text{mean savings}) - (\text{savings})_i]^2 \times WF_i \right\}^{1/2} \quad (4.37)$$

where WF is the weighting factor and SD_s is the savings deviation.

Sample Results

Some sample results are described in the following to provide a deeper understanding of each mode's application.

Sample Results for Mode I – Without Uncertainty

Two examples are considered to show how the program works. For the first case, we predict the possible customer adoption and energy impacts of lighting technology when the expected savings and rebates are specified. A set of input data are listed in Tables 4.11, 4.12, and 4.13. The expected savings can never exceed the maximum savings. The evaluation is done on the lighting technology displays and the computed results are shown in Tables 4.14, 4.15, and 4.16 with italic. This case predicts, for example, that if the expected savings and rebate for residential lighting are 45% and 25% with one year useful life, then 37.2% of the customers would adopt the new lighting technology. When the percentage of customers contacted is 65%, the initial cost of the lighting equipment is \$60, and the consumer confidence is 50%, the customer adoption is then modified to 12.1% by Equation 4.9. Although the initial cost is low, the percentage of customers contacted and consumer confidence are not high, so the modified adoption number is significantly lowered. If the residential lighting energy use and power demand are 120 MWh and 25 MW with 60% peak use, there would be a 6.5 MWh reduction in residential lighting energy use and a 0.8 MW reduction in power demand.

For the second case, the suggested rebate is to be estimated when the expected savings and customer adoption are given for a heat pump application. A set of heat pump input data are given in Tables 4.17, 4.18, and 4.19. The computation is

Table 4.11: An example of lighting useful life, expected savings and rebates.

Lighting	Useful Life (years)	Maximum Savings (%)	Expected Savings (%)	Rebate (%)
Residential	1	50	45	25
Commercial	1	60	40	35
Industrial	1	50	35	30

Table 4.12: An example of lighting customers contacted, initial cost, and consumer confidence.

Lighting	Customers Contacted (%)	Initial Cost (\$)	Consumer Confidence (%)
Residential	65	60	50
Commercial	85	150	95
Industrial	75	100	70

Table 4.13: An example of lighting peak use, energy use, and power demand.

Lighting	Peak Use (%)	Energy (MWh)	Demand (MW)
Residential	60	120	25
Commercial	100	300	85
Industrial	95	180	60

Table 4.14: A sample result of customer adoption for lighting.

Lighting	Expected Savings (%)	Rebate (%)	Annual Adoption (%)
Residential	45	25	37.2
Commercial	40	35	38.7
Industrial	35	30	33.9

Table 4.15: A sample result of modified adoption for lighting.

Lighting	Annual Adoption (%)	Customers Contacted (%)	Initial Cost (\$)	Consumer Confidence (%)	Modified Adoption (%)
Residential	37.2	65	60	50	12.1
Commercial	38.7	85	150	95	25.0
Industrial	33.9	75	100	70	17.7

Table 4.16: A sample result of energy and demand impacts for lighting.

Lighting	Peak Use (%)	Energy Use (MWh)	Power Demand (MW)	Energy Reduction (MWh)	Demand Reduction (MW)
Residential	60	120	25	6.5	0.8
Commercial	100	300	85	30.0	8.5
Industrial	95	180	60	11.2	3.5
Total	-	600	170	47.7	12.8

Table 4.17: An example of heat pump useful life, expected savings, and customer adoption.

Heat Pumps	Useful Life (years)	Maximum Savings (%)	Expected Savings (%)	Annual Adoption (%)
Residential	15	40	25	2.5
Commercial	15	40	35	3.6

Table 4.18: An example of heat pump customers contacted, initial cost, and consumer confidence.

Heat Pumps	Customers Contacted (%)	Initial Cost (\$)	Consumer Confidence (%)
Residential	75	500	50
Commercial	95	1,000	90

Table 4.19: An example of heat pump peak use, energy use, and power demand.

Heat Pumps	Peak Use (%)	Energy (MWh)	Demand (MW)
Residential	50	10,000	330
Commercial	95	15,000	670

implemented on the heat pump technology displays and the calculated numbers are shown in Tables 4.20, 4.21, and 4.22 with italic. This case estimates, for example, that if the expected savings and annual adoption for residential heat pump are 25% and 2.5% with an useful life of 15 years, then the suggested rebate is 51.5%. Consider the percentage of customers contacted to be 75%, the initial cost of the heat pump equipment to be \$500, and the consumer confidence to be 50%, the annual adoption is then modified to 0.7%. If the residential heat pump energy use and power demand are 10,000 MWh and 330 MW with 50% peak use, there would be a 18.7 MWh reduction in energy use and a 0.3 MW reduction in demand.

We can view the results or re-perform the calculation on the sector displays, such as re-evaluating residential lighting on residential sector display. The final advice can be reviewed on summary displays.

Sample Results for Mode II – Fuzzy Logic

A residential lighting example is used to illustrate how the program works when using fuzzy logic. The expected savings, rebate, and customer adoption are distributed from “very low”, “low”, “medium”, “high”, to “very high”, as defined in Figure 4.4. If useful life is one year, expected savings is “high”, and rebate is “medium”, the program outputs the suggested annual adoption as “medium”, as shown in Table 4.23. The evaluated linguistic annual adoption can be defuzzified to a number of $(45.6 \pm 3.2)\%$.

If the percent of customers contacted is 90%, the initial cost of the lighting equipment is \$50, and the consumer confidence is “very high”, then the modified customer adoption number is $(41.0 \pm 2.9)\%$. Because the percentage of customers

Table 4.20: A sample result of rebates for heat pumps.

Heat Pumps	Expected Savings (%)	Rebate (%)	Annual Adoption (%)
Residential	25	51.5	2.5
Commercial	35	77.7	3.6

Table 4.21: A sample result of modified adoption for heat pumps.

Heat Pumps	Annual Adoption (%)	Customers Contacted (%)	Initial Cost (\$)	Consumer Confidence (%)	Modified Adoption (%)
Residential	2.5	75	500	50	0.7
Commercial	3.6	95	1,000	90	1.5

Table 4.22: A sample result of energy impacts for heat pumps.

Heat Pumps	Peak Use (%)	Energy Use (MWh)	Power Demand (MW)	Energy Reduction (MWh)	Demand Reduction (MW)
Residential	50	10,000	330	18.7	0.3
Commercial	95	15,000	670	80.7	3.4
Total	-	25,000	1,000	99.5	3.7

Table 4.23: A sample calculation for linguistic annual adoption.

Expected Savings	Rebate	Annual Adoption
<input type="radio"/> very high	<input type="radio"/> very high	<input type="radio"/> very high
<input checked="" type="radio"/> high	<input type="radio"/> high	<input type="radio"/> high
<input type="radio"/> medium	<input checked="" type="radio"/> medium	<input checked="" type="radio"/> <i>medium</i>
<input type="radio"/> low	<input type="radio"/> low	<input type="radio"/> low
<input type="radio"/> very low	<input type="radio"/> very low	<input type="radio"/> very low
$\Rightarrow (45.0 \pm 10.0)\%$	$\Rightarrow (45.0 \pm 15.0)\%$	$\Rightarrow (45.6 \pm 3.2)\%$

contacted is very high, the initial cost is very low, and the consumer is confident with the product, the modified adoption number is only lowered by about 5% and the program would still output the customer adoption as “medium”.

Assume the peak use is 50%, energy use is 100 MWh, and power demand is 20 MW for residential lighting, the energy and demand reductions are computed to be (18.42 ± 5.39) MWh and (1.84 ± 0.53) MW when defuzzifying the expected savings to be $(45.0 \pm 10.0)\%$.

For the second case, a suggested rebate can be evaluated when expected savings and customer adoption are specified. If expected savings is “high” and annual adoption is “high”, for example, the residential lighting rebate is calculated to be “high”, as shown in Table 4.24. The linguistic rebate can be defuzzified to a numerical value of $(75.0 \pm 15.0)\%$. The results for energy and demand impacts could also be adjusted for percentage of customers contacted, consumer confidence, and initial cost.

Sample Results for Mode III – Dempster-Shafer Theory

A residential lighting example is employed to demonstrate how the program works when using Dempster-Shafer theory. For the first case, a set of data are given

Table 4.24: A sample calculation for linguistic rebate.

Expected Savings	Rebate	Annual Adoption
<input type="radio"/> very high	<input type="radio"/> very high	<input type="radio"/> very high
<input checked="" type="radio"/> high	<input checked="" type="radio"/> <i>high</i>	<input checked="" type="radio"/> high
<input type="radio"/> medium	<input type="radio"/> medium	<input type="radio"/> medium
<input type="radio"/> low	<input type="radio"/> low	<input type="radio"/> low
<input type="radio"/> very low	<input type="radio"/> very low	<input type="radio"/> very low
$\Rightarrow (45.0 \pm 10.0)\%$	$\Rightarrow (75.0 \pm 15.0)\%$	$\Rightarrow (57.5 \pm 12.5)\%$

in Table 4.25 in which the computed results are expressed in italic. If the maximum savings is 58% and a 45% rebate is chosen, for example, the Dempster customer adoption is calculated to be $(41.7 \pm 3.3)\%$.

If the percent of customers contacted is 65%, the initial cost of the lighting equipment is \$50, and the consumer confidence is 85%, then the modified customer adoption is $(23.0 \pm 1.8)\%$. The modified adoption number is moderately lowered even though the initial cost is very low and the consumer confidence is high, because the consumers contacted rate is modest.

If the peak use is 60%, energy use is 210 MWh, and power demand is 36 MW

Table 4.25: Some sample results for Dempster adoption.

Maximum Savings (%)	Rebate (%)	Annual Adoption (%)
25	9.0	<i>12.0 ± 0.0</i>
35	17.0	<i>20.5 ± 1.7</i>
45	40.0	<i>34.7 ± 2.4</i>
58	45.0	<i>41.7 ± 3.3</i>
60	35.0	<i>36.8 ± 3.3</i>

Table 4.26: Some sample results for Dempster rebate.

Maximum Savings (%)	Rebate (%)	Annual Adoption (%)
20	<i>2.0 ± 1.7</i>	7.0
40	<i>52.7 ± 4.3</i>	37.5
50	<i>61.5 ± 5.5</i>	45.0
58	<i>84.1 ± 6.7</i>	57.5
60	<i>77.1 ± 7.1</i>	55.0

for residential lighting, the energy reduction is (18.21 ± 7.80) MWh and demand reduction is (1.87 ± 0.80) MW.

Example data for the second case are given in Table 4.26. The evaluated residential lighting rebates are shown with italic. The Dempster rebate is calculated to be $(84.1 \pm 6.7)\%$ when the maximum savings is 58% and annual adoption is 57.5%, for example. The influence of customers contacted, initial cost, and consumer confidence can also be incorporated into the results of energy and demand reductions as for the first case.

Verification of Performance

According to Ignizio (1991), the performance measurement of knowledge-based systems includes three phases: productivity, organization, and personnel.

1. Productivity

- accuracy of solution
- improvement over existing procedures
- computational benefit

- ease of use, updating, and revision
- clarity of output
- appropriateness of software and hardware selection

2. Organization

- costs of software and hardware
- cost savings
- profit potential
- improved decision making

3. Personnel

- training requirement
- job enhancement
- morale

For the productivity measure, since the focus of this project is on methodology development and actual data is not immediately available, the accuracy is difficult to verify. This tool should help existing procedures by allowing users to evaluate different scenarios from different points of view. One significant feature of the system is that it is implemented on a personal computer with a very high computing speed. To shift from one display to another takes only a few seconds. The system is very friendly for end users to use and update information; however, only knowledge engineers familiar with LEVEL5 and having a background in curve fitting may revise the system. The output is clear and easily understood. Building the utility prediction

system on a personal computer using LEVEL5 was very successful, so these tools were quite appropriate.

As for the organization measure, both of the software and hardware are inexpensive. The cost savings are hard to evaluate at this point, but a profit potential is expected because the system improves decision making.

For the personnel measure, the operation of the prediction system is easy, so technical training is not required. Since the system is used to support decision making, the quality of demand-side management programs should be enhanced and the morale of the staff promoted.

People often compare the decisions provided by a knowledge-based system with those of a human expert; however, accuracy is only one of the measures. For example, a KBS may duplicate the decision of a human expert, but it may take considerable time and resources to develop the program. So, the productivity gains from using the expert system must be balanced by the costs to develop the system. The productivity gains are usually difficult to quantify.

Discussion

The three major parameters are expected savings, rebate, and customer adoption. Expected savings and customer adoption are uncertain, but rebate could be either certain or uncertain.

All variables in Mode I are assumed to be deterministic. This is not true in real life, however it offers a good structure for the problem.

Fuzzy logic is an excellent mechanism for representing uncertainty since linguistic variables can be defined by fuzzy sets. Linguistic and defuzzified numerical

representations are provided to the end user at the same time. Thus, the user may have more sense about the evaluation. The expected savings had to be defuzzified when evaluating energy and demand impacts, but it is hard to assign an appropriate magnitude to “very high”. However, a mean value is assigned even though it could be greater than the maximum savings.

Dempster-Shafer theory is another good uncertainty representing mechanism. A disadvantage of this method is the insufficiency of combination functions. More specifically, when customer adoption is evaluated, the magnitude of input rebate must be less than or equal to maximum savings; when rebate is evaluated, maximum savings can not be less than input customer adoption. It is not often that we are interested in Dempster adoption number when the input value of a rebate is greater than maximum savings, but it could happen.

A comparison of the adoption and rebate deviations for the first case is shown in Table 4.27. Adoption is evaluated when expected savings and rebate are specified. The numbers are taken from the sample results. A fuzzy adoption for residential lighting is $(45.6 \pm 3.2)\%$. The percentage of the deviation for fuzzy adoption is $3.2/45.6 = 6.7\%$. A Dempster adoption for residential lighting is $(41.7 \pm 3.3)\%$. The percentage of the deviation for Dempster adoption is $3.3/41.7 = 7.9\%$. The adoption deviation for the Dempster-Shafer mode is about the same as for the fuzzy logic mode under the similar input. The adoption range for fuzzy logic mode is 42.4–48.8% and that for Dempster-Shafer mode is 38.4–45.0%. More than 40% of fuzzy adoption is overlap with Dempster adoption.

A sample comparison for the percentages of energy and demand reduction deviations is given in Table 4.28. A fuzzy energy reduction is (18.42 ± 5.39) MWh and, thus,

Table 4.27: Percentage comparison of adoption and rebate deviations for the first case.

Mode	Adoption	Rebate
Fuzzy Logic	$\frac{3.2}{45.6} = 6.7\%$	$\frac{15.0}{45.0} = 33.3\%$
Dempster-Shafer	$\frac{3.3}{41.7} = 7.9\%$	$\frac{0.0}{45.0} = 0\%$

Table 4.28: Percentage comparison for energy and demand reduction deviations for the first case.

Mode	Energy Reduction	Demand Reduction
Fuzzy Logic	$\frac{5.39}{18.42} = 29.3\%$	$\frac{0.53}{1.84} = 28.8\%$
Dempster-Shafer	$\frac{7.80}{18.21} = 42.8\%$	$\frac{0.80}{1.87} = 42.8\%$

the percentage of the deviation for the fuzzy energy reduction is $5.39/18.42 = 29.3\%$. A Dempster energy reduction is (18.21 ± 7.80) MWh and, thus, the percentage of the deviation for the Dempster energy reduction is $7.80/18.21 = 42.8\%$. Similarly, a fuzzy demand reduction is (1.84 ± 0.53) MW and the percentage of the deviation for the fuzzy demand reduction is $0.53/1.84 = 28.8\%$. A Dempster demand reduction is (1.87 ± 0.80) MW and the percentage of the deviation for the Dempster demand reduction is $0.80/1.87 = 42.8\%$. The energy and demand deviations for the fuzzy logic mode are close to 30%, and those for the Dempster-Shafer mode are about 43%.

Table 4.29: Percentage comparison of adoption and rebate deviations for the second case.

Mode	Adoption	Rebate
Fuzzy Logic	$\frac{12.5}{57.5} = 21.7\%$	$\frac{15.0}{75.0} = 20.0\%$
Dempster-Shafer	$\frac{0.0}{57.5} = 0\%$	$\frac{6.7}{84.1} = 8.0\%$

An adoption and rebate deviation comparison of the second case for the similar input is shown in Table 4.29. Rebate is predicted when expected savings and adoption are specified. The numbers are referring to the sample results. A fuzzy rebate is $(75.0 \pm 15.0)\%$. Percentage of the deviation for the fuzzy rebate is $15.0/75.0 = 20.0\%$. A Dempster residential lighting rebate is $(84.1 \pm 6.7)\%$. Percentage of the deviation for the Dempster rebate is $6.7/84.1 = 8.0\%$. The rebate range for fuzzy logic mode is 60.0–90.0% and that for Dempster-Shafer mode is 77.4–90.8%. Ninety-four percent

of Dempster rebate is overlap with fuzzy rebate.

The mean values and deviations for different modes should be about the same. The main reason for the differences is because the different ways that uncertainty is represented. Human input is required to determine the shapes of the membership function distributions for the fuzzy logic mode and basic probability assignments for the Dempster-Shafer mode. Different input for these quantities will give different uncertainties in the results. It is difficult to assess which method actually is better at representing uncertainty.

CHAPTER 5. SUMMARY AND CONCLUSION

The goal of this project is to investigate the propagation of uncertainty in a knowledge-based system that assesses energy management strategies for new gas and electric technologies that can help reduce energy consumption and demand. The new technologies that have been investigated include lighting, electric heat pumps, motors, refrigerators, microwave clothes dryers, freeze concentration, electric vehicles (EVs), gas furnaces, gas heat pumps, engine-driven chillers, absorption chillers, and natural gas vehicles (NGVs) distributed throughout the residential, commercial, industrial, and transportation sectors.

New lighting, electric heat pumps, and industrial motor systems are the significant contributors for electrical energy savings. The maximum energy savings for lighting is 30–60% of current energy usage for lighting, for electric heat pumps is 20–40%, and for industrial motor systems is in the range of 35–50%. The energy savings of new refrigerators is expected to be 25–30%. Microwave clothes dryers are being developed with an expected energy savings of 20%. Freeze concentration is continuously creating a number of new applications. The savings of individual applications are varied, for milk concentration the savings is 50%. An estimate of energy savings for EVs ranges from 25% to 40% of conventional gas-powered automobiles. The expected savings of the next generation of EVs is projected to be 60%.

The new generation of residential gas furnaces will be more convenient, quieter, cheaper, and more efficient than conventional furnaces. Gas heat pumps can be installed in household or small commercial stores with a maximum energy savings of 50%. Engine-driven chillers and absorption chillers are suitable for large commercial buildings. Double-effect absorption systems are 50% more energy efficient than the gas chillers used 20 years ago. An advanced triple-effect unit is being developed, which will provide an additional 50% hike in efficiency when compared to double-effect units. The operating costs of NGVs in Iowa is 40-50% lower than for automobiles.

The description of a complex assessment system may be simplified by allowing some degree of uncertainty. There are several mechanisms that can be used to handle uncertainty, such as probability theory, certainty factors, Dempster-Shafer theory, fuzzy logic, rough sets, non-numerical methods, and network model theory. Application of these theories except network model theory to rule-based systems enables us to represent uncertainty in production rules. Uncertainty can be propagated through the rules and combined to give the uncertainty in the conclusions. The proper application of uncertainty provides an effective and efficient way to represent knowledge.

A computer program has been developed to assess the impacts of rebate programs on customer adoption of new technologies and hence the reductions in energy and demand. The computer program is an interactive knowledge-based system (KBS). The most important part of a KBS is its knowledge base that consists of facts and production rules. The rules are developed through intuition, experience, and judgment of human experts. A correlation for rebate, expected savings, and customer adoption is also used in the knowledge base for this program. Predictions for annual adoption

of a new technology are made for specified useful life, rebate, and expected savings; or a suggested rebate can be determined for specified useful life, expected savings, and annual adoption. With input for energy use and demand for each technology, the impacts of rebate programs on energy use and power demand can be evaluated. End users can modify their input data to try different cases, or they can restart the evaluation with a new set of data without leaving the program.

Three modes have been programmed; one in which uncertainty is not considered, another where fuzzy logic with linguistic variables is used to represent uncertainty, and one in which uncertainty is represented using Dempster-Shafer theory with basic probability assignments. Linguistic variables represent uncertainty using words such as “few”, “modest”, and “rather”. The fuzzy logic membership functions for rebate, expected savings, and customer adoption are classified as “very low”, “low”, “medium”, “high”, or “very high”. Dempster-Shafer basic probability assignment numbers are assigned to expected savings and rebate to predict annual adoption, or assigned to expected savings and annual adoption to evaluate rebate when useful life is known.

The adoption of energy-efficient gas and electric technologies will benefit consumers, utilities, and the environment. A key issue is to increase the market penetration of these technologies through successful energy management programs.

Fuzzy logic and Dempster-Shafer theory are appropriate methods to be applied in utility prediction knowledge-based systems to estimate energy and demand impacts. Human input is required to determine the shapes of the membership functions for fuzzy logic mode and basic probability assignments for Dempster-Shafer mode. Different input for these quantities will give different uncertainties in the results. It

is difficult to assess which method is better at representing uncertainty.

This report and the knowledge-based system should help utilities determine these new technologies that are most promising and these policies that should be emphasized in their energy management programs.

Future Work

Future work related to this project could include:

1. Updating the information for the technologies discussed in this work and searching for other new technologies.
2. Revising the knowledge-based system using feedback from utilities.
3. Comparing results with and without uncertainty in the curves for rebate, expected savings, and adoption.

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APPENDIX A. SET OPERATIONS

A set is a collection of well-defined elements. Elementary set theory is referred to in many literatures, such as Gordon (1967), Hirst and Rhodes (1971), Hausdorff (1978), and Milewski (1989). Several notations and operations for uncertainty study will be reviewed in the following sections.

Notations

The notations will be used are listed and explained.

R	set of all real numbers
\in	belongs to; is an element of; is a member of
\notin	not belong to; is not an element of; is not a member of
$[a, b]$	closed interval; $x \in R, a \leq x \leq b$
U	universal set
S	sample space
$\{a, b, c\}$	set described as a list
$\{x g(x)\}$	set described by a rule
$A \cup B$	union of A and B
$A \cap B$	intersection of A and B
$\bigcup_{i=1}^n A_i$	union of A_1, A_2, \dots, A_n

$\bigcap_{i=1}^n A_i$	intersection of A_1, A_2, \dots, A_n
A^c	complement of A
\emptyset	empty set; a set with no elements
$A \subseteq B$	A is a subset of B
$A \subset B$	A is a proper subset of B
$A - B$	relative complement of B with respect to A
\vee	or
\wedge	and
\forall	for each
\exists	there exists
\oplus	combination
Σ	summation
$f : A \rightarrow B$	f is a function from A to B
(x, y)	ordered pairs
$A \times B$	Cartesian product of A and B ; $(x, y) \in A \times B$ if and only if $x \in A$ and $y \in B$
2^S	power set of S ; the collection set of all subsets of S
$2^S \times 2^S$	the set of all ordered pairs in sample space; $(A, B) \subseteq S \times S$ if and only if $A \subseteq S$ and $B \subseteq S$

Subsets and Power set

If every element of A is an element of B , then A is a subset of B . We express it by

$$A \subseteq B$$

If A is a subset of B and there exists an element of B which does not belong to A , then A is a proper subset of B . We denote it by

$$A \subset B$$

A set of n elements contains $C(n, m)$ subsets of m elements.

$$C(n, m) = \frac{n!}{m!(n-m)!} \quad (\text{A.1})$$

where $n!$ is the product of positive integers from n to 1.

$$n! = n \times (n-1) \times (n-2) \times \cdots \times 1 \quad (\text{A.2})$$

and by definition $0! = 1$. The total number of subset is

$$C(n, 0) + C(n, 1) + \cdots + C(n, n) = 2^n \quad (\text{A.3})$$

A power set is the collection of all subsets of a given set A . If A contains n elements, then its power set 2^A contains 2^n elements. For example, let

$$A = \{a, b, c\}$$

then

$$2^A = \{\emptyset, \{a\}, \{b\}, \{c\}, \{a, b\}, \{a, c\}, \{b, c\}, \{a, b, c\}\}$$

There are 3 elements in A , thus 8 elements in 2^A .

Basic Operations

The fundamental operations of set theory are:

- **Union:** The elements of $A \cup B$ belong to at least one of A and B .

$$A \cup B = \{x | x \in A \vee x \in B\} \quad (\text{A.4})$$

The notation can be extended to cases more than two sets. The union of 3 sets is

$$A_1 \cup A_2 \cup A_3 = \{x | x \in A_1 \vee x \in A_2 \vee x \in A_3\} \quad (\text{A.5})$$

$$= \{x | x \in A_i, \text{ for some } i = 1, 2, 3\} \quad (\text{A.6})$$

The union of n sets can be denoted by

$$\bigcup_{i=1}^n A_i = A_1 \cup A_2 \cup \dots \cup A_n \quad (\text{A.7})$$

$$= \{x | x \in A_i, \text{ for some } i = 1, 2, \dots, n\} \quad (\text{A.8})$$

- **Intersection:** The elements of $A \cap B$ is the common elements of A and B .

$$A \cap B = \{x | x \in A \wedge x \in B\} \quad (\text{A.9})$$

The intersection of 3 and n sets are

$$A_1 \cap A_2 \cap A_3 = \{x | x \in A_1 \wedge x \in A_2 \wedge x \in A_3\} \quad (\text{A.10})$$

$$= \{x | x \in A_i, \text{ for each } i = 1, 2, 3\} \quad (\text{A.11})$$

and

$$\bigcap_{i=1}^n A_i = A_1 \cap A_2 \cap \dots \cap A_n \quad (\text{A.12})$$

$$= \{x | x \in A_i, \text{ for each } i = 1, 2, \dots, n\} \quad (\text{A.13})$$

- Complement:

$$A^c = \{x | x \in U \wedge x \notin A\} \quad (\text{A.14})$$

The union of a set A and its complement set A^c makes the universal set.

$$A \cup A^c = U \quad (\text{A.15})$$

- Difference: The set of elements which belong to A but not to B is called the relative complement of B with respect to A .

$$A - B = \{x | x \in A \wedge x \notin B\} \quad (\text{A.16})$$

Similarly, the relative complement of A with respect to B is

$$B - A = \{x | x \in B \wedge x \notin A\} \quad (\text{A.17})$$

By the same idea, we have

$$U - A = A^c \quad (\text{A.18})$$

- Commutativity:

$$A \cap B = B \cap A \quad (\text{A.19})$$

$$A \cup B = B \cup A \quad (\text{A.20})$$

- Associativity:

$$(A \cap B) \cap C = A \cap (B \cap C) \quad (\text{A.21})$$

$$(A \cup B) \cup C = A \cup (B \cup C) \quad (\text{A.22})$$

- Distributivity:

$$A \cap (B \cup C) = (A \cap B) \cup (A \cap C) \quad (\text{A.23})$$

$$A \cup (B \cap C) = (A \cup B) \cap (A \cup C) \quad (\text{A.24})$$

- DeMorgan Laws:

$$C - (A \cap B) = (C - A) \cup (C - B) \quad (\text{A.25})$$

$$C - (A \cup B) = (C - A) \cap (C - B) \quad (\text{A.26})$$

APPENDIX B. USER'S GUIDE FOR MODE I

The goal of this knowledge-based system is to help assess demand-side management strategies for utilities. Three modes have been developed; the first one in which uncertainty is not considered, the second one where fuzzy logic with linguistic variables is employed to represent uncertainty, and the third one in which uncertainty is represented using Dempster-Shafer theory with basic probability assignments. In Mode I, uncertainty is not considered. The attributes of user-defined objects and a tutorial are described in detail.

Attributes of User-Defined Objects

User-defined objects are classified into five groups: basic, technology, sector, summation, and calculating objects. The attributes of user-defined objects are listed and explained in the following.

Attributes of Basic Objects

Basic objects include residential lighting, commercial lighting, industrial lighting, residential heat pump, commercial heat pump, residential motor, industrial motor, residential refrigerator, commercial refrigerator, residential microwave dryer, commercial microwave dryer, and freeze concentration. Their attributes are:

- **Maximum savings (in %):** The maximum expected energy reduction of the new technology when applied, in percent of current usage per application.
- **Expected savings (in %):** The expected energy reduction of the new technology when applied, in percent of current usage per application. The expected savings of the new technology must be equal to or less than the maximum savings.
- **Rebate (in %):** The percentage of the initial cost of the new technology that is paid to the customers. Rebate of the new technology is either input by the end user or evaluated when useful life, expected savings, and annual adoption are specified.
- **Customer adoption (in %):** The percentage of current usage for which customers will utilize the new technology.
- **Useful life (in years):** How long an equipment of the technology can be used.
- **Annual adoption (in %):** Customer adoption is modified by useful life because in practice an equipment will not be replaced until it breaks down. Annual adoption of the new technology can be either input by the end user or evaluated when useful life, expected savings, and rebate are specified.
- **Peak use (in %):** The percentage of the equipment for the technology that is used during peak hours.
- **Energy (in MWh):** The total annual energy consumed by the current technology.
- **Demand (in MW):** The power peak demand of the current technology.

- Energy reduction (in MWh): The annual energy savings if the current technology is replaced with an energy-efficient new technology.
- Demand reduction (in MW): The power demand reduction if the current technology is replaced with an energy-efficient new technology.
- Customers contacted (in %): The percentage of customers that are contacted by utilities about the new technology.
- Initial cost (in \$): The first or replacement cost for the new technology.
- F_{ic} : Initial cost factor, $0 \leq F_{ic} \leq 1$. F_{ic} decreases with the increase of initial cost. The relationship between F_{ic} and initial cost is nonlinear. The initial cost, from 0 to ∞ , is divided into several sections and thus each section has a F_{ic} , as shown in Table 4.2.
- Consumer confidence (in %): Confidence that the consumers have that the new technology will meet their expectations.
- Modified adoption (in %): Annual adoption as modified according to the percentage of customers contacted, initial cost, and consumer confidence.

Attributes of Technology Objects

Technology objects include lighting, heat pump, motor, refrigerator, microwave dryer. Since freeze concentration is applied in the industrial sector only, it does not need an object in this group. Their attributes are:

- Technology energy (in MWh): Total annual energy consumed by the technology in all sectors.

- **Technology demand (in MW):** Total power demand of the technology in all sectors.
- **Technology energy reduction (in MWh):** Total annual energy saved by the more efficient technology in all sectors.
- **Technology demand reduction (in MW):** Total power demand reduction by the more efficient technology in all sectors.

Attributes of Sector Objects

Sector objects include residential, commercial, and industrial. Their attributes are:

- **Sector energy (in MWh):** Total annual energy use of a sector.
- **Sector demand (in MW):** Total power demand of a sector.
- **Sector energy reduction (in MWh):** Total annual energy saved by more efficient technologies in a sector.
- **Sector demand reduction (in MW):** Total demand reduction by more efficient technologies in a sector.

Attributes of Summation Object

The summation object is united. The attributes are:

- **Total energy (in MWh):** Total annual energy use.

- Total demand (in MW): Total power demand.
- Total energy reduction (in MWh): Total annual energy saved by more efficient technologies.
- Total demand reduction (in MW): Total power demand reduction by more efficient technologies.

Attributes of the Calculating Object

The calculating object is a solver, which is inherited by each of the basic objects.

The attributes of solver are:

- c_1, c_2, \dots, c_9 : Curve fitting coefficients for customer adoption.
- d_1, d_2, \dots, d_9 : Curve fitting coefficients for rebate.
- x_0 : Rebate reference, a constant for the transformation of variable of rebate.
- y_0 : Expected savings reference, a constant for the transformation of variable of expected savings.
- z_0 : Customer adoption reference, a constant for the transformation of variable of customer adoption.
- r_x : Rebate interval, another constant for the transformation of variable of rebate.
- r_y : Expected savings interval, another constant for the transformation of variable of expected savings.

- r_z : Customer adoption interval, another constant for the transformation of variable of customer adoption.

Tutorial

The knowledge-based system in which uncertainty is not considered is an interactive program. The operating procedures and an example are given to show the capability of this system.

Operating Procedures

The deterministic mode KBS is user friendly. Since it is an interactive system, the end user will be shown what to do for the next step on the current display. The color space is for data input. The end user can keep the defaults or make reasonable changes. The general procedures for operating the deterministic mode are described as follows:

1. Start the program from LEVEL5 OBJECT.
2. An introduction display will be shown.
3. Enter the main screen by clicking .
4. Select a technology or sector to be investigated on main screen. The end user can come back after the current selected item has been done.
5. Input new data or keep the defaults for useful life, maximum savings, and expected savings. Predictions for annual adoption of the new technology are evaluated for specified rebate, or a rebate can be determined for specified annual adoption.

6. Enter another display by clicking [More Factors on Adoption](#) to consider the influence of customers contacted, initial cost, and consumer confidence on annual adoption.
7. Input appropriate data to modify annual adoption.
8. Enter the energy impact display by clicking [Energy Impacts](#).
9. Input the data for peak use, energy, and demand to evaluate energy and demand reductions.
10. The end user can switch among deterministic analysis, more factors on adoption, and energy impacts displays to adjust the numbers.
11. Implement the evaluation for different cases for the technology or sector.
12. Return to the main screen to pick up another evaluation or stop the evaluation.
13. Review the evaluated advice, when all evaluations are done, through the summary displays by clicking [rebate and adoption summary](#) for rebate and adoption summary or clicking [energy impact summary](#) for energy and demand reductions summary.
14. Exit the program.

An Example

An example for operating the knowledge-based system without uncertainty consideration is given. Residential lighting is the technology used to investigate adoption

and commercial heat pump technology is picked up to demonstrate rebate evaluation. The steps for obtaining knowledge and revising information are illustrated below.

1. Start LEVEL5 OBJECT.
2. Select Open/Run from the File menu to request opening and running a file.
3. Open the file determin.knb.
4. A title “The Energy Policy Assessment Knowledge-Based System Deterministic Mode” and some explanations are there.
5. Click the **CONTINUE** button to continue the operation.
6. Select **lighting** on main screen to predicate customer adoption.
7. The lighting deterministic analysis display is for lighting rebate and annual adoption evaluation. The input expected savings cannot exceed the maximum savings, otherwise an input warning message will show up. Either the annual adoption or rebate can be specified by the user. When one item is keyed in, the other item is computed automatically. If the rebate rate is negative, another warning message will be given. Let’s try 45% expected savings and 20% rebate.
8. The evaluated annual adoption is 35.2%.
9. Click **More Factors on Adoption** to consider the influence of some variables on adoption.
10. Input customers contacted as 85%, initial cost as \$50, and consumer confidence as 90%.

11. The modified adoption is 26.9%.
12. Click Energy Impacts to enter the energy impact display.
13. Change new technology peak use to 40% and input energy use and power demand with 100 MWh and 20 MW.
14. The energy and demand reductions are 12.1 MWh and 0.9 MW.
15. Switch among deterministic analysis, more factors on adoption, and energy impacts displays to try different cases for residential lighting.
16. Return to the main screen by clicking Main Screen after this evaluation is done.
17. Select residential display to revise information for residential lighting.
18. Change the expected savings to 35% and rebate to 30%.
19. The new annual adoption is 33.9%.
20. Click More Factors on Adoption to modify new adoption number.
21. Keep customers contacted and initial cost but change consumer confidence to 60%.
22. The new adoption number is modified to 17.2%.
23. Change energy use to 300 MWh and demand to 50 MW.
24. The energy reduction is revised to 18.1 MWh and demand reduction is adjusted to 1.2 MW.

25. Return to the main screen again.
26. Select technology to evaluate rebate for a commercial heat pump.
27. On the heat pump deterministic analysis display, keep the default value, 15 years, for useful life and input expected savings as 35% and annual adoption as 2.5%.
28. The evaluated rebate is 39.5%.
29. Return to the main screen.
30. Click the button in main screen to review the rebates and customer adoption.
31. Click button to review the energy and demand impacts.
32. Return to the main screen.
33. Exit the system by clicking .
34. Leave LEVEL5 OBJECT by selecting Exit from the File menu or continue the next tutorial.

Comments

The values of maximum savings were acquired from available literature. If new information is obtained, the end user may change it through the instance editor. The default values of expected savings are maximum savings.

The end user can modify the input data during operation to try different cases or restart the evaluation with a new set of data without leaving the program. On the other hand, the end user can leave the knowledge-based system at anytime by selecting Exit from the File menu on each display.

APPENDIX C. USER'S GUIDE FOR MODE II

In this mode, fuzzy logic is used to represent uncertainty. As mentioned in Chapter 4, each technology should have its own correlation for rebate, expected savings, and customer adoption; however, the same correlation is employed for each technology's application with minor modifications for customer adoption due to useful life of the technology. One more object, fuzzy, is used to implement the fuzzy logic capability. The attributes of this object and the tutorial are given below.

Attributes

- **Linguistic expected savings:** The expected energy reduction for the new technology when applied. Values: "very high", "high", "medium", "low", "very low".
- **Linguistic rebate:** The statement of the initial cost of the new technology that is paid to the customer. The rebate for the new technology is either selected by the end user or evaluated when useful life, annual adoption, and expected savings are specified. Values: "very high", "high", "medium", "low", "very low".
- **Linguistic annual adoption:** The statement of current usage for which customers will utilize the new technology. The annual adoption of the new technology can

be either selected by the end user or evaluated when rebate and expected savings are specified. Values: “very high”, “high”, “medium”, “low”, “very low”.

- Useful life (in years): How long the equipment of the technology can be used before needing replacement.
- Fuzzy adoption number (in %): The defuzzified value of the linguistic customer adoption.
- Annual adoption number (in %): The fuzzy adoption number modified by useful life because equipment will not be replaced if it still works.
- Fuzzy rebate number (in %): The defuzzified value of the linguistic rebate.
- Initial cost (in \$): The first or replacement cost for the new technology.
- Consumer confidence (linguistic): The consumer confidence for using the new technology. Values: “very high”, “high”, “medium”, “low”, “very low”.
- F_{ic} : Initial cost factor, $0 \leq F_{ic} \leq 1$. F_{ic} is decreasing with the increase of initial cost. The relationship between F_{ic} and initial cost is not linear. The initial cost, from 0 to ∞ , is divided into several sections and thus each section has a F_{ic} , as shown in Table 4.2.
- F_{cc} : Consumer confidence factor, $0 \leq F_{cc} \leq 1$. F_{cc} is decreasing with the decrease of consumers confidence. Each consumer confidence, from “very high” to “very low”, has a F_{cc} , as given in Table 4.6.

- **Modified fuzzy customer adoption (in %)** : The annual adoption number is modified according to consumers contacted, initial cost, and consumer confidence.

Tutorial

The knowledge-based system with fuzzy logic uncertainty representation is an interactive program. The operating procedures and an example are given.

Operating Procedures

The system will show the end user what to do for the next step on the current display after it is started. The general procedures are described as follows:

1. Start the knowledge-based system from LEVEL5 OBJECT.
2. An introduction display will show up.
3. Enter the main screen by clicking **CONTINUE**.
4. Select a technology to be investigated and input the useful life of the equipment for this technology.
5. Click **Fuzzy Analysis** to begin the evaluation.
6. Select evaluation variable: "calculate adoption" or "calculate rebate". A possible annual adoption of the new technology can be predicted for specified rebate and expected savings; or a suggested rebate is determined for specified expected savings and annual adoption.

7. Click **More Factors on Adoption** to consider the influence of consumers contacted, initial cost, and consumer confidence on annual adoption.
8. Input appropriate data to modify annual adoption.
9. Enter energy impacts display by clicking **Energy Impacts**.
10. Input appropriate data for peak use, energy, and demand to predict energy and demand reductions.
11. The end user can switch among fuzzy analysis, more factors on adoption, and energy impacts displays to adjust selections or numbers.
12. Evaluate different cases.
13. Return to the main screen to pick up another technology to be evaluated or stop the evaluation.
14. Exit the program by clicking **QUIT** when the desired evaluations are done.

An Example

A demonstration example for operating the knowledge-based system with fuzzy logic uncertainty representation is given. Residential lighting is the technology to be investigated.

1. Start LEVEL5 OBJECT.
2. Select Open/Run from the File menu.

3. A title “The Energy Policy Assessment Knowledge-Based System Fuzzy Logic Mode” and some explanations are there.
4. Open the file flogic.knb.
5. Click **CONTINUE** button to enter the main screen.
6. Select residential lighting to be evaluated. Since the default useful life is about the same as residential lighting’s life, keep it.
7. Click **Fuzzy Analysis** button to begin the evaluation.
8. Pick up the variable to be evaluated. The default is “calculate adoption”. Let’s keep it.
9. Specify the expected savings as “very high” and rebate as “low”.
10. The evaluated adoption is “high” and the defuzzified adoption number is $(52 \pm 3)\%$.
11. Consider the influence of consumers contacted, initial or replacement cost, and consumer confidence by clicking **More Factors on Adoption**.
12. Specify the percent of customers contacted as 95%, initial cost as \$50, and consumer confidence as “high”.
13. The modified adoption number is $(45 \pm 3)\%$.
14. Click **Energy Impacts** to evaluate energy and demand reductions.
15. Specify peak use as 50%, energy use and power demand as 100 MWh and 20 MW.

16. The energy and demand reductions are (34.9 ± 12.5) MWh and (3.4 ± 1.2) MW.
17. Switch among fuzzy analysis, more factors on adoption, and energy impacts display to adjust selection or numbers.
18. Return to the fuzzy analysis display by clicking Fuzzy Analysis.
19. Change the evaluating variable selection from “calculate adoption” to “calculate rebate”.
20. Specify the expected savings as “medium” and adoption as “medium”.
21. The evaluated rebate is “medium” and the defuzzified adoption number is $(45 \pm 13)\%$.
22. Return to the main screen by clicking Main Screen.
23. Exit the program by clicking QUIT
24. Leave LEVEL5 by selecting Exit from the File menu or continue the next tutorial.

Comments

The end user can modify the input data during operation to try different cases or implement another evaluation with a new set of data without leaving the program. Meanwhile, the end user can leave and restart the system through the control bar at any display by selecting Exit and Restart, respectively.

APPENDIX D. USER'S GUIDE FOR MODE III

Dempster-Shafer theory is employed to represent uncertainty propagation in this mode. As for fuzzy logic mode, the same correlation for rebate, expected savings, and customer adoption is used for each technology in each sector with modifications for adoption according to useful life. Another object, dempster, is created for this application.

Attributes

The primary attributes of this object are the same as for Mode I, thus only the three major input parameters are repeated over here.

- **Maximum savings (in %):** The maximum expected energy reduction of the new technology when applied, in percent of current usage per application. The maximum savings in this mode is designed ranging from 15% to 60% referring to the information in Tables 2.14, 2.15, and 2.16.
- **Rebate (in %):** The percentage of the initial cost of the new technology that is paid to the customers. Rebate of the new technology is either selected by the end user or evaluated when useful life, expected savings, and annual adoption are specified.

- Annual adoption (in %): The percentage of current usage for which customers will utilize the new technology. The percentage of annual adoption of a new technology can be either selected by the end user or computed when useful life, maximum savings, and rebate are specified.

Tutorial

The knowledge-based system with Dempster-Shafer uncertainty propagation is an interactive program. The operating procedures and an example are provided.

Operating Procedures

The procedures for implementing this mode are similar to fuzzy logic mode. The general procedures are described as follows:

1. Start the program from LEVEL5.
2. An introduction display is shown.
3. Click to enter the main screen.
4. Select a technology to be investigated and input the useful life of the equipment for the technology.
5. Click to begin the evaluation.
6. Select evaluation variable: "calculate adoption" or "calculate rebate". Annual adoption of the new technology is predicted for specified maximum savings and rebate, or a rebate can be determined for specified maximum savings and annual adoption.

7. Click **More Factors on Adoption** to consider the influence of some variables on adoption.
8. Input appropriate data to modify the adoption number.
9. Enter the energy impacts display by clicking **Energy Impacts**.
10. Input the data for peak use, energy, and demand to evaluate energy and demand reductions.
11. The end user can switch among Dempster-Shafer analysis, more factors on adoption, and energy impacts displays to try different cases.
12. Return to the main screen to select up another technology to be evaluated or stop the evaluation.
13. Exit the program when evaluations are done.

An Example

An example for operating the knowledge-based system with Dempster-Shafer theory is given. Residential lighting is the technology to be investigated.

1. Start LEVEL5.
2. Select Open/Run from File menu.
3. Open the file dempster.knb.
4. A title "The Energy Policy Assessment Knowledge-Based System Dempster-Shafer Mode" and some explanations are there.

5. Click the **CONTINUE** button to continue the operation.
6. Select residential lighting to be investigated on the main screen and keep the useful life of one year.
7. Click **Dempster-Shafer Analysis** button to begin the evaluation.
8. Select the variable to be evaluated. The default is “calculate adoption”. Let’s keep it.
9. Specify the maximum savings as 45% and rebate as 40%.
10. The evaluated Dempster annual adoption is $(34.7 \pm 2.4)\%$.
11. Consider the influence of consumers contacted, initial cost, and consumer confidence by clicking **More Factors on Adoption**.
12. Specify the percent of customers contacted as 80%, initial cost as \$50, and consumer confidence as 70%.
13. The modified adoption number is $(19.4 \pm 1.3)\%$.
14. Click **Energy Impacts** to evaluate energy and demand reductions.
15. Specify peak use as 50%, energy use and power demand as 100 MWh and 25 MW.
16. The energy and demand reductions are (9.8 ± 2.3) MWh and (1.2 ± 0.2) MW.
17. Switch among Dempster-Shafer analysis, more factors on adoption, and energy impacts displays to adjust the numbers.

18. Return to the analysis display by clicking **Dempster-Shafer Analysis**.
19. Change the evaluating variable selection from “calculate adoption” to “calculate rebate”.
20. Specify the expected savings as 50% and annual adoption as 45%.
21. The evaluated Dempster rebate is $(61.5 \pm 5.5)\%$.
22. Return to the main screen by clicking **Main Screen**.
23. Exit the system by clicking **QUIT** after the evaluations are done.
24. Leave LEVEL5 by selecting Exit from the File menu.

Comments

The limitation of the Dempster-Shafer mode is that the input value of rebate or customer adoption can not exceed maximum savings, however, the magnitude of the evaluated result could be greater than maximum savings.

End users can modify their input data during operation to try different cases or perform another evaluation without leaving the program, as in the fuzzy logic mode. End users can also leave the knowledge-based system, at any display, by selecting Exit from the control bar or restart the system through the control bar by selecting Restart.