RENEWABLE ENERGY IN ELECTRIC UTILITY CAPACITY PLANNING: A DECOMPOSITION APPROACH WITH APPLICATION TO A MEXICAN UTILITY

by

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(ABSTRACT)

Many electric utilities have been tapping such energy sources as wind energy or conservation for years. However, the literature shows few attempts to incorporate such non-dispatchable energy sources as decision variables into the long-range planning methodology. In this dissertation, efficient algorithms for electric utility capacity expansion planning with renewable energy are developed.

The algorithms include a deterministic phase which quickly finds a near-optimal expansion plan using derating and a linearized approximation to the time-dependent availability of non-dispatchable energy sources. A probabilistic second phase needs comparatively few computer-time consuming probabilistic simulation iterations to modify this solution towards the optimal expansion plan.

For the deterministic first phase, two algorithms, based on a Lagrangian Dual decomposition and a Generalized Benders Decomposition, are developed. The Lagrangian Dual formula-

tion results in a subproblem which can be separated into single-year plantmix problems that are easily solved using a breakeven analysis. The probabilistic second phase uses a Generalized Benders Decomposition approach. A depth-first Branch and Bound algorithm is superimposed on the two-phase algorithm if conventional equipment types are only available in discrete sizes. In this context, computer time savings accrued through the application of the two-phase method are crucial.

Extensive computational tests of the algorithms are reported. Among the deterministic algorithms, the one based on Lagrangian Duality proves fastest. The two-phase approach is shown to save up to 80 percent in computing time as compared to a purely probabilistic algorithm.

The algorithms are applied to determine the optimal expansion plan for the Tijuana-Mexicali subsystem of the Mexican electric utility system. A strong recommendation to push conservation programs in the desert city of Mexicali results from this implementation.

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I wish to dedicate my work to , , , and .

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Chapter I

INTRODUCTION

The major goal of the electric utility industry is to provide reliable service at minimal cost given the varying demands of customers. Uncertainties in forecasting contingencies such as future demand and forced outages of generation units greatly complicate this task. Mathematical programming has been used extensively in such areas as planning the optimal economic operation of power systems, scheduling hydro units, and finding the optimal expansion path for generation capacity, transmission lines, etc. (for an overview, see CARPENTIER and Merlin, 1981, and for early applications, see SANDIFORD et al, 1956). This dissertation applies mathematical programming to generation capacity planning.

There are different kinds of power plants, e.g. hydroelectric, coal-fired, oil-fired, gas-fired, nuclear plants, etc. Until the 1960's, electric utilities expanded their capacity almost entirely with these traditional types of plants. The oil embargo of 1973, however, jolted people to an awareness that fossil fuels and even uranium supplies will eventually be depleted. For example, if current growth trends persist, oil and natural gas could be depleted as early as 50 years from now (STOBAUGH and Yergin, 1979).

Most politicians and scientists concerned with our energy future agree that alternatives to a fossil fuel economy must be found. Some stress the importance of nuclear energy, fission, fast breeder and eventually fusion technology. Others advocate a transition to renewable energy sources for environmental and long-term economic reasons.

It has been argued that the only feasible solution for even short-term energy problems can be a large effort in conservation and solar energy. (In our context, we will use the term 'solar energy' to include energy sources such as the direct use of the sun's rays to generate heat or electricity, wind, ocean thermal and biomass energy.) To accelerate the usage of conservation and solar equipment, it has been suggested that electric utilities get involved in the marketing of such equipment in some way (STOBAUGH and Yergin, 1979). Measures like utility financing or leasing of solar installations, consulting or contracting for installation, and even direct utility ownership, have been discussed. Besides getting involved in solar and conservation projects of individual customers, utilities also have the option of investing in large solar power plants, i.e. solar thermal or photovoltaic installations.

For both the above implementations of solar technology, the same question arises for the utility: how much solar capacity would be economical to install? An important difference between solar energy and the more traditional energy sources complicates this question. While fossil fuels and uranium are usually available day and night, any season of the year, all types of solar energy and even energy savings due to conservation display highly variable patterns. For example, at night and during cloudy periods a solar thermal power plant does not produce any energy, and in contrast with the usage of fossil fuels in conventional power plants, the clouds cannot be controlled by the flip of a switch. Storage devices, mostly heat storage in the form of rock beds or other thermal masses, can be used to increase the reliability of solar power, but in many cases this does not prove to be economical.

This dissertation therefore investigates mathematical programming approaches for electric utility capacity planning, which selects and dispatches an optimal mix of equipment types, possibly including solar generation and storage capacity as well as conservation investments. Of necessity, the peculiarities and characteristics of solar energy and conservation must be explicitly accounted for in this program.

The algorithms developed in this dissertation include a deterministic first phase which quickly finds a near-optimal expansion plan using derating and a linearized approximation to the time-dependent availability of renewable energy sources. A probabilistic second phase needs comparatively few computer-time consuming probabilistic simulation iterations to modify this solution towards the optimal expansion plan.

For the deterministic first phase, two algorithms, based on a Lagrangian Dual Decomposition and a Generalized Benders Decomposition, are developed. The Lagrangian Dual formulation results in a subproblem which can be separated into single-year plantmix problems that are easily solved using breakeven analysis. The probabilistic second phase also uses a Generalized Benders Decomposition approach, which results in a linear master program and an operating subproblem. A depth-first Branch and Bound algorithm can be superimposed on the two-phase algorithm if conventional equipment types are only available in discrete sizes. In this context, computer time savings accrued through the application of the two-phase method are crucial.

Extensive computational tests of the algorithms are reported. Among the deterministic algorithms, the one based on Lagrangian Duality proves fastest. The two-phase approach is shown to save up to 80 percent in computing time as compared to a purely probabilistic algorithm.

The developed methodology is applied to a project in Mexicali, Baja California, Mexico.[1] In particular, in the framework of electric utility capacity planning, it is determined whether it would be advantageous for the local utility to endeavour into promotion activities for solar cooling systems and conservation, and if so, to what extent. The Baja California Norte electricity system, described in more detail in Chapter 8, currently consists of 677 MW of installed capacity, serving primarily the cities of Tijuana and Mexicali. It is not connected to the central Mexican electricity network.

In the following chapter, literature on all aspects of electric utility planning, on renewable energy sources and in particular on the interface of electric utilities and renewable energy, is reviewed. Then, various alternative capacity planning approaches including deterministic and probabilistic features, as well as integrality considerations, are developed in Chapters 3 through 6. Chapter 7 compares the computational speed and accuracy of the different approaches. The application of the algorithm on the data for the Mexican utility leads to the results described in Chapter 8. Finally, Chapter 9 concludes with proposals for

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[1] The author has been working on the project with the Mexican Instituto de Investigaciones Electricas (IIE) in Cuernavaca, Morelos, Mexico, for the academic year 1983/84.

further extending the scope of the algorithms.

Chapter II

LITERATURE REVIEW

The literature review is organized as follows. To aid understanding and to introduce notation, some general concepts used in electric utility planning are first reviewed. In particular, the basics of reliability modeling are explained. This is followed by an exposition of the various approaches taken toward capacity planning; the more important models are displayed in detail. Some literature on other aspects of utility planning and even more general energy models are also reviewed. Thereafter, the solar energy - electric utility interface is investigated. Technical and economical as well as social, legal and behavioral aspects of solar energy and of its interface with utilities are covered. The few previous attempts of incorporating solar energy in electric utility capacity planning are again describe~~s~~d in some detail. Finally, some issues related especially to the Mexicali project are addressed. The thermodynamic concepts underlying solar cooling are explained. Furthermore, some discussion in the literature on whether the application of renewable energy technology is a good choice for developing countries, is reviewed. This issue is of importance since Mexico can in many aspects still be regarded as a developing country.

2.1 ELECTRIC UTILITY PLANNING CONCEPTS

The basic planning concepts to be reviewed below are explained in many books, see, e.g., VARDI and Avi-Itzhak, 1981.

2.1.1 Demand

2.1.1.1 Load Curve

In most utility planning models, demand is considered an exogenous variable (ANDERSON, 1972). It varies widely between different times of the day and seasons. A typical load curve for a day is given in Figure 1. The typical shape of a yearly load curve depends on whether the utility experiences summer or winter peaks. In southern states, where little heating during winter months, but much air-conditioning in summer months is required, the peak demand usually occurs in the summer. In northern states winter peaks are prevalent. A typical yearly load curve for a winter peaking utility is given in Figure 2.

2.1.1.2 Load Duration Curve

If the chronological load curve is rearranged so that the peak load appears first, and the load decreases as duration increases, a load duration curve is obtained. If for some duration y, the load duration curve f(.) takes the value

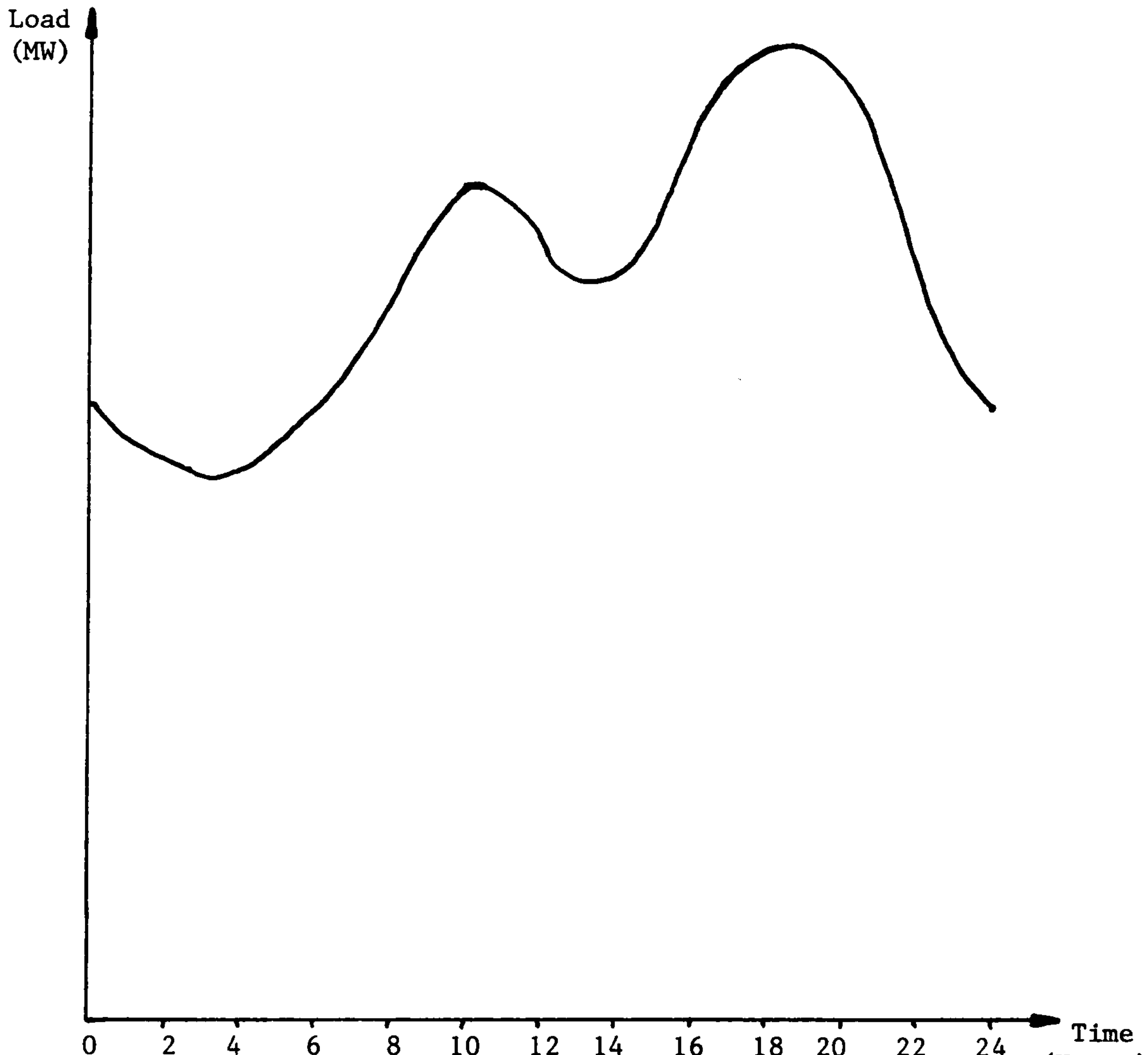

Figure 1: Example of a Daily Load Curve

$f(y)=L$, for example, then this indicates that the load is greater than or equal to L for a duration of y. A load duration curve, derived from the chronological curve, is also shown in Figure 2. It is usually assumed that load duration curves are monotone decreasing and differentiable, and that their inverses, denoted from here on by $F(y)$, exist. The presence of a base load, i.e. a load demanded all the time, violates differentiability, but is easily accomodated in most models. Often, areas under a load duration curve are classified as base, intermediate and peak loads. A base load is the amount demanded during the whole period, while peak loads are only demanded for short periods. An example of this classification is also shown in Figure 2.

2.1.1.3 Load Factor

In this context, a utility's load factor is defined as the ratio of average load and peak load. Thus, the more peaked a load duration curve is, the smaller is the load factor. Because a steep load duration curve makes necessary the installation of much equipment which is only used a small fraction of time, it is desirable to have a relatively flat curve.

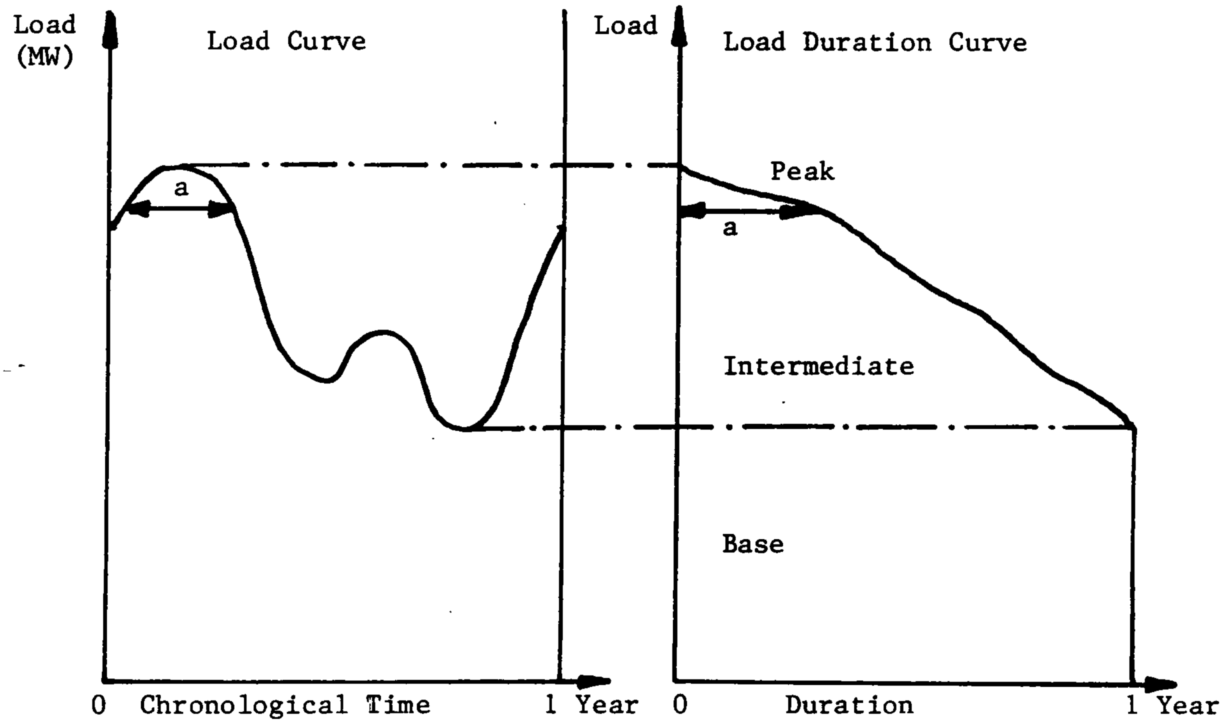

Figure 2: Yearly Load Curve and Load Duration Curve

2.1.2 Equipment Types

Currently, the main methods of producing electricity are with hydroelectric plants (with or without storage and with widely varying capacities), and nuclear and fossil fuel fired plants (coal or oil). Peaking units, mostly gas turbines and pumped-storage hydro plants, are also used. These plant types all have different cost characteristics which make them suitable for supplying either base, intermediate or peak loads.

Gas turbines have low capital but very high operating (fuel) costs and are therefore used for peak loads only. Fossil fuel plants have higher capital costs and lower operating costs and are mostly used for intermediate loads. Nuclear plants have very low operating costs, but extremely high capital costs. They are cost effective only if run almost all the time, and are therefore used for base loads only. Run-of-river hydro plants (without reservoirs) are used for base loads because of their almost zero operating costs. With reservoirs, the possible energy output of hydro plants is determined and limited by the water inflow; this is called an energy constraint. Each hydro plant's unique combination of capacity and available energy determines what section of the load curve it is operated in.

It is usually assumed that the operating costs of different plants are ordered such that $g_1 < g_2 < \ldots$, while for capital costs $c_1 > c_2 > \ldots$ holds. This assumption is valid for the following reason. If both the capital and the operating costs for a particular plant type are comparatively higher than for another type, the first plant type would never be economical to install.

2.1.3 Dispatching

Once an equipment mix is selected, the problem is to meet the varying demand at minimal operating cost. In actual operation, utilities employ incremental loading procedures. As can be shown easily, a system's operating cost is minimized when at all times, the marginal or incremental production costs of all plants are equal (this assumes that operating cost curves are modeled nonlinearly). When additional complications like start-up and shut-down costs and times, hydro energy constraints, spinning reserve requirements, etc., are included, finding the optimal operation schedule is very difficult. Mathematical programming has often been applied on this problem (see, e.g., CELOVIC et al, 1981, EL HAWARY and Christensen, 1979).

In order to keep capacity planning models tractable, the production costing subroutines incorporated in such larger models usually assume merit order dispatching. For any given load, the plant with the least operating cost is dispatched first, then the one with the next higher operating cost, and so on until the demand is met. Thus, the units with the least operating cost will be operated most of the time, while peaking units with higher operating costs are really only used for peak demand periods. It should be noted that merit order dispatching is identical to incremental loading if operating costs are linear.

A plant's capacity factor is defined as the fraction of time the plant is operated. This factor does not only depend on the plant's position in the merit order, but also on its availability which is restricted by maintenance requirements and forced outages.

2.1.4 Reliability

Given that the load cannot be forecast with complete certainty, and that forced outages of generation equipment occur at random times, it is possible that the load exceeds the available capacity. This is called system outage, black-out, or loss of load. Probabilistic methods have been widely employed to model system reliability, and several reliability indices have been suggested, among them the loss-of-load probability (LOLP) and the loss-of-energy probability (LOEP). A commonly accepted standard in the industry is to keep the LOLP to one day in 10 years. Methods of computing the various indices will be treated in more detail below.

2.1.5 Pricing

The pricing problem is tied to other problems in electric utility planning in three ways:

- Prices influence demand and thus both capacity expansion and operating costs.
- It has long been established in the economic literature that at the welfare optimum, prices should reflect marginal costs.
- If linear or nonlinear programming is used to find the optimal capacity expansion plan, the dual variables can be interpreted as marginal costs (OYAMA, 1983, SHERALI et al, 1982, 1983).

2.1.5.1 Marginal Cost Pricing

The rule that prices should equal marginal costs can be based both on formal analysis and on intuitive arguments. The short mathematical derivation given below follows the one given in the appendix of BERLIN et al, 1974. The intuitive arguments can be found in BOITEAUX, 1964, as well as in BONBRIGHT, 1961.

In the economic literature, welfare W is defined as total benefit TB minus total cost TC to society: $W = TB - TC$. Both TB and TC being functions of the produced quantity Q, let $g(Q)$ be the production cost function, and $P=d(Q)$ be the demand function representing society's willingness to pay for varying amounts Q. Then, total benefits are defined as the integral of the demand function. Thus,

$$W = \int_0^Q d(q)dq - g(Q).$$

Maximizing welfare yields the necessary condition

$$\frac{dW}{dQ} = d(Q) - \frac{dTC}{dQ} = P - g'(Q) = 0, \text{ and therefore}$$

$P = g'(Q)$, which says that prices should be set at marginal costs.

BOITEAUX, 1964, presents arguments for pricing electricity at long-run marginal costs. Selling at costs ensures that society's economic optima are also seen optimal by the individual, and marginal cost is the actual cost of expanding service to meet additional demand.

Pricing at short-run marginal cost would imply having constantly changing tariffs, depending on the instantaneous operating cost. When more capacity is installed than is necessary to meet the peak demand, short-run marginal costs do not include any capital costs. But when the installed capacity is insufficient, short-run marginal cost is infinitely high since it is impossible to serve any additional demand at peak times. For these reasons it is more reasonable to price electricity at long-run marginal costs, which do include capital cost components. It should be noted, however, that newest technology makes it seem possible to apply so-called spot pricing (OUTHRED and Schweppe, 1980), with which the consumer would indeed be charged constantly varying rates. The rationale behind such a seemingly chaotic scheme is to make the consumer aware of even the slightest variations in production costs, and to induce him to choose his consumption level according to these price signals.

The vast literature on peak load pricing, starting with the seminal paper by STEINER, 1957, and not ending with the important contribution by WENDERS, 1976, and its generalization by SHERALI et al, 1982, on peak load pricing with diverse technology, is not reviewed here in more detail, since it is not directly related to the topic at hand. However, a detailed review of the peak load pricing literature can be found in STASCHUS, 1982.

2.1.6 Renewable Energy and Conservation in Utilities

In the whole U.S., conservation investments are currently the most economically and financially attractive energy investments (STOBAUGH and Yergin, 1979). Many conservation measures have payback times of only one year or less (BIRD and Marshall, 1982, PEZZEY and Baldwin, 1982). Solar space heating, especially with passive designs, and solar water heating are also economical in many parts of the country (BEZDEK et al, 1979, HIRST et al, 1979, KLEIN, 1978). Wind energy conversion systems (WECS) can presently produce electricity at a cost competitive with electric utility costs, and their price is expected to decrease with the advent of WECS mass production. These economic factors induce many utilities to consider renewable energy options in their expansion plans (see, e.g., GOULD, 1983, NWPPC, 1983, SLR, 1981a and 1981b). The most important options considered include windfarms, low- or zero-interest loans to customers for conservation and solar investments, marketing of such equipments by the utility itself, and the investment in solar thermal or solar photovoltaic power plants. These options will be addressed in more detail in a subsequent section.

2.2 RELIABILITY

Power system reliability modeling has developed from using very simple and crude approaches to using quite sophisticated and very efficient statistical concepts, all within the last fifteen years. In the context of capacity planning, the most important reliability issue is the possibility that because of an unfortunate combination of plant failures and unexpectedly high demands, the demand cannot be met, and a dreaded blackout occurs. Thus, although for the individual customer, power outages due to interruptions in the transmission and distribution network are much more probable than regionwide blackouts, this section will concentrate on reliability issues associated with demand forecast uncertainties and random plant outages.

2.2.1 Plant Outages and the Equivalent Load Duration Curve

Up into the 1970's, the deterministic derating method of treating plant outages was in widespread use. In that method, a plant's capacity is multiplied by its availability rate (one minus its forced outage rate), and for all planning purposes, it is pretended that this derated capacity is available all the time. As elaborated in CAMPBELL, 1981, this method yields biased results; the utilization of plants serving intermediate loads is overestimated while peaking plant utilization is severely underestimated (also see FINGER, 1979).

Probabilistic models started to gain acceptance in the late 1960's. (For a bibliography on such modeling attempts, see BILLINTON, 1971.) In a simple probabilistic approach, each plant's availability is modeled as a binomial random variable, with the forced outage rate q representing the fraction of time the plant is unavailable, and p=1-q representing the time it is available.

BILLINTON, 1970 uses this information to construct so-called outage probability tables. In these tables, the probability of any possible combination of plants in the system being down and up, is calculated from the individual plant outage probabilities, reasonably assuming independence. However, this information cannot very easily be used in the capacity planning framework.

The next step in the development was the derivation of the equivalent load duration curve (ELDC), as used by BALERIEAUX et al, 1967 and BOOTH, 1972a, and well explained in VARDI and Avi-Itzhak, 1981 (also see VARDI et al, 1977a). The ELDC concept uses the fact that meeting the given demand with a unit of x MW being unavailable is equivalent to meeting the demand plus x MW with all the plants being available. It is most instructive and also computationally most feasible to construct the ELDC recursively as follows.

The first unit in the merit order, i.e. the unit with the least operating cost, is always loaded first as long as it is available. Given its capacity x_1 and the inverse load duration curve F(.), its expected energy production is

$$p_1 \int_0^{x_1} F(y)dy.$$

The second unit in the merit order is loaded above the first one as long as the first one is available, but is loaded as the first unit when the first one is unavailable. Thus, its expected energy production is

$$p_2 \left(p_1 \int_{x_1}^{x_1+x_2} F(y)dy + q_1 \int_0^{x_2} F(y)dy\right),$$

which is equivalent to

$$p_2 \int_{x_1}^{x_1+x_2} (p_1F(y) + q_1F(y-x_1))\, dy$$

The term in square brackets can now be termed the ELDC faced by unit 2. Thus, the general recursive formula for the ELDC faced by unit i+1, denoted by EF_i, is:

$$EF_i(y) = p_iEF_{i-1}(y) + q_iEF_{i-1}(y-x_i)$$

This process is continued until the outage probabilities of all units have been accounted for, and the system's ELDC has been arrived at. As explained in VARDI and Avi-Itzhak, 1981, the process can also be interpreted as a convolution of the demand with the added demand for unit outages. Introducing demand forecast uncertainty by adding another random variable representing random variations around the forecasted demand is then straightforward, since all that is required is a convolution with another variable. Extensions of this basic model to account for hydro and storage plants are also relatively straighforward (see FINGER, 1979, NASSAR and Grubar, 1983).

It must be noted, however, that these convolution processes all require that the convolved variables be independent, an assumption that is reasonable for conventional plants and demand, but becomes highly questionable when dealing with solar energy. This point will be addressed in subsequent sections.

2.2.2 Measures of Reliability

The most commonly used reliability measure is the loss of load probabilitỵ(LOLP). A well accepted standard for power system design is a target LOLP of one day in ten years, although some researchers regard this standard as too high (TELSON, 1975).

The LOLP can be very easily computed from the system's ELDC as follows. Since the system's ELDC represents the total probabilistic demand for plant outages and consumer demand, the LOLP is given by

$$\mathrm{LOLP} = EF_{I+1}\left(\sum_{i=1}^{I} x_i\right),$$

i.e. by the function value of the ELDC associated with the total installed capacity of the system.

Another popular reliability measure, the loss of energy probability LOEP, can also be obtained from the ELDC. Being defined as the expected amount of energy demanded that cannot be served, it can be calculated as

$$\mathrm{LOEP} = \int_{0}^{Q} EF_{I+1}\left(z+\sum_{i=1}^{I} x_i\right) dz,$$

where again, Q denotes the system's peak load.

An important reliability modeling approach is the frequency and duration approach (see, e.g., PATTON et al, 1979 and 1980). It utilizes information on the time between breakdowns and repair time of each plant, and models the available system capacity as a continuous time Markov process. For the simple case of just two plants, the possible states of the Markov process are depicted in Figure 3. The time until failure and the repair time are modeled as exponential random variables, with associated failure and repair rates λ and μ, respectively (see BILLINTON, 1970). From this model, a Markov state transition matrix can be constructed, as shown in Figure 3, and the steady state probabilities of having certain capacities available can be computed (for a derivation of the formulas needed for such calculations, see CINLAR, 1975). These steady state probabilities can then be visualized in outage probability tables of the form described above.

Some more unconventional reliability measuring systems can be found in CHEOUG and Dillon, 1979, HAZEN et al, 1980 and SAHINOGLU et al, 1983.

2.2.3 The Cumulant Method for Reliability Analysis

Recently, some researchers (RAU and Schenk, 1979, RAU et al, 1979, 1980, SCHENK and Rau, 1978, SCHENK et al, 1981, STREMEL, 1981a, 1981b, 1982b) have developed a series expansion approach for the representation of the ELDC. As described in STREMEL and Rau, 1979, the binomial outage distribution of each unit is represented by its first four, six or eight cumulants. The convolution of all outage distributions with the demand frequency distribution is then simplified to adding the cumulants of all distributions, which causes a great savings in computer time. The development of formulas for computing the cumulants can be found in STREMEL, 1981a and 1982b, together with tables of numerical values. Some theoretical background is provided in CRAMER, 1974, FISHER and Cornish, 1960, and KENDALL and Stuart, 1963. Maintenance scheduling and other complications can

Four State Transition Diagram

(Two Generators)

State	Machine 1	Machine 2	Rate of Departure	Available Capacity
1	up	up	$\lambda_1+\lambda_2$	c_1+c_2
2	down	up	$\mu_1+\lambda_2$	c_2
3	up	down	$\lambda_1+\mu_2$	c_1
4	down	down	$\mu_1+\mu_2$	0

where

λ = mean time to failure
μ = mean repair time
c = capacity

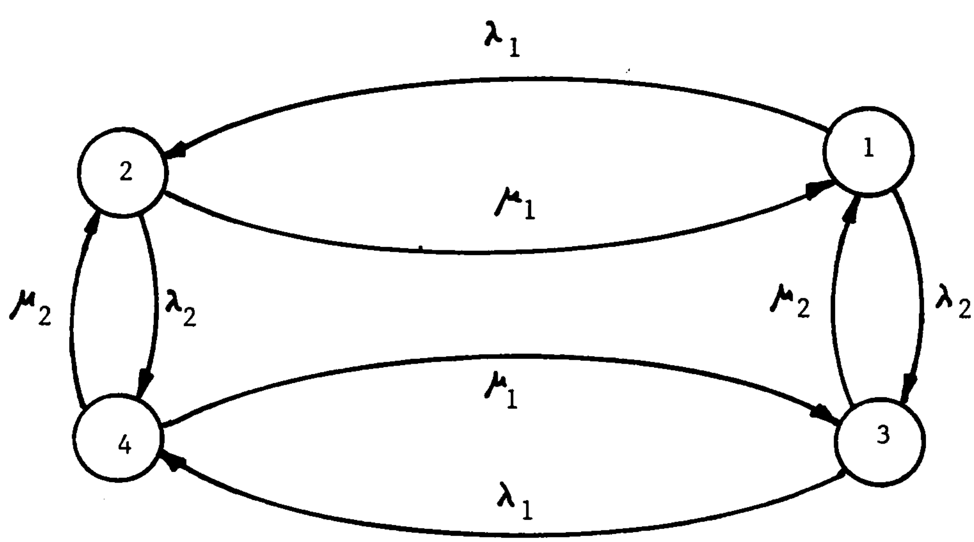

Figure 3: Markov Process Representation of Unit Outages

also easily be accomodated with the cumulant method (STREMEL, 1980). It should also be noted that some other names have been used for essentially the same method, such as the method of moments or Gram-Charlier expansion.

As pointed out by CARAMANIS et al, 1983, this method not only yields accurate results when applied to production costing and reliability evaluation (for best accuracy, eight cumulants should be used), but also reduces computer time by a factor of 4 to 15, as compared with various conventional algorithms. Furthermore, it has the important advantage that it yields analytical expressions for the ELDC, so that for the first time, the incorporation of probabilistic production costing into nonlinear programming approaches to capacity planning is possible. Previously, only the incorporation into dynamic programming based methods such as WASP, or into other enumerative schemes, was possible (see, e.g., BOOTH, 1972b, JENKINS and Joy, 1974). Of course, the method of cumulants can also be incorporated into WASP, causing a considerable saving in computer time (SCHENK et al, 1981).

A final caveat is however in order. Some researchers (see, e.g., LEVY and Kahn, 1982, but also CARAMANIS et al, 1982b) discovered, when testing the accuracy of the cumulant approximation to the ELDC, that for small systems, or for systems where some unit alone comprises a large percentage of total available capacity, this approximation becomes quite poor. Concerning this problem, CARAMANIS et al, 1982b, note that for such small systems, computational efficiency is not such an overriding concern anyway, so that the conventional Baleriaux-Booth-type of convolution methods can be used.

2.3 CAPACITY EXPANSION PLANNING

ANDERSON, 1972 gives the most often cited overview on modeling for capacity expansion planning for electric utilities. (For similar overviews, see BERRIE, 1967, BERRIE and Anderson, 1969, and TURVEY, 1968a.) In his introduction, Anderson justifies the application of mathematical modeling to the problem. First, the enormous investments involved motivate a detailed treatment. The complexity of the problem also requires the application of formal mathematical models. The problem of which plant types to operate under what load conditions, is already quite complex. If the objective is to develop not only the static optimal plant mix, but a dynamic capacity expansion plan, a plant's position in the merit order and its capacity factor in future years will be influenced by future investments. This as well as other complications make the capacity expansion problem so complex that more guesswork, as opposed to mathematical programming, would most likely find only inferior, suboptimal solutions.

After this initial justification, Anderson proceeds to formulate in generic terms the mathematical programs most often used. The objective always is to minimize the sum of operating and capital costs, subject to such constraints as: all demand must be met with the capacity available; if applicable, energy constraints for hydroelectric generation must be satisfied; and specified LOLPs must not be exceeded.

In the most general case, the objective function takes the following form:

$$\min \sum_{v=1}^{T} \sum_{i=1}^{I} c_{iv} x_{iv} + \int_{0}^{T} \sum_{v=0}^{T} \sum_{i=1}^{I} g_{iv}(t)\, U_{iv}(t)\, dt ,$$

where

$t=T$ = planning horizon,

v = vintage (years of commissioning new plants),

$v=0$ = plants already installed,

$i=1,..,I$ = plant types,

c_{iv} = capital cost of equipment i for vintage v,

x_{iv} = capacity of plant type i, vintage v,

$g_{iv}(t)$ = discounted operating cost of plant i,v,

$U_{iv}(t)$ = power output of plant i,v at instant t.

Thus, the first term in the objective function represents the system's total capital cost, while the second term represents total operating cost.

Often it is more convenient to use a discrete approximation of this function:

$$\min \sum_{v=1}^{T} \sum_{i=1}^{I} c_{iv}x_{iv} + \sum_{t=1}^{T} \sum_{v=0}^{t} \sum_{i=1}^{I} g_{ivt}U_{ivt}d_t ,$$

where d_t = width of time interval considered at time t.

The most important constraints may be stated mathematically in the following general terms:

$$\sum_{i=1}^{I} \sum_{v=0}^{T} U_{ivt} \geq Q_t , \quad t=1,..,T,$$

where Q_t is the demand at t.

(Demand must be met at all times.)

$$0 \leq U_{ivt} \leq a_{iv}x_{iv},$$

for i=1,..,J ; v=0,..,T ; t=1,..,T ;

where a_{iv} is the availability of plant i,v.

(No plant can be operated above its peak available capacity.)

$$\Pr\left(\sum_{i=1}^{I} \sum_{v=0}^{T} a_{iv}x_{iv} - Q_t \geq 0\right) \leq e , \quad t=1,..,T,$$

where Q_t = yearly peak demand,

e = specified LOLP.

(The specified LOLP cannot be exceeded.)

The reader may note that in many countries, system reliability is not secured by planning with this type of constraint, but by installing a certain margin of spare capacity to meet demands above expected peak demand. Then, the reliability constraint takes the following form:

$$\sum_{i=1}^{I} \sum_{v=0}^{T} a_{iv} x_{iv} \geq Q_t(1+m), \quad t=1,..,T,$$

where m denotes the margin of spare capacity. This margin, often set by utilities at 20%, has to be determined carefully, considering the forced outage rates of the installed plants.

It may be noted in passing here that more complex models include constraints dealing with peculiarities of mixed hydro-thermal systems and the issue of hydro scheduling and investment planning.

This general formulation of the capacity expansion problem can be modified in many ways. It can be extended so that issues like optimal replacement, optimal locations of plants, transmision optimization, nuclear fuel cycling or optimal storage policy for hydro plants are included. On the other hand, simplifying assumptions can be made which change the structure of the problem.

If one maintains a nonlinear load curve - as opposed to discretizing it -, then the durations of operation of plants are nonlinear functions, thus resulting in a nonlinear objective function. Sometimes even nonlinear operating costs are assumed, which occur when a plant's efficiency changes with its loading. In this nonlinear case, the problem is essentially formulated as described above. For some time during the 1960's, most planners preferred nonlinear over linear models because of their less extensive computer storage requirements.

If the load duration curve is broken down into blocks of varying widths d (as shown in Figure 4), the problem can be formulated as a linear program. This approach is described in the following subsection.

If one is only interested in finding the optimal plant mix for the static case, all parameters dealing with the vintage of new plants can be deleted. The resulting simpler problem is presented in Subsection 2.3.3.

2.3.1 Basic Linear Programming Models

MASSE and Gibrat, 1957, were the first ones to apply linear programming to investments in the electric power industry. In their 1957 article they justify in great length the use of this 'complicated' approach. But of course, compared to programs used today, theirs is very simple. They do not consider any type of uncertainty, and they assume linearity of costs. Their program minimizes total cost subject to constraints for guaranteed power, peak power, annual energy production and limited funds; that is, instead of working with the load curve itself, they pick a few key values that represent its main characteristics (see also MASSE, 1962).

Most later linear programming applications represent the load duration curve with a histogramm (Figure 4), see for instance ADAMS et al, 1972, ANDERSON, 1972, BEGLARI and Laughton, 1974, BERRIE and Anderson, 1972, SHERALI et al, 1982.

The basic form of the models is:

$$\min \sum_{i=1}^{I} \sum_{v=1}^{T} c_{iv} x_{iv} + \sum_{i=1}^{I} \sum_{t=1}^{T} \sum_{v=0}^{t} \sum_{p=1}^{P} g_{itvp} U_{itvp} d_p,$$

where d_p is the width of a block of the discretized load duration curve. The linear constraints are similar to the ones in the general nonlinear program. The two most important constraints, for meeting all demand and using no more than available capacity, take the following form:

$$\sum_{i=1}^{I} \sum_{v=0}^{t} U_{itvp} \geq Q_{tp}, \quad t=1,..,T, \ p=1,..,P$$

$$0 \leq U_{itvp} \leq a_{ivt} x_{iv}, \quad i=1,..,I; \ v=0,..,t; \ t=1,..,T; \ p=1,..,P.$$

As is shown in SHERALI et al, 1982 (the initial work in this area was done by TURVEY, 1968a), this basic LP formula-

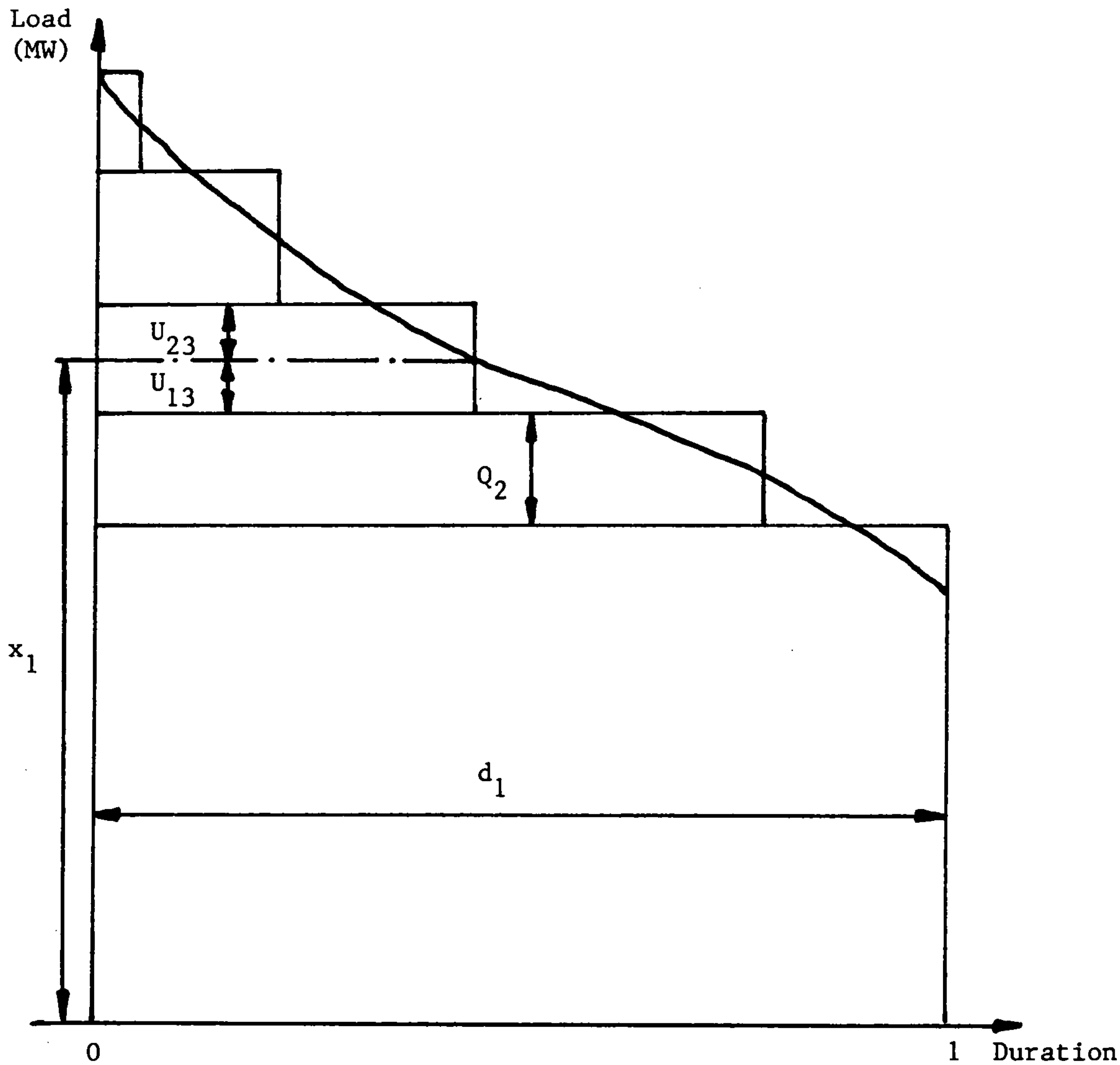

Figure 4: Block Representation of a Load Duration Curve

tion yields the same optimal solution as the traditional, straightforward breakeven analysis. The breakeven analysis is demonstrated geometrically in Figure 5. It finds the optimal plant mix only on the basis of capital and operating costs, other constraints not considered. Its rationale is that for an incremental load occuring for a duration y, it is cheapest to buy incremental capacity such that the capacity type has the minimal $(c_i + g_i y)$ from among all plant types i when operated over the duration y. The breakeven analysis can be used as part of a complex multi-year optimization, see, e.g., BEGLARI and Laughton, 1975, PHILLIPS et al, 1969.

During some time in the 1960's, many planners preferred nonlinear over linear approaches in spite of the comparitive ease of solving linear programs (BESSIERE, 1971, PHILLIPS et al, 1969). The reason for this was the large computer memory requirements of the linear approach described above, caused mainly by the many $x \geq U$ type of constraints. However, linear programming was again preferred later, after the so-called method of z-substitutes had been developed, which cut down the number of capacity constraints by a factor 1/p (ADAMS et al, 1972, ANDERSON, 1972, BEGLARI and Laughton, 1974).

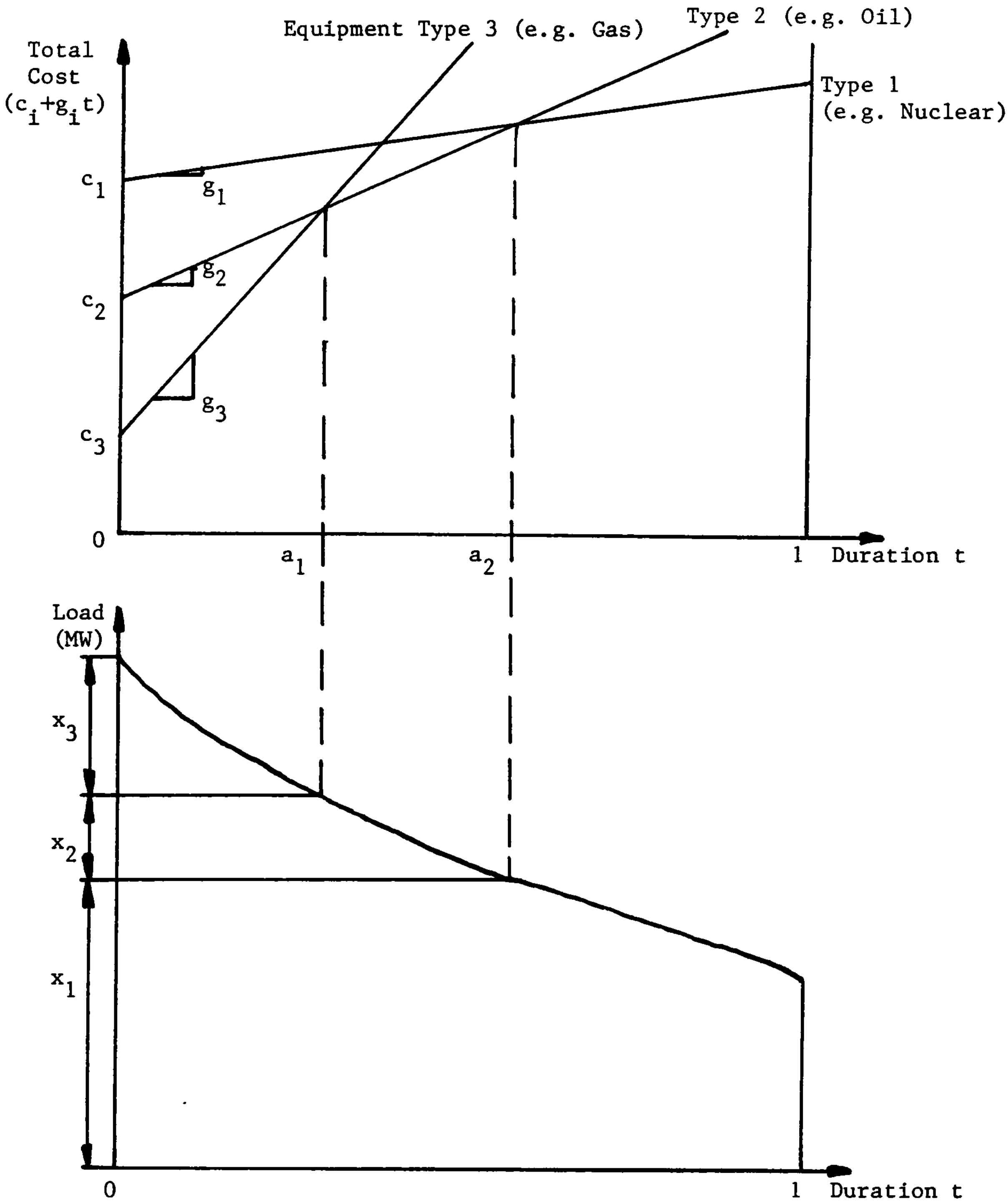

Figure 5: Breakeven Analysis

2.3.2 Basic Nonlinear Programming Models

A major incentive for developing the method of z-substitutes was that computers in the early 1960's could not handle the vast number of capacity constraints in the original LP formulation. BESSIERE, 1971 and PHILLIPS et al, 1969 developed a nonlinear programming approach that overcame this problem.

The main idea is to prearrange all installed and possible new capacity in merit order before starting the algorithm. That is, the plants are indexed such that $0 < g_1 < g_2 < .. < g_I$ holds for the operating costs. Then, all capacity constraints are satisfied implicitly as soon as capacities are assigned by the algorithm, i.e. the capacity constraints do not have to appear in the problem.

For the following derivation, let plant type j and vintage v be represented by the single index w=1,..,W. Let, as defined above, x_w be the capacity of type w, and let F(.) be the inverse load duration curve (the time index t is left aside for the moment). Then, define

$$X_w = \sum_{u=1}^{w} x_u \text{ , as shown in Figure 6.}$$

The cost of operating plant w in merit order is given by

$$\int_{X_{w-1}}^{X_w} g_w F(y)dy = g_w(G(X_w)-G(X_{w-1})),$$

where $G(X_w) = \int_0^{X_w} F(x)dx$, and where $X_0=0$.

The total operating cost is obtained by adding this over w=1 to W (using $g_{W+1}=0$):

$$OC = \sum_{w=1}^{W} (g_w - g_{w+1}) G(\sum_{u=1}^{w} x_u)$$

Using this total operating cost in the objective function, and re-introducing subscripts i, v and t, the capacity expansion problem takes the following form:

$$\min \sum_{i=1}^{I} \sum_{v=1}^{T} c_{iv} x_{iv}$$

$$+ \sum_{t=1}^{T} \sum_{i=1}^{I} \sum_{v=0}^{t} (g_{ivt} - g_{i,v+1,t}) G_t(\sum_{\iota=1}^{i} \sum_{u=0}^{v} x_{\iota u})$$

$$\text{s.t.} \sum_{i=1}^{I} \sum_{v=0}^{T} x_{iv} \geq Q_t \text{ , for } t=1,..,T \text{ ,}$$

where again Q_t is the peak demand in t.

Thus the total operating cost is given in terms of plant capacities, operating costs and the inverse load duration curve. Capacity constraints are already implicitly satisfied. This is a considerable reduction in program size as compared to the LP formulation. However, the objective function is quite complex, nonlinear, nonseparable, but at least convex (PHILLIPS et al, 1969, SOYSTER et al, 1981). So the program can be solved on computers without great difficulties; this type of model has been used in France and Britain for quite some time (BESSIERE 1971).

2.3.3 Static Models: Optimal Plant Mix

The optimal plant mix problem can be regarded as a subproblem of the capacity expansion problem, modified such that already existent plants are not taken into account, and that no investment decisions are made for future years. Only the static optimal capacity mix is sought. Again, linear or nonlinear programming can be applied. For exemplification, it suffices to display the linear programming approach:

$$\min \sum_{i=1}^{I} c_i x_i + \sum_{i=1}^{I} \sum_{p=1}^{P} g_i U_{ip} d_p$$

$$\text{s.t.} \quad \sum_{i=1}^{I} U_{ip} \geq Q_p \quad , \ p=1,..,P$$

$$0 \leq U_{ip} \leq a_i x_i \quad , \ i=1,..,I \ ; \quad p=1,..,P$$

Of course, as with all other models, constraints for hydro generation, LOLPs, and other complications can be easily added. If no other constraints are added, the simplest solution method for this program is via breakeven analysis as described above. HAMAN et al, 1981 and STOUGHTON et al, 1980 describe recent applications of breakeven-type analyses for plant mix problems.

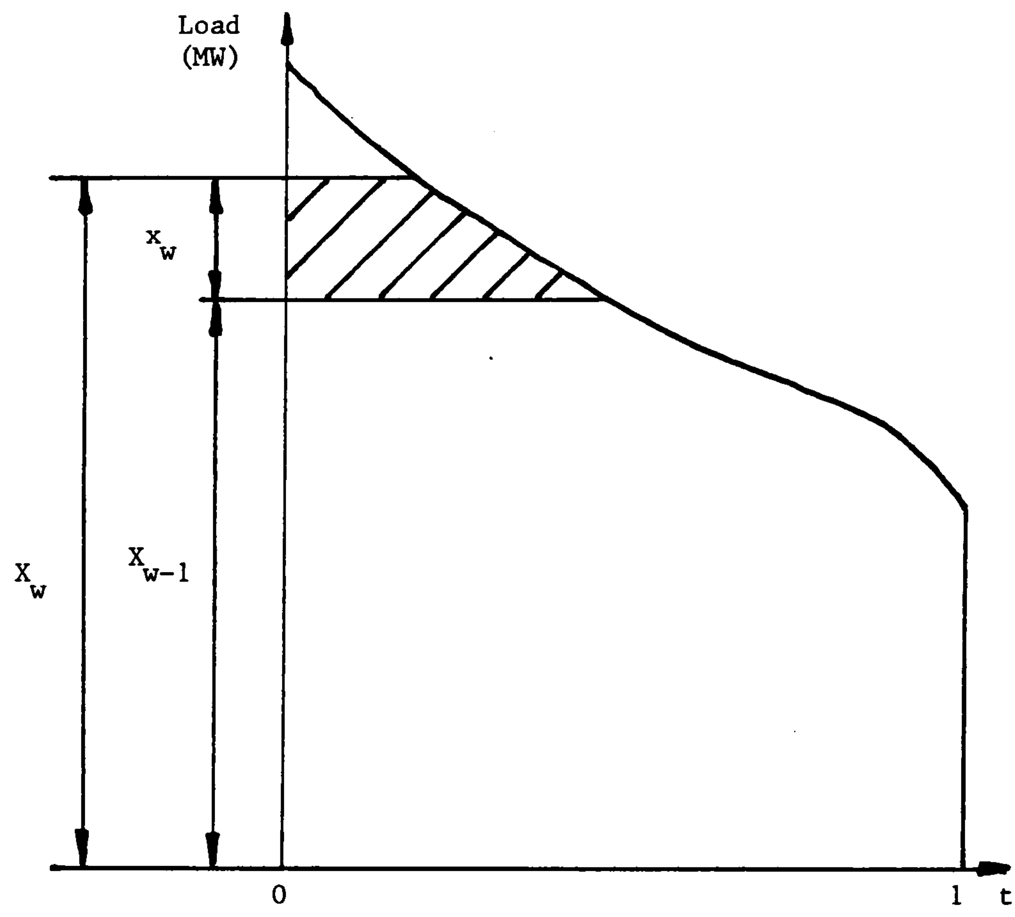

Figure 6: Nonlinear Programming Approach

2.3.4 Benders Decomposition and Capacity Planning

An efficient and elegant approach to deal with large scale mathematical programs is to use decomposition techniques. COTE and Laughton, 1979 describe the application of the Benders Partitioning Method to power system planning (BENDERS, 1962).

They use a matrix representation of the capacity expansion problem to illustrate the approach. Let C and G be the vectors of capital and operating costs, associated with the vectors of capacity and operating decisions, X and Z, respectively. Let $AX \geq Q$ represent demand constraints in matrix form, and let $GX + HZ \geq B$ represent capacity constraints. Then, the expansion problem takes the following form:

Expansion Problem EXP

$$\min C^T X + F^T Z$$

$$\text{s.t. } AX \geq Q$$

$$GX + HZ \geq B$$

$$X, Z \geq 0$$

If X is fixed, a simple production problem results, which can be solved very efficiently by applying merit order loading. This suggests the representation of EXP as follows:

Decomposed EXP (DEXP)

$$\min_{X \varepsilon S(X)} \quad C^T X + \min \begin{bmatrix} F^T Z & \\ \text{s.t.} & HZ \geq (B - GX) \\ & Z \geq 0 \end{bmatrix}$$

where $S(X) = (X/AX \geq Q,\ X \geq 0)$.

Introducing dual variables Λ, the dual of the production problem can be written as follows:

Dual Production Problem DPP

$\max \Lambda^T(B-GX)$

s.t. $\Lambda^T H \leq F$

$\Lambda \geq 0$

Note that the dual feasible region is independent of X, and that the optimal solution will be at one of the extreme points of the feasible region.[2] Therefore DPP can be represented as

$$\max_{\Lambda \varepsilon L} \Lambda^T(B-GX) \ ,$$

where $L=(\Lambda_1, \Lambda_2, \ldots, \Lambda_K)$, and Λ_k represents an extreme point of DPP's feasible region.

After manipulations, the total problem can therefore be written as follows:

Problem in Decomposed Form PDF

---

[2] since an optimum exists to the inner minimization problem above for all $X \varepsilon S(X)$

$$\min C^T X + y_0$$
$$\text{s.t. } AX \geq Q$$
$$\Lambda^T(B - GX) \leq y_0 \quad \text{for all } \Lambda \varepsilon L$$
$$X \geq 0$$

The following algorithm which uses these concepts, is quoted from COTE and Laughton, 1979:

> Step 1: Solve a relaxation of PDF where the set L has been replaced by a subset L*. This yields an investment plan X* together with a lower bound on the optimal value of PDF or equivalently of EXP. This relaxation is called the master.
>
> Step 2: Using the investment plan X*, the production problem is solved yielding a production schedule U*, dual variables Λ*, and an upper bound on the optimal value of EXP, given by $C^T X^* + F^T U^*$. Control is returned to Step 1.
>
> The algorithm is stopped when both lower and upper bound fall within a predefined value ε of each other. Because the set L is finite, the algorithm converges to the optimal solution in a finite number of steps.

Cote and Laughton cite good computational results with the application of this method. They claim that it compares favorably with other decomposition approaches and other methods of solving expansion planning problems.

2.3.5 Generalized Benders Decomposition and Capacity Planning

BLOOM, 1983 (see also 1982) describes an approach similar to Cote and Laughton's in its concepts, but much more accurate in its representation of system reliability. Bloom formulates the capacity expansion problem as follows:

<u>Capacity Expansion Problem CEP</u>:

$$\min C^T X + \sum_{t=1}^{T} EG_t(Z_t)$$

$$\text{s.t. } UE_t(Z_t) \le e_t \qquad t=1,..,T$$

$$0 \le Z_t \le \delta_t X \qquad t=1,..,T$$

where

X = vector of plant capacities

C = vector of plant present value capital costs

Z_t = vector of plant utilization level in period t

$EG_t(Z_t)$ = present value expected operating cost function in t

$UE_t(Z_t)$ = expected unserved energy function in t

e_t = desired energy reliability level in t

δ_t = matrix sorting plants into merit order in t

T = number of periods in planning horizon

Bloom uses Generalized Benders Decomposition (GEOFFRION, 1972), which is based on the concept of Lagrangian Duality (as for instance described in BAZARAA and Shetty, 1979), to solve the above problem. When the plant capacities X are fixed, one obtains T operating subproblems of the following form. Note that this decomposition approach is quite similar to Cote and Laughton's, but that in contrast to Cote and Laughton's method, the following subproblem accounts for reliability in a probabilistic simulation context, and is therefore nonlinear (see Section 2.2 for elaboration on reliability modeling via probabilistic simulation).

<u>Operating Subproblem OSP</u> (time subscript t is suppressed):

$$\min EG(Z) = \sum_{i=1}^{I} g_i p_i \int_{Y_{i-1}}^{Y_i} EF_i(y)dy$$

$$\text{s.t. } UE(Z) = \int_{Y_I}^{\infty} EF_{I+1}(y)dy \le e$$

$$0 \le Z \le \delta X$$

where

$i=1,..,I$ = plant indices in merit order

g_i = operating cost of ith plant

p_i = availability of ith plant (1-forced outage rate)

EF_i = equivalent load duration curve faced by ith plant (see Reliability section)

Y_i = cumulative utilization of first i plants in merit order

Bloom then proceeds to decompose program CEP:

<u>Decomposed Problem DP</u>

$$\min_{X\ge 0,\ X\varepsilon\Omega} \quad C^T X + \sum_{t=1}^{T} \begin{bmatrix} \min EG_t(Z_t) \\ \\ \text{s.t. } UE_t(Z_t) \le e_t,\ 0 \le Z_t \le \delta_t X \end{bmatrix}$$

where the set Ω consists of all capacity vectors X which allow a feasible solution in all of the subproblems, and translates into a constraint set for the master program given below.

Bloom shows that the subproblem has the strong duality property, and therefore the inner optimization can be replaced by its Lagrangian Dual:

$$\max_{\lambda_t,\mu_t \geq 0} \left\{ \min_{Z_t \geq 0} (EG_t(Z_t) + \mu_t(UE_t(Z_t)-e_t) + \lambda_t(Z_t - \delta_t X)) \right\}$$

where λ and μ are vectors of dual multipliers associated with the capacity and reliability constraints, respectively.

After manipulations, he arrives at a master program of the following form:

<u>Master</u> <u>Program</u> <u>MP</u>

min σ

$$\text{s.t. } \sigma \geq C^T X + \sum_{t=1}^{T} (EG_t^k + \lambda_t^k \delta_t (X^k - X)) \quad k=1,..,K_1$$

$$\sum_{t \varepsilon \Gamma_k} UE_t^k + \mu_t^k \delta_t (X^k - X) \leq \sum_{t \varepsilon \Gamma_k} e_t \quad k=1,..,K_2$$

$$X \geq 0$$

where

k = index of trial solutions

K_1 = number of feasible trial solutions

K_2 = number of infeasible trial solutions (the K_2 constraints form part of the set Ω)

X^k = vector of plant capacities of kth trial solution

X = plant capacities of current trial solution

σ = total cost of current trial solution

EG_t^k = expected operating cost of kth solution in t

λ_t^k = vector of dual multipliers of kth solution in t

UE_t^k = expected unserved energy of kth solution in t

Γ_k = set of periods t in which the kth solution is infeasible

μ_t^k = vector of multipliers associated with infeasible subproblems in t for trial solution k

This master program is a linear program, and can therefore be solved efficiently. Furthermore, the subproblem can be solved efficiently with the probabilistic simulation algorithm using convolution techniques (BOOTH, 1972a), or even more efficiently using the Method of Moments (STREMEL, 1982b, CARAMANIS et al, 1983). The dual solution to the subproblem can be found with the help of the Kuhn Tucker Conditions (see BAZARAA and Shetty, 1979, for example). The assembled decomposition algorithm then proceeds similarly to the one quoted in the previous subsection, and need not be stated explicitly here. In summary, one can note that Bloom's approach provides a very elegant and seemingly computationally efficient way of incorporating probabilistic production costing into a mathematical program for capacity expansion.

2.3.6 Stages of Capacity Expansion Planning

ANDERSON, 1972 describes the capacity planning process as consisting of three stages: marginal analysis, simulation and global models. In a marginal analysis stage, one substitutes one feasible expansion candidate by another, attempting to find the one that minimizes total cost. The main problem with this approach is the amount of computer time needed. For a simple comparison between two investment alternatives using marginal analysis, see TURVEY, 1963.

Simulation programs calculate the minimal operating cost for each constellation of plants. In general, the load curve is integrated, and the area multiplied with the appropriate operating costs. The more realistic probabilistic production costing approach has been described above. Additional difficulties arise when the system includes hydro units; much research has gone into the field of optimizing the operation of hydro-thermal systems (e.g., see SACHDEVA, 1982 for a bibliography on the topic, ARVANITIDIS and Rosing, 1970, BONAERT et al, 1971, BONAERT and Koivo, 1973, DILLON et al, 1980, EL HAWARY and Christensen, 1979, GAGNON et al, 1974, GASSFORD and Karlin, 1958, LOGENDRAU and Oudheusden, 1981, MANNE, 1960, PEREIRA and Pinto, 1982, TYREN, 1969). However, despite these and other additional difficulties, it is now possible to incorporate even complex production costing routines into global capacity planning models, as exemplified by BLOOM, 1983.

Global models try to find the optimal capacity expansion path with just one algorithm, avoiding the time-consuming trial and error approach of the marginal analysis. Examples of global models are the linear and nonlinear programming approaches described above. Other examples with more unusual approaches include BORISON et al, 1983, employing a state-of-the-world decomposition approach, LENCZ, 1969, who combines an LP with the method of operational games, LOUVEAUX, 1980, who uses a multistage stochastic program with recourse, NOONAN and Giglio, 1977, who employ a nonlinear mixed integer program and solve it with Benders Decomposition, PETERSEN, 1974, who constructs a dynamic programming algorithm, and SAWEY and Zinn, 1977, who use a mixed integer linear programming formulation with consideration of the spatial transmission network.

The most sophisticated capacity planning model in widespread use today, WASP, also employs dynamic programming (see JENKINS and Joy, 1974). The problem is broken up into years as the stages of the dynamic program, and the costs of each feasible expansion plan in each year are determined using probabilistic production costing, financial analysis, and other subroutines. When applied on large systems, this approach encounters the problem that for each year, too many feasible combinations of plants, i.e. expansion plans, have to be simulated, since in the dynamic programming framework, one has little chance of fathoming nonoptimal solutions within a stage. The code tries to overcome this problem by giving the user the opportunity to direct the program into the direction of solutions that are believed to be near-optimal. However, the use of mathematical programming techniques such as in BLOOM, 1983 seems to be a more elegant approach to directing the program towards better solutions.

Keeping the newer developments in mind, it must however be noted that several authors report how the three stages mentioned above have been applied successfully in the capacity planning process. BESSIERE, 1971, describes how a combination of marginal analysis and a nonlinear program is used for the Investment '85 model of Electricite de France, and JENKIN, 1974, describes a similar approach of the British CEGB (for the current planning methodology at EDF, see FEINTUCH, 1983). BERRIE, 1966, GALLOWAY et al, 1966, and NITU et al, 1969, also employ this general type of approach. APERJIS et al, 1982, and MERRILL et al, 1982, describe a more recent approach also consisting of various stages, with the main purpose being to account for forecast uncertainties (also see BECKER et al, 1978).

Whichever kind of global model one uses, to be able to keep a complex 30-year expansion plan from getting too big for even today's efficient computers, one has to make some simplifying assumptions. Although it is now possible to incorporate probabilistic production costing (BLOOM, 1983) and even nonlinear operating costs and incremental loading (AMMONS and McGinnis, 1983a and 1983b, ZAHAVI et al, 1977) into global models, many technical issues still have to be assumed away. Examples of engineering criteria that must be satisfied by an expansion plan resulting from the run of a global model are stability, short-circuit performance, the control of watts, vars, and voltage, and spinning reserve requirements (see ANDERSON, 1972). Similar technical problems not incorporated in global models are optimal load flow, minimal loss and economic dispatching (see, e.g., BOTTERO et al, 1982, EL ABIAD, 1983, EL HAWARY and Christensen, 1979, GROSS, 1979, HAPP, 1974, KIRCHMAYER, 1958, SASSON and Noulin, 1969, SULLIVAN, 1977).

Related planning issues also not addressed in global models include siting decisions for energy facilities. KEENEY, 1980, and KEENEY and Sicherman, 1983, employ the decision analysis framework to take into account economic, environmental, socioeconomic, health and safety, and public attitude issues in the siting process. They use multiattribute utility functions to evaluate and compare different candidate sites with respect to the various objectives mentioned. COHON et al, 1980, develop a multiobjective linear program for power plant siting decisions. EVANS et al, 1982, similarly develop multiobjective optimization techniques for capacity planning (also see KAVRAKOGLU and Kiziltan, 1983). An interesting multiobjective generation planning algorithm is given in RUTZ et al, 1978. These authors solve one linear program at a time for expansion planning, starting with the objective considered most important. For solving the same program with the other, less important objectives, an additional constraint is included that ensures that the solution does not deviate too far from the optimal level of the first objective.

Since the oil crisis of 1973, the planning environment for electric utilities has drastically changed. From a climate featuring almost guaranteed 7% annual demand growth and declining real costs of plants, the industry was suddenly thrown into a climate of extreme uncertainty in almost all areas, particularly in demand growth, fuel and construction costs, and environmental regulation (LOWE and Lewis, 1981). This triggered a number of investigations into the effects of uncertainty on utility planning, see for instance BORISON et al, 1983, DEES et al, 1978, GARVER et al, 1976, LUCAS and

Papaconstantinou, 1982, MANNE, 1974 and 1976, SANGHVI and Limaye, 1979. It also led many utilities into financial problems (FORD and Youngblood, 1983), in particular in the Pacific Northwest where two out of five planned and partly built nuclear plants had to be cancelled (OLSEN, 1982).

Finally it must be noted that all capacity models reviewed so far feature cost-minimization as the objective and assume demand as given. Some models which are economic in nature examine America's or even the world's total energy situation with demand treated as a variable, others attempt to maximize welfare instead of minimizing cost, and yet others treat the desirable reliability level as a variable. Such models are reviewed in the following subsection.

2.3.7 Comprehensive Power System Optimization

A very general type of model, in which power systems constitute but a small part, are so-called energy-economy models. Often approached as an input-output-type of analysis, energy-economy modeling attempts to provide insights into the complex interactions and interdependencies between the consumption of various fuels, uncertainties concerning future prices, and the correlation of energy consumption and economic growth, to name just a few areas of interest. Such broadly scoped models are for instance presented in AHN and

Seong, 1983, ERLENKOTTER and Trippi, 1977, GRENON, 1978, HOFFMANN and Wood, 1976, HUGHES and Mesarovic, 1978, KAVRAKOGLU, 1982, 1983, MANNE, 1974, RAPOPORT et al, 1978, RATH-NAGEL and Voss, 1981, SAMOUILIDIS and Minopoulos, 1982, WYANT, 1983.

Other authors try to determine the economically efficient allocation of electrical energy, using a welfare maximization objective. Decision variables in such models are the capacity expansion path, operation schedules, and the electricity price. For example, URI, 1975 solves such a problem using the Kuhn-Tucker conditions. ROWSE, 1978 and 1980, presents a similar approach, deriving tradeoffs between prices, supply quantities, capacity and environmental protection. SASSON and Merrill, 1974, and TURVEY, 1963 are other examples of similar models. SAMOUILIDIS et al, 1983, use an interesting LP sector planning model that incorporates minimization of the individual's cost to determine the amount of energy conservation to be used in Greece.

One problem that has only recently gained attention in the literature is the determination of the optimal level of power system reliability. As noted in Section 2.2, most power system planning today is based on an almost arbitrarily chosen target LOLP of one day in ten years (TELSON, 1975). To bring power system reliability closer to the societal optimum, several authors suggest to incorporate the cost of an outage or blackout into capacity planning (KHATIB, 1978, KOVAL and Billinton, 1979, MUNASINGHE and Gellerson, 1979, MUNASINGHE, 1980a, SANGHVI et al, 1982, STREMEL, 1982a). Up to now, this is not done mainly because of the difficulties associated with estimating such a cost. TELSON, 1975 as well as other authors (BENTAL and Ravid, 1982, BERRIE, 1978, SHIPLEY et al, 1972) use the gross national or regional product divided by the yearly electricity consumption in the nation or region as a measure of the cost of an outage of unit magnitude. However, MUNASINGHE, 1979, and MUNASINGHE and Gellerson, 1979, reject that approach as too simplistic, and instead suggest a methodology that separately estimates the outage costs for the residential, commercial and industrial sectors. Factors such as the duration of the outage, whether or not it is long enough so that fruits in supermarkets can spoil, the time of occurrence of the outage, whether or not it occurs in the early evening when many residential customers depend on electricity for their TV or radio entertainment, are taken into account. Statistical methods are used to derive outage costs from such information as functions of time and duration of occurrence. Case studies are also given.

When outage cost data become available, it can be used in the capacity planning process (SANGHVI et al, 1982, STREMEL, 1982a), and the optimal reliability level can be determined. TELSON, 1975, arrives at the conclusion that the one day in ten years level is too high, i.e. that lower reliability would be economically more efficient.

2.4 RENEWABLE ENERGY SOURCES

In 1979, President Carter announced the national goal to supply 20% of the nation's energy needs with solar energy by the year 2000 (SHAMA, 1981, for more up to date targets, see ROWE, 1982). The public opinion on renewable energy technologies is overwhemingly positive, as opposed to the coal and nuclear options (FARKAR et al, 1979). However, actual adoption of solar systems by consumers has been slow (SHAMA, 1981). Many energy policy oriented articles assess the potential of renewable energy sources and the strategies needed to achieve faster adoption (BACH and Matthews, 1979, BEN-DAVID et al, 1977, BEZDEK et al, 1982, CORBETT and Hayden, 1980, COREY, 1982, Energy Digest, 1982, HAYES, 1979, HIRST et al, 1982, PURI, 1979, RAMAKUMAR, 1981, REED, 1979, REISS, 1983, ROBERTS, 1979, RYLE, 1977, TOURYAN, 1982, WEINBERG, 1979).

For instance, one of the most important governmental measures to promote solar energy is the tax credit. Currently, the federal government offers a 40% tax credit for solar investments, and additional state tax credits often raise that amount to 65% (see, e.g., CONE, 1982, JOHNSON, 1979, ROESSNER et al, 1980).

How penetration goals can be translated into cost and performance goals, is described in WARREN, 1983, for instance. It should also be noted that much of the interest in renewable energy technologies is not only due to their long-term economic advantages, but also to their low environmental impacts (e.g. MANNING, 1983, SCHNEIDER, 1979). One exception to this would perhaps be the large scale exploitation of biomass plantations (MARGARIS, 1983).

In the following two sections, the renewable energy potential and possible promotion strategies are reviewed in more detail.

2.4.1 Renewable Energy and Conservation Equipment

PONOMARYOV and Ward, 1983, give an overview over the various renewable energy technologies and their economics. The technologies most widely commercialized by now are certainly solar energy and wind. However, by far the most economical energy investment today is in conservation (CRAIG and Reeds,

1980, GATES, 1983, LOVINS, 1977, MEIER, 1981, MEIER et al, 1982, PEZZEY and Baldwin, 1982, STOBAUGH and Yergin, 1979, WHITE, 1981). Conservation includes all measures that help to save energy, ranging from adding insulation to houses over using efficient lighting to planning efficient mass transit systems. It is beyond the scope of this work to enumerate all possible kinds of conservation; utility efforts to encourage certain kinds of conservation will be addressed below.

Wind mills have been used for water pumping and grain grinding for over 2000 years in many parts of the world (SHAMA, 1981). In the U.S., they were used extensively in the western rangelands, before rural electrification and cheap oil made them uneconomical. Today, newer and more efficient designs can produce electricity at a price competitive with utility rates (LOWE, 1980, SHAMA, 1981, also see KRAVIEC, 1981a, and MARTIN and Diesendorf, 1983). Single small wind mills are being used to power residential homes, arrays of medium-sized windmills feed several MW into the utility grid, especially in California and Hawaii, and experimental, mostly horizontal axis wind energy conversion systems (WECS) of up to 3 MW are already operating in the utility grid in Europe as well as in the U.S. (BWEA, 1982, EVANS, 1982, VOSBURGH, 1983).

The use of solar energy is economical for space and water heating in many parts of the country, while for air conditioning it is not widely enough commercialized yet (MUNEER and Hawas, 1981). Most economical are passive systems that essentially use the building itself as a solar collector. Large southern windows allow the sun's rays to enter the house, thick walls store the heat, and vents are usually the only moving parts (FELDMAN and Wirtshafter, 1980). Active systems for heating or cooling mostly employ flat plate collectors situated on the roof or in the garden. In the collector which has a glass or other transparent cover, water or air is heated by the sun's energy, and circulated to a storage device and into the pipes and vents heating the house. For storage, water, rock beds and other methods are used (for a description of possible system constellations, see, e.g., LECKIE et al, 1981). Solar cooling systems use the collected heat as input into a Rankine or absorption thermodynamic cycle to transport heat from the living area to the outside (see, e.g., KARAKI and Wilbur, 1977). Their technical details will be explained in a subsequent section.

Solar energy can be used to produce electricity in two ways, with photovoltaic cells and with solar thermal power plants. Photovoltaic cells convert sunlight directly into electricity. They consist of two layers of slightly different semiconductor materials (mostly silicon), which creates the effect that when a photon, i.e. a particle of light, hits the cell and releases an electron, negative and positive charges move in opposite ways, and a current is produced. See BOLTON, 1983, for an overview on solar cells.

The cells can easily be grouped into large or small arrays to produce energy in large or small quantities, respectively. While the operating cost of these cells is near zero, the relatively high capital cost has so far restricted their use to extreme situations such as in space programs or in remote radar stations (KRAVIEC, 1981b). The Department of Energy projects, however, that continuing improvements in production technology will bring their cost down further from the present \$5/W to \$0.50/W within the next ten years, so that they would be competitive with conventional power production technologies by 1990 (ALPER, 1979, REDFIELD, 1981). See, e.g., SIMBURGER, 1983, for specific engineering design issues associated with photovoltaic power plants.

Pilot solar thermal installations, also called power towers, are in operation or under construction in many parts of the world (GRETZ, 1980 and 1982, SELVAGE, 1980, WEINGART, 1979). TERAGAWA and Gates, 1983, investigate their potential benefits in the U.S. The plants consist of large arrays of mirrors positioned in a semicircle around a central receiver, tracking the sun's rays. For large plants, two-axis tracking mirrors are used, while for smaller applications, one-axis tracking mirrors can lead to high enough temperatures (SHAMA, 1981). These mirrors concentrate the rays onto the receiver in which the concentrated energy generates steam. The steam is then sent through a conventional turbine and valve cycle, the turbine drives a generator which produces the electricity. The mirrorfields constitute a major part of the cost, and aside from the more usual optimization problems related to the power producing cycle, optimization of the mirrorfield is a very complex task (BOY-MARCOTTE, 1980, COSKUNOGLU, 1983, FRANCIA, 1980).

Part of the steam can be used to heat large rock beds or other storage devices. By drawing heat from storage, the installation can continue producing electricity during night time and cloudy periods (KALHAMMER, 1979, RADOSERICH and Wyman, 1983). Then, the operation schedule of the storage device needs to be optimized as described for instance in DECHAMPS et al, 1980.

Solar thermal systems can also be used to repower conventional power plants. That has the advantage that the part of the capital cost for the turbine cycle is shared by the solar and the conventional plant (BROWN et al, 1982). However, in such a setting, the solar system could not be accredited any capacity credit.

In future large scale projects, electricity could also be used to produce hydrogen by electrolysis as a means for longer term energy storage. The hydrogen could be easily stored, transported and used as a clean fuel for many purposes; in this way, the whole world's energy needs could be met with very large solar power plants (BOCHRIS and Handley, 1978, CLAVERIE and Dupas, 1979, RALPH, 1972, RAMAKUMAR et al, 1975).

Other important renewable energy sources include biomass, ocean thermal energy conversion (OTEC), geothermal energy, and of course hydropower. Hydroelectric plants, run-of-river or with dams and storage reservoirs, have been used very extensively. Whole regions of the country such as the Pacific Northwest (NWPPC, 1983) and whole countries such as Norway (KRAL, 1980) depend on hydropower for more than half of their electricity. Although much of the potential in the U.S. is already developed, PURPA[3] and its requirement that utilities buy energy from small independent producers (LOCK, 1980, LORNELL, 1981), have induced a new surge in mini-hydro development. Many old dams in the Northeast are retrofitted for electricity production, and many small streams in the whole nation are proposed for hydro development (see, e.g., PALMER, 1983). The cost of electricity from such develop-

[3] the Public Utility Regulatory Policies Act of 1978, also mentioned below in Section 2.5.3

ments is very often well below current rates.

The term biomass covers many different technologies, ranging from the compostation of farm residues to alcohol in biodigesters (LECKIE et al, 1981) to the burning of urban wastes in municipal power plants, to plantations of fast-growing trees for use as fuelwood. Some of these methods have already been used economically on a large scale (GOLDEMBERG, 1979), whereas others are only economical in special cases (especially biodigesters, see LECKIE et al, 1981).

OTEC technology is very young, and so far very few pilot plants exist. It uses the temperature differential between the upper and lower layers of tropical oceans to power a turbine driving a generator. Cost projections indicate that OTEC may become an economical alternative for electricity production (SHAMA, 1981), but still much research remains to be done (see DUGGER et al, 1983, for an overview on OTEC technology).

Geothermal energy is already being used for electricity production at several suitable sites (ASPNES and Zarling, 1982, EDMUNDS, 1977, HUACUZ, 1982), but the number of sites with sufficient heat in accessible depths is too limited to let this energy source make a major contribution. However, it can be very economical if site conditions are favorable.

2.4.2 Renewable Energy Modeling

Several aspects of renewable energy technologies need to be modeled to enable prudent decisions on their implementation. To begin with, the availability of the raw resource, be it sunshine or wind, is often a random variable and thus deserves probabilistic modeling. The various design parameters of a renewable energy system can be optimized in an optimization model. And the energy output of a renewable energy installation needs to be modeled for use in capacity planning or other broadly scoped models.

2.4.2.1 Energy Resource Availability

Very obviously, wind and sunshine availabilities vary significantly over the course of a day, but even the water inflow into a hydro plant's reservoir varies over the course of a year and with rainfall (SMITH, 1981). Therefore, it is important for stand-alone uses of such resources as well as for utility applications, to incorporate the uncertainty associated with the resource's availability into planning methods. Probabilistic modeling offers the best way of doing this for long-range planning.

JUSTUS, 1978 gives a very detailed account of the different possible methods of modeling wind speeds. As indicated in COROTIS et al, 1978, and ESKINAZI and Cramer, 1982, the

Weibull and Rayleigh distributions are gaining general acceptance as the most appropriate means of representing the variation of wind speeds. These distributions, fitted to local data, can then be used to model the output of a WECS, either probabilistically, or within a simulation program. Examples of wind power availability models include ANDERSON et al, 1978, and HASLETT and Carlin, 1981.

The modeling of sunshine availability, i.e. the modeling of cloudcover occurence, has not received as much attention in the literature as wind modeling. HAMLEN et al, 1978, suggest the use of a Brownian motion model. In general, simulation seems to be preferred over the use of exactly specified probability distributions. An overview on insolation modeling is given by BOES, 1979.

2.4.2.2 Renewable Energy System Optimization

DEVINE et al, 1978, give a list of what kinds of optimization models have been applied on various renewable energy technologies. Examples range from determining the optimal combination of collector and storage size for a residential solar water heating system to optimizing the mirror fields of solar thermal power plants. SALIEVA, 1976a and 1976b, discusses the systems aspects of such optimization tasks.

VOSBURGH, 1983, and BWEA, 1982, give overviews over the design issues concerning WECS. POWELL, 1981 and 1982, as well as LYSEN, 1982, discuss the modeling of the optimal relationship between rated and cut-in windspeed of WECS designs (also see DIESENDORF and Fulford, 1979). REINERT, 1983, includes storage optimization in a mathematical programming model for WECS design; storage dispatch is modeled assuming the application of the linear decision rule (REVELLE et al, 1969). KALAITZAKIS and Vachtsevanos, 1982, report on the optimization of WECS systems that are to be integrated with the grid.

ANDERSON and Rauch, 1977, and KLEIN et al, 1979, report on the application of optimization techniques, in particular linear programming, on solar heating system design. For similar reports, see BROOKS and Duchon, 1982, FEUSTEL et al, 1980, MICHELSON, 1982, NOLL and Wray, 1979. For stand-alone applications, a solar system can be optimized using LOLP-related concepts (OFRY and Braunstein, 1983). ROACH et al, 1979, compare different solar heating designs economically. Optimal control theory can be and has been applied to control the operation of solar systems, e.g. of the pumps moving liquids from the collector to storage. For a good overview on that field, see DORATO, 1983. However, BLODGETT et al, 1978, report that such sophisticated controls often are not cost-effective.

2.4.2.3 Renewable Energy Output

For all kinds of economic studies of renewable energy systems, their output has to be modeled. For decisions of individual homeowners on the adoption of a solar space or water heating system, relatively crude models using monthly insolation averages can be used. One widely applied method is the so-called f-Chart method, as described in KREITH and West, 1980. Such simple-to-use methods are nevertheless based on extensive simulations of solar systems for locations in all regions of the country (LECKIE et al, 1981, see also CHOUARD et al, 1976). Furthermore, simple methods must be developed for use by individual homeowners. For instance BELDING, 1978, advocates as simple a method as life-cycle costing for the homeowners' evaluation of conservation investments.

For decisions involving more capital, e.g. for utility decisions on whether or not to include renewable energy sources as a major element in the capacity expansion plan, more accurate models are needed. Often, separate simulation studies are run for each site and each renewable energy technology under consideration. In such studies, the weather is simulated hour by hour throughout a year or longer, and simultaneously, the system's performance is simulated (e.g. the cutting in or furling of a WECS, see ASSARABOWSKI and Maukaskas, 1981, or the heat transfer mechanisms in a solar device). The final output consists of an hour-by-hour account of produced energy.

BALCOMB et al, 1977, and BUTZ et al, 1974, report on some of the earliest attempts to simulate the performance of passive and active solar systems (also see BALCOMB, 1980), later simulation codes include the one by HOWELLS and Marshall, 1983. O'DOHERTY, 1982, presents a similar simulation program for solar thermal installations.

Although simulation is certainly an accurate approach, it needs too much computer time for real large-scale planning efforts, which justifies the development of probabilistic models of renewable energy output. Such probabilistic models will be reviewed in more detail in the subsection on capacity credit, where their incorporation into utility planning is also addressed.

2.4.3 Consumer Acceptance of Renewable Energy Systems

Given that conservation is so economically attractive, as, e.g., described in BIRD and Marshall, 1982, NWPPC, 1983, PEZZEY and Baldwin, 1982, SHAMA, 1983, STOBAUGH and Yergin, 1979, it is amazing that not more people invest in low-cost conservation measures. As SHAMA, 1983, reports, only six percent of all U.S. single-family homes have adopted conservation measures in an optimal way (also see REISTER, 1982, SMILEY, 1979). Similarly, although demand is growing (BROWN and Brown, 1981), and although solar water heating is very economical in sunshine states, even California, which is the most progressive state in solar adoption (PULLIAM and Hedgecock, 1980), features only 2.5% households with any kind of solar devices (most of these are pool heaters, see SHAMA, 1981). This high potential/low adoption dichotomy has triggered interest in the diffusion of solar energy innovations (see ROESSNER et al, 1979, SCHIFFEL et al, 1978a and 1978b, SHAMA, 1981 and 1983), and on political ways to overcome social and institutional barriers (BLUMSTEIN et al, 1980, NADER and Milleron, 1979, PACKER, 1979, PENNER, 1979, SAWYER and Feldman, 1978, SCHIFLETT and Zuckerman, 1978, SPARROW, 1982, VAN GOOL, 1980).

Among others, SHAMA, 1981 and 1983, stresses the importance of the behavioral aspect of diffusion processes. The market penetration of a new technology usually takes a long time, depending on factors such as its relative superiority (economically and in other aspects), the perceived risk associated with adopting it, its compatibility with current lifestyles and values, its perceived complexity, the degree to which it can be tried on limited scales, and the communicability of the innovation results (ROGERS and Shoemaker, 1971). The diffusion of an innovation over time usually follows an S-shaped curve. Innovators, who constitute 2.5% of the market, adopt first, early adopters (13.5%) follow, then the early majority (34%), the late majority (34%), and finally the so-called laggards (16%). Adopters have been found to go through the following five stages in the adoption process: awareness, interest, evaluation, trial, and adoption (see ROGERS and Shoemaker, 1971, for these concepts).

Other findings of diffusion research include the observation that early adopters usually are less interested in the economics of the adoption than in other attributes related to status and opinion leadership. Findings like these, when applied on solar incentive policymaking, suggest that in the early stages of solar commercialization, which is the state in which most solar technologies still esist, non-monetary marketing efforts may be more important than economic incentives, while economic competetiveness becomes the overriding factor in the decisions of later adopters (SHAMA, 1981).

Based on diffusion research results, primarily on the S-shaped adoption curve and the late, but overriding importance of economic features, several models for the diffusion of renewable energy technologies have been developed (e.g. see BUSH and Munjal, 1979, VORIES and Strong, 1980, for an overview). Although these models constitute the current state of diffusion modeling, they still need much improvement. In particular, more behavioral results, which as of now do not exist, need to be included before the results of such models can be trusted (BURNS, 1980, SCHIFFEL et al, 1978b, SHAMA, 1981).

Other authors also stress the importance of the social sciences contribution in spreading the use of solar energy and conservation. For example, CROSSLEY, 1979, advocates popularization campaigns, and YAVAZ and Riecken, 1981, emphasize the importance of the opinion leadership process.

2.5 THE RENEWABLE ENERGY - ELECTRIC UTILITY INTERFACE

It has been suggested by many authors (the best known example is the prestigeous Harvard Energy Report by STOBAUGH and Yergin, 1979), and it has already been tried out in several cases (GIARMAN, 1983, LAITOS et al, 1982, NWPPC, 1983, SLR, 1980a, 1981a, 1981b, 1981c), that electric utilities get involved in spreading renewable energy technology. Reasons for this are (STOBAUGH and Yergin, 1979):

1. Utilities have the potential for rapid market penetration since customers trust them;
2. they have access to low rates for borrowing money;
3. they can offer reliable service and maintenance.

It should be noted that the utility involvement addresses the innovation attributes described above. In particular, they can enhance solar energy's relative economical advantage by offering rebates, interest-free loans or other incentives, they can lower risk by guaranteeing service and maintenance or by helping in the selection of high-quality equipment, they can reduce perceived complexity and enhance communicability with information campaigns, and they can replace limited trial with demonstration projects.

In line with these different goals of utility involvement, many different schemes have been considered, which FELDMAN and Wirtshafter, 1980, list and comment on (also see PAGE and Mitsock, 1979). Up to today, the most common form of utility involvement uses financial incentives in the form of rebates or low- or no-interest loans (BOLEYN, 1981, SLR, 1981b, 1981c). In this way, solar water and pool heating as well as various cost-effective conservation measures, most importantly basic home weatherization, are to be promoted. Home energy audits, performed by utilities (under the Residential Conservation Service, see RANDOLPH, 1980b), are another utility activity that can reduce loads (see, e.g., HIRST et al, 1981a).

GARDELS, 1981, discusses whether rebates or loans are more appropriate and under what conditions. COLTON, 1982, assesses the possible effects of mandatory utility financing of solar and conservation investments. KAHN, 1980 and 1982, discusses the various regulatory options a utility has for sponsoring financial incentive programs. Among the options not yet mentioned are leasing arrangements, solar subsidiaries, and, for municipal utilities, the use of tax-free bonds for financing.

A group at the Oak Ridge National Laboratory does continuing research on the evaluation of utility programs. In particular, they propose methods for estimating the energy savings due to home energy audit and financial incentive programs. For examples of their work, see BERRY, 1982, BERRY et al, 1981 and 1983, HIRST et al, 1981b and 1983, GRADY and Hirst, 1981, SODERSTROM et al., 1981.

A related scheme, although not run by electric utilities, is the formation of municipal solar utilities that lease out and maintain solar water and pool heaters for a fixed monthly charge, often guaranteed to be lower than electric heating costs (RANDOLPH, 1980a, 1981, SAITMAN and Garfield-Jones, 1981, SLR, 1982).

The question as to what extent any kind of solar subsidies are economically efficient, is addressed in BEZDEK and Sparrow, 1981, and HAMLEN and Tschirhart, 1980. Consumers, large and small producers of solar equipment, HVAC-contractors and utilities all express different interests and fears regarding this issue (e.g. MCCLUNEY, 1979). An overview of the issues involved is given in BEZDEK and Cambel, 1981 (also, in more detail, in IGT, 1978). The major issues can be classified as technical, economic and financial, legal, rate-base and regulatory, and consumer interest issues, and will be addressed in the following subsections.

2.5.1 Technical Issues

Possible technical effects of the intertie of renewable energy plants such as WECS or solar thermal installations with the utility grid have been investigated by many authors in the electrical engineering literature. Important affected fields are protection and safety, operational problems and dispatching strategies, and distribution systems. All studies agree that the introduction of renewable energy technologies into the grid does not cause any serious technical problems as long as they do not constitute more than ten percent of the system's generating capacity (ZAININGER and Bell, 1981). Thus, technical issues will not place any constraints on the use of renewable energy in utilities in the near future, which is why the studies in that field are only enumerated below: BIRAN and Braunstein, 1976, BORGESE, 1980, BUTT, 1982, GLATZEL, 1980, GOODMAN, 1980, JANSSEN, 1982b, KINLOCH et al, 1980 and 1982, MEIER and Macklis, 1982, MOYLE et al, 1982, PARK and Zastrow, 1982, RAHMAN, 1980, TABORS and White, 1982, and YAMAYEE and Peschon, 1981, give overviews on the technical issues involved. In more detailed analyses, CAMPEN, 1982, analyzes the harmonics and power factor effects of solar photovoltaic interties with the grid, CURTICE and Reddoch, 1983, assess load frequency control impacts, DUB and Pape, 1983, look at requirements for wind speed forecasting when WECS are to be operated in a utility grid, HINRICHSEN and Nolan, 1982, investigate the dynamics and stability of WECS, PATTON et al, 1982, address utility protection problems, SCHLUETER et al, 1983a and 1983b, investigate the effect of wind gusts on the operation of utility networks containing WECS, SIMBURGER and Cretcher, 1983, discuss load following impacts of wind farms, and SIMKOVITZ and Kassakian, 1976, as well as ZAININGER and Bell, 1981, analyze a WECS with respect to control and dynamic problems.

2.5.2 Capacity Credit of Renewable Energy Installations

An important question, featuring both technical and economic aspects, is: how much conventional capacity is replaced by a renewable energy plant intertied with a utility? This question has been addressed in numerous articles in the electrical engineering literature. It is of great importance for calculations of the cost avoided through the operation of qualifying renewable energy facilities under PURPA (see Section 2.5.3).

This question arises because both wind and solar power, the two most important renewable energy sources today, are of intermittent structure, so that the dispatching of solar and wind installations cannot be planned according to need; their power has to be used when it is available. This has led some authors to state that for each MW of renewable energy capacity, the utility has to provide another MW of conventional backup capacity, and that the only benefit of renewable sources is equal to the conventionally generated energy they replace (BAE and Devine, 1978, DAVIS and Sandberg, 1980, PARK and Zastrow, 1982).

But the majority of the authors in this field use simulation or probabilistic models to determine capacity credits, and arrive at more optimistic conclusions (ANDREWS, 1976, DIESENDORF and Martin, 1980). For example, GIORSETTO and Utsurogi, 1983, arrive at a capacity credit of 30 MW for a wind power installation in Hawaii rated at 80 MW. Particularly good results are often obtained when WECS are combined with solar and possibly even hydro installations, since the different types of energy sources display different patterns of availability (DE ALMEIDA et al, 1983, FISCHL et al, 1979, TODD et al, 1978).

Although there still exists some confusion in the literature as to which definition of capacity credit to adopt (HASLETT and Diesendorf, 1981), the effective load carrying capability (ELCC) approach seems to be gaining general acceptance. It was originally developed by GARVER, 1966, and was first suggested for application on WECS by KAHN, 1979, and is defined as follows. The ELCC of a renewable energy plant is the additional peak load the system could encounter with the renewable energy plant, and still have the same LOLP it had without that plant.

Almost all researchers employ the so-called negative load approach to determining a plant's ELCC. This amounts to using either hour-by-hour simulation or some probabilistic representation to determine renewable energy output, and to subtract that output from the utility's demand curve. Then, the demand is artificially raised until the original LOLP is arrived at (most researchers raise the whole load duration curve by the given amount, rather than raising only the peak load). The difference between the raised and the original peak demand is the ELCC.

The only not straightforward part of this method lies in determining the renewable energy output over time. When simulation is used, excessive computer time requirements are encountered, while with the use of probabilistic representations, in some cases the results are not accurate enough.

Although capacity credit investigations can be useful to compare alternative renewable energy options, or to assess whether or not any capacity credit at all is warranted, it is most desirable to incorporate renewable energy options into all sectors of electric utility planning, such as reliability analysis, production scheduling and capacity planning. DAVITIAN, 1978, argues that capacity credit investigations do not work towards that objective, and therefore are redundant. It must be noted, however, that the same methodologies developed for assessing capacity credit, can also be incorporated into the planning fields mentioned.

But when incorporating renewable energy output models into capacity planning, it becomes very important that computer time requirements are not excessive, since so many different capacity expansion options have to be assessed. Therefore, simulation based models are not attractive for this purpose.

However, many researchers have preferred simulation models for capacity credit analysis as well as for the evaluation of renewable energy options for an expansion plan, because simulation accurately models any interdependencies between load and renewable energy output. Examples of such simulation based studies are CHENOWETH and Patton, 1978, DAY and Malone, 1981 and 1982, HARPER et al, 1982, JONES and Moretti, 1976, PESCHON et al, 1978, SORENSEN, 1978, YAMAYEE and Ma, 1983.

If the ELCC is to be determined probabilistically using an ELDC approach (see Section 2.2 or VARDI and Avi-Itzhak, 1981), for the convolution process to be valid, independence of all random variables has to hold. Some authors neglect any possible interdependencies and can thus readily model renewable energy output as a random variable to be convolved with demand and the outage probabilities of conventional plants (see, e.g., KAHN, 1979, MORETTI and Jones, 1982, RAMAKUMAR and Deshmukh, 1979, SCHENK et al, 1980, SCHENK and Chan, 1981, TABORS et al, 1981). They can then use the so-derived ELDC for ELCC calculations.

On the other hand, CARLIN, 1983, develops a probabilistic model that can take into account nonzero correlation between wind speeds, i.e. renewable energy production, and load. MARTIN and Carlin, 1983, do a case study with this method and emphasize the need for many years worth of data because of the great importance of the relative magnitudes of wind speeds and load. Other examples of more sophistication in outage modeling of WECS are DESHMUKH and Ramakumar, 1982, who use a Markov process representation of wind power availability for a WECS reliability evaluation, and JANSSEN, 1982a, who uses a frequency and duration approach.

HASLETT and Kelledy, 1979, HASLETT, 1981a, and HASLETT and Diesendorf, 1981, explicitly test for interdependence between load and wind power availability in Ireland and arrive at a correlation coefficient of 0.15. But since that coefficient is much lower when only peak loads are considered, which are most important for ELCC calculations, they argue that convolution can nevertheless be used. FEGAN and Percival, 1980, point out some problems associated with the assumption of such independence. In particular, a near zero correlation between load and renewable energy output only means that there is no relation between rising load and rising energy production over the course of the day. However, it may well be the case that there is a strong relation between rising load and rising production in the morning hours, and a strong relation between rising load and falling production in the evening, so that the two contradictory relations cancel each other out for the calculation of the overall correlation.

GIORSETTO and Utsurogi, 1983, take into account the dependence that occurs when many WECS in a windfarm experience the same wind regime. They use conditional probability distributions to arrive at the overall availability distribution for the whole windfarm, which they then convolve with the ELDC.

Several authors examine not only the capacity credit of renewable energy installations, but also their capital credit, i.e. the amount of capital the utility does not need to invest due to the renewable energy plant (CHENOWETH and Patton, 1978, DAY and Malone, 1982, GUPTA et al, 1980, HARPER et al, 1982, JONES and Moretti, 1976, MARTIN and Diesendorf, 1982, MORETTI and Jones, 1982, PERCIVAL and Harper, 1981, WIRTSHAFTER et al, 1982). These authors determine the optimal capacity mix or expansion path both with and without the renewable energy plant under consideration. In most cases, adding the renewable energy plant results in a different capacity mix, with some capital savings due to its ELCC, but also some capital savings due to the replacement of expensive base capacity by less expensive intermediate capacity. This replacement is possible because of the energy production of the renewable energy plant. Thus, capital credit usually appears more favorable than ELCC-type capacity credits.

It must be noted, however, that this procedure is not equivalent to the unrestricted incorporation of renewable energy options into capacity planning. The studies described above only model one single, specific renewable energy installation, and determine its economic feasibility. In contrast, an unrestricted incorporation into capacity planning would require that the capacity and type of renewable energy investments be determined in the algorithm itself. The very few and rudimentary studies conducted so far on that issue, are described below.

2.5.2.1 Renewable Energy Options Incorporated Into Capacity Planning

A previous study by the author (SHERALI and Staschus, 1984, 1985) attempts to incorporate solar energy into capacity planning. In that approach, the time-dependence of solar output is accounted for by splitting the planning period into smaller periods with different solar energy availabilities, while for each subperiod, randomness in sunshine avaialbility is modeled through derating. Although this derating approach is not as accurate as desirable, it makes possible the application of efficient tangential approximation techniques for determining the optimal capacity expansion plan including solar investments. Linear as well as nonlinear programming concepts were used in a Benders Decomposition framework to develop these techniques.

SCHENK et al, 1980, and SCHENK and Chan, 1981, incorporate renewable energy options into capacity planning using the method of moments, but neglect interdependence issues. However, CARAMANIS et al, 1982a, and CARAMANIS, 1983, outline an elegant approach to incorporating renewable energy options into capacity planning. Their method uses a Gram-Charlier expansion of all random variables needed for construction of the ELDC, similar to Schenk's approach. Interdependence of load and renewable energy output is first taken out of the data through application of Gram-Schmidt Orthogonalization (see BELLMAN, 1970).

However, CARAMANIS et al, 1982a, 1982b, caution any user of the possibility that the Gram-Schmidt Orthogonalization may not yield truly statistically independent variables, but may only make the first two moments appear independent. They also suggest the following statistical method to test for independence of the higher moments. A standard probability theory result states that the sums of the cumulants of independent random variables are equal to the cumulants of the sum of these variables. Thus, one can test whether or not renewable contributions and load, after having been orthogonalized using the Gram-Schmidt procedure, are independent, by testing this equality for higher than second cumulants.

The author has conducted several tests of this type with various typical solar energy data sets, and has found that indeed the orthogonalization often does not yield cumulants that satisfy this equality. In fact, in some cases even the sign of the cumulants appeared wrong with respect to the one this equality would demand. This dependence problem would render the whole approach described in CARAMANIS et al, 1982a, inappropriate for such cases.

A state-of-the-art expansion planning package, incorporating the orthogonalization developed by CARAMANIS et al, 1982a, into the Generalized Benders Decomposition expansion planning models developed by BLOOM, 1983, described above, and into dynamic programming based algorithms, is available under the name EGEAS (CARAMANIS et al, 1982b).

2.5.3 Social and Legal Issues

One concern of consumer groups and solar equipment producers alike is a well functioning, competitive market in solar equipment, contracting and installation (BOSSONG, 1982). If utilities would get involved in the actual contracting and installation of solar equipment, consumers fear that they would not only monopolize the installation market, but would also, through their power of selecting producers, effectively monopolize the solar equipment market (ASHBURY and Mueller, 1971, MANNELLA, 1982, ROSENBERG, 1977, SMACKEY, 1978 and 1982). This could in turn lead to a lack of innovativeness in these monopolized markets, and the case of solar energy would be more hurt than served. However, as long as utilities restrict themselves to giving financial incentives and general information, this problem can be avoided.

A question more legal in nature is whether utilities, as regulated monopolies for providing electricity, should be allowed to venture into the conservation and solar markets at all. (For an overview on legal issues, see MILLER, 1982, as well as LAITOS and Feuerstein, 1979.) While the National Energy Conservation Policy Act of 1978 still prohibited utilities to become involved in financial incentive programs, the Energy Security Act of 1980 allowed such measures (RANDOLPH, 1980b, SATLOW, 1981). SCHROEDER and Miller, 1982, discuss this issue in much detail, and arrive at the conclusion that such financial incentive programs are valid according to all generally accepted regulatory standards (also see HUGHITT, 1982).

A related regulatory issue concerns the rates at which utilities buy back power from small renewable energy producers, and the rates they charge for backup of solar or wind systems. As mentioned above, the Public Utility Regulatory Policies Act of 1978 (PURPA) requires utilities to buy back power at the full avoided cost, but in most states there is still much discussion on how high these buyback rates should be set. Utilities often try to pay significantly less than their rates, while owners of systems feeding power into the grid argue that avoided cost is much higher (FEUERSTEIN, 1979, MORRIS, 1983). With the current rules (EISENSTADT, 1981, SLR, 1980b), utilities only pay allowances for capacity credits of qualifying facilities if firm power commitments are provided. However, a probabilistic capacity credit analysis as described in Section 2.5.2 could provide an indication of the capacity value of qualifying renewable energy installations even when no firm power is guaranteed.

The current involvement in renewable resources of many utilities notwithstanding (e.g. GOULD, 1983, SLR, 1981b, 1981c), many other utilities are still very reluctant to enter an unknown field of energy so different from the energy sources they are used to. MEADOWS, 1979, gives several behavioral reasons for this reluctance. For similar overviews on institutional barriers to solar energy use, see CARMICHEAL et al, 1981.

Utilities are particularly concerned with their load factor, and fear that the load factor will decrease when many people adopt solar heating systems, requiring electric backup only on bad weather days when loads tend to be high. In detailed investigations however, BRIGHT and Davitian, 1979 and 1982, find that the marginal cost of solar backup electricity is no higher than normal marginal costs.

An important social issue associated with utility financial programs for the promotion of conservation is that with these programs, none of their customers should be worse off than without them. One possible way to guarantee this has been applied in the design of conservation .programs in the Pacific Northwest (see, e.g., BOLEYN, 1981, BERRY and Hirst, 1983).

In most parts of the country, the marginal cost of providing electricity, which incorporates only the high capital cost of new plants, is significantly higher than average cost, which also incorporates the lower capital costs of older plants. When one customer installs some conservation measures for which the utility pays part of the cost, the effect on that customer is only positive, since he gets the full benefits of the measures in terms of savings on his utility bill, without bearing the full cost. A non-participant, however, receives no direct benefits, pays part of the cost of the incentive program with his bill, and may even get worse off when due to the energy savings of the first customer, the utility's capital cost has to be spread over less kWh, causing the rates to rise.[4] Non-participants do receive indirect benefits, since due to energy savings, the

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[4] This issue and a possible solution to the planning difficulties associated with it, is also briefly addressed in Chapter 9.

utility may be able to avoid construction of otherwise necessary new and expensive power plants. Thus, the policy adopted by some utilities in the Pacific Northwest is to sponsor conservation projects only up to a cost per saved kWh that is equivalent to the difference between the marginal and the average cost of one kWh produced by the utility (BERRY and Hirst, 1983). For one kWh conserved, the utility loses the revenue equal to its average cost, but saves new construction and other expenses equal to its marginal cost, which is why non-participants are made no worse off when the utility sponsors conservation with this difference.

Other social issues concerning utility involvement in solar energy include the problems regarding how customers in rental housing should be reached, given that the landlord would have to install the conservation measures while the tenants would receive their benefits. This is largely a problem of legal and contractual arrangements (RANDOLPH, 1980a). Another legal problem not directly concerning the utilities is the protection of solar access, i.e. guaranteeing that no new high-rise construction can shade an already installed solar system. That problem and possible solutions are addressed in great detail in EISENSTADT, 1982, and JAFFE and Duncan, 1979.

2.6 SOLAR COOLING

Because of its importance for the Mexicali Project, solar cooling technology is briefly reviewed here. KARAKI and Wilbur, 1977, provide a monograph on solar cooling technology. Two basic thermodynamic processes are used for solar cooling, the Rankine vapor compression cycle and the absorption cycle (also see DUFFIE and Beckman, 1974, HOLMAN, 1974, KREITH and Kreider, 1978, NEAL, 1980, SAYIGH, 1977).

The Mexican Institute of Electrical Research (IIE) has been operating a test solar cooling facility on their office in Mexicali, which employs the absorption cycle (HUACUZ, 1982). KARAKI and Wilbur, 1977, give the following reasons why absorption cycle cooling is to be preferred over other methods (also see YELLOTT, 1983). It features a high state of development, its performance in solar applications has been demonstrated, it is relatively simple, and it uses less pumping power than the vapor compression cycle. Karaki and Wilbur also recommend the lithium-bromide-water absorption technology over a water-ammonia combination, since with lithium-bromide and water, higher coefficients of performance (COP, see KAUSHIK et al, 1983) can be achieved at the temperatures typically provided by solar collectors, lower required pressures make lower pumping power possible, and there are no restrictions on use because of explosiveness.

Disadvantages of lithium-bromide are that salidification and consequent clogging of the system is possible, and that the salt is relatively expensive. Because the lithium-bromide absorption cycle appears best fit to solar applications, it was chosen for the pilot project in Mexicali (HUACUZ, 1982). This is why only this process will be described in more detail below.

Descriptions of absorption cycle cooling can be found in many books on thermodynamics and solar engineering (see, e.g., ANDERSON, 1974, DUFFIE and Beckmann, 1974, HOLMAN, 1974, KREITH and Kreider, 1978, SAYIGH, 1977). FARBER, 1974, FARBER et al, 1977, and FELLI, 1983, also provide such background. Using a solar collector for heat input does not change the basic process (for technical details on collectors, see, e.g., ASHRAE, 1978), so that only the thermodynamic process is described in detail below.

The absorption process is depicted graphically in Figure 7; the following description of the process follows closely the concise explanation in SHAMA, 1981. The refrigerant, water, is dissolved in the absorbent, lithium-bromide. This solution is heated in the generator, vaporizing part of the refrigerant and leaving behind a reduced concentration of the refrigerant in the working fluid. Solar collectors provide the heat input for the generator. The refrigerant vapor moves to the condenser, gets cooled back to the liquid phase, and then passes through a valve, releasing pressure, to the evaporator. Due to the lower pressure, the refrigerant again evaporates into a cool vapor. Here the actual cooling effect takes place, as air from the building is circulated through the evaporator and heat is exchanged with the refrigerant. Finally, the warmed refrigerant moves back to the absorber and is recombined with the absorbent. This rich solution is pumped back to the generator and the cycle starts over.

As with almost all applications of solar energy, solar cooling systems have been simulated to model their output over time. ANAND and Deif, 1979, ANAND et al, 1982, KAUSHIK et al, 1982, LOEF and Tybout, 1974, and TYBOUT and Loef, 1970, report on such simulation studies. BARTLETT, 1977, and LOEF and Tybout, 1974, discuss the influence of site-specific and regional conditions on the economic feasibility of solar cooling. ALLEN, 1974, reports on aspects of the optimization of solar-powered absorption systems.

There exists general agreement in the literature that solar cooling by itself is as yet not economical. LORSCH, 1983, arrives at the conclusion that solar absorption cycle cooling currently is three to four times as expensive as conventional systems. KELLY and Logee, 1982, compare some

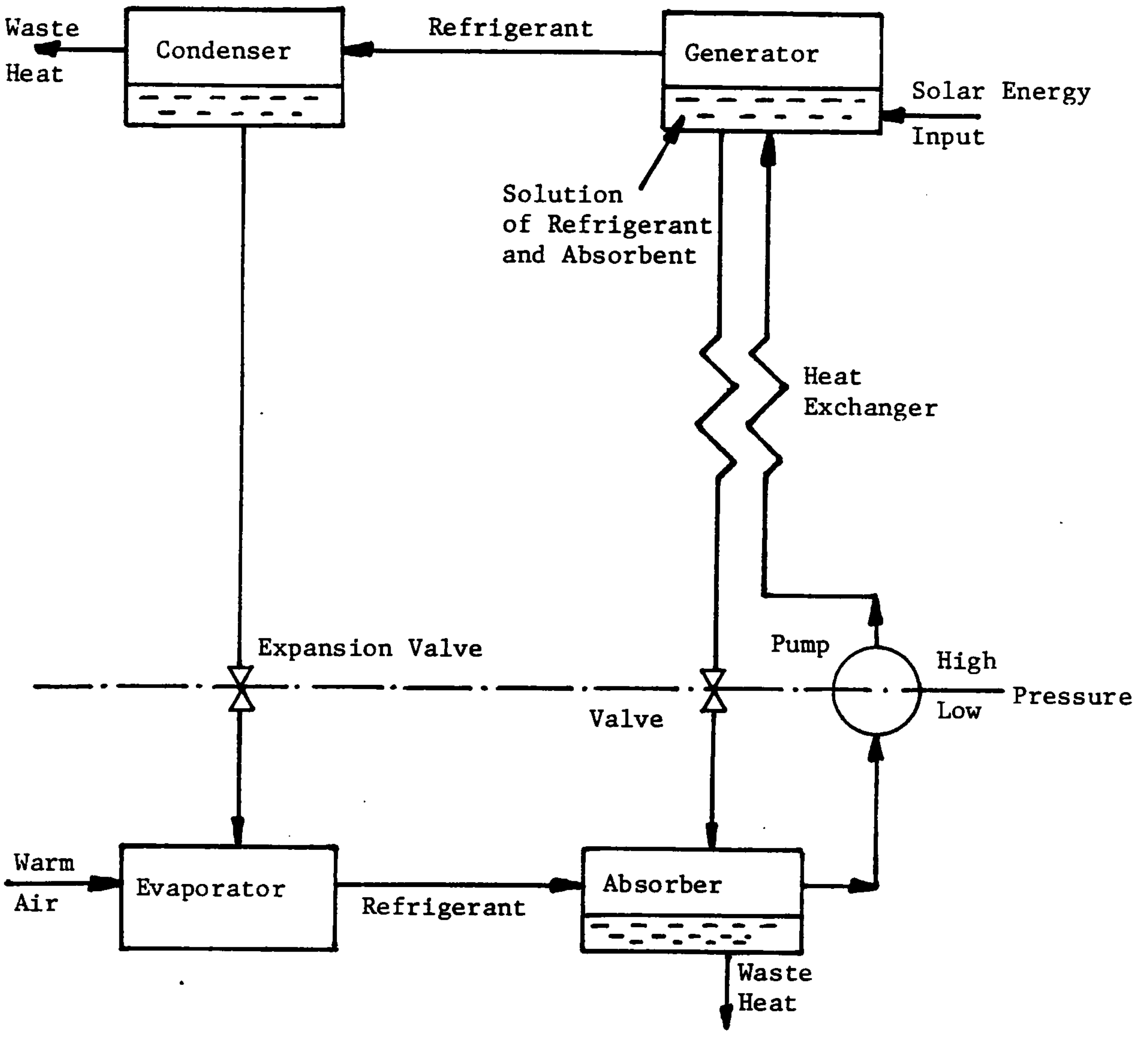


Figure 7: Absorption Cycle Cooling

experimental solar cooling systems in the U.S. and report significant operational problems. However, SHAMA, 1981, concludes that solar cooling coupled with solar space or water heating systems can be economical. VENHUIZEN, 1982, examines the infant U.S. market for solar cooling systems and reports on innovative developments.

The findings on economic feasibility of solar cooling being not very encouraging, it appears appropriate to also consider conservation options for reducing cooling loads. ILYAS, 1982, discusses environmental and behavioral issues that influence cooling loads and could be used to conserve energy. TIWARI et al, 1982, review the method of cooling by water evaporation on the roof, a method also advocated because of its lower initial cost by HAY 1974. Even simpler conservation measures such as installing overhangs over windows to reduce solar gain, caulking to reduce infiltration of hot air, or adding insulation (as described in LECKIE et al, 1981, for example) could also be cost-effective.

2.7 RENEWABLE ENERGY AND THE THIRD WORLD

Many authors have advocated the extensive use of renewable energy technologies by developing countries for the following reasons (ARNOLD, 1979, BERRIE and Leslie, 1978, BROWN and Howe, 1978, ESTEFAN, 1980, GOLDEMBERG, 1979, HOFFMAN and Johnson, 1979, HOWE, 1980, LEQUEUX, 1980, MUNASINGHE, 1983, PACHAURI, 1982, PARIKH 1979, RAMAKUMAR and Hughes, 1981, RAMAKUMAR, 1983, REVELLE, 1979, ROSENBLUM et al, 1980):

1. Most of the poorest developing countries lie in the tropics, with an abundance of sunshine and excellent potential for solar energy applications.
2. Renewable energy technologies require less capital than conventional energy technologies, which is an important factor in the chronically capital-short countries of the Third World.
3. When renewable energy systems for remote villages are compared with their connection to the national electricity grid, often the renewable energy option looks particularly attractive since the investment for long power transmission lines can be saved (MARTINEZ and Mager, 1982, MINDER and Gilly, 1981, USMANI, 1978). Also when compared to remote Diesel generators, solar options are often economically attractive (ROSENBLUM, 1983).

4. Particularly efficient total energy systems are possible when each use is matched with the quality of the energy source, i.e. if no high quality energy form like electricity is used for such low quality needs as space heating (KREITH et al, 1980). Such total energy systems are for instance advocated by RAMAKUMAR, 1977, and RAMAKUMAR and Hughes, 1981.
5. The use of renewable energy sources can help developing countries short in foreign exchange currencies to save such currencies which they would otherwise have to spend for oil imports. This argument gains the more weight the higher oil prices climb in the future.
6. For less developed countries, renewable energy technologies can be simpler and easier to understand by the native population, and often, the country's own resources can be used for the equipment. This makes such equipment more appropriate than high-technology, large-scale power plants imported from developed countries.

MACKILLOP, 1980a and 1980b, disagrees with that logic and argues that many renewable energy technologies are still too expensive, and that they should first be fully developed in the developed world before being introduced into developing countries. The capital-richer developed countries should bear all the risk and cost of developing new technologies. He suggests that the developed world make a serious effort to save oil so that this resource can become cheaper and better available for developing countries (MACKILLOP, 1981). In his opinion, the points enumerated above are not valid for most developing countries when renewable energy is compared with cheap oil and simple and reliable oil-burning equipment.

On the other hand, many studies conclude that renewable energy systems are indeed economical for Third World countries (e.g. BIFANO, 1982, FRENCH, 1980, JAGADEESH et al, 1981). Thus, the author tends to agree with the vast majority of the researchers that as long as the technologies are currently well developed, as is the case with passive and active solar heating, biodigesters and WECS, they can and should be applied in the Third World, for the other non-economic reasons cited above.

If no renewable sources are used, the rapidly growing demand for electricity could put too heavy a burden on the financial situation of those countries. DUNHERLEY, 1979, for instance examines the popular hypothesis that rural energy needs are far below urban demands in developing countries, and arrives at the conclusion that this is only so due to greater poverty in rural areas. As soon as the standard of living rises in such rural areas, the energy demand can be expected to rise steeply. He as well as GOLDEMBERG, 1980, therefore suggest large scale renewable energy projects such as large hydro developments and large wind farms. Some authors, e.g. AYYASH, 1983, and CECELSKI, 1982, advocate conservation programs even for developing countries, where one would assume a low potential for conservation due to the low per capita energy consumption. However, in cities, the potential appears to be significantalready.

HAYES and Kadyszewski, 1981, REVELLE, 1980, and THALHAMMER et al, 1978, discuss aspects of aid from developed countries for energy development in the Third World, particularly in the form of technology transfer and research and development. MEIER and Mubayi, 1983, MUNASINGHE, 1980c, and SAMOUILIDIS and Derakes, 1983, report on energy-economy models of the type described above, applied on the special situation in developing countries. In MUNASINGHE, 1980b, marginal cost pricing is recommended strongly for developing countries. Finally, FINON and Lapillonne, 1983, and MARTIN and Modiano, 1980, address the problem of procuring accurate data in Third World countries, a serious problem that the author had to face in the Mexicali project.

Chapter III

FORMULATION OF A CAPACITY PLANNING MODEL

3.1 MOTIVATION FOR A TWO-PHASE APPROACH

As noted in the Literature Review, in terms of accuracy, the use of probabilistic production costing is indispensable in capacity planning. However, one of its principal disadvantages is the large amount of computer time needed for the repeated convolution processes. Use of the cumulant method can overcome this problem, but as has been reported in the literature (see, e.g., LEVY and Kahn, 1982), in certain cases, notably for small systems (less than 5000 MW), or when very large plants are part of a medium-sized system (e.g. with additions amounting to 50 percent of installed capacity, or even 20 percent as in TVA's experience), accuracy of the series approximation to the equivalent load duration curve becomes very poor. (We remark here that this research is to be applied on a very small system, i.e. on the 677 MW system of Baja California Norte.)

When renewable energy technologies are to be modeled probabilistically, further problems arise. As has been described above, most researchers prefer hour-by-hour simulation of the renewable energy plant's contribution, in order to avoid all problems conçerning statistical dependence of load and renewable contribution. This, of course, increases required computation times drastically.

As described in Section 2.5.2.1, CARAMANIS et al, 1982, suggest an alternative, computationally more efficient approach based on Gram-Schmidt Orthonogalization and Gram-Charlier Series representations of load and renewable contributions. However, the Gram-Schmidt Orthogonalization they use to simulate statistical independence between the load and the renewable energy contributions, does not always result in sufficiently independent random variables. (Significant discrepancies in results were obtained when using this method on typical solar energy data.)

The computational inefficiencies of standard probabilistic methods such as simulation of renewable contributions and numerical convolution, together with the possible inaccuracies of the Gram-Schmidt Orthogonalization approach, led the author to consider an alternative approach. Because of the large inaccuracies of the cumulant method when applied on small power systems like the one in Baja California Norte, the traditional probabilistic methods, simulation and numerical convolution, have to be used for probabilistic production costing in the Mexicali Project. This, however, increases computer time requirements greatly. Therefore, the following two-phase approach is adopted.

In a first phase, deterministic models of reliability, i.e. derating, are applied, leading with great computational efficiency to a deterministically optimal capacity expansion plan. It can be assumed that this deterministic optimum falls close to the one that would be obtained using probabilistic methods. Thus, in a second phase, traditional probabilistic methods are used to perturb the deterministic optmimum by using first-order approximations toward the probabilistic optimum. This provides not only an efficient alternative to solving the probabilistic problem directly via an approach such as BLOOM's, 1983, but it also facilitates the consideration of discrete plant capacity availabilities. This integrality consideration, without an efficient deterministic method, would undoubtedly be prohibitive.

In the following chapters, the details of the deterministic and the probabilistic models are given. Integrality issues concerning the sizes of conventional plants to be installed, often ignored in the literature, are also addressed in a subsequent chapter. The remaining sections in this chapter cover formulations of the models as well as some convexity properties.

3.2 A GENERIC CAPACITY PLANNING MODEL

Generically, the electric utility capacity expansion problem consists of the following objective and constraints:

min CC + OC

s.t. reliability constraint

capacity bounds

where

CC = total capital cost

OC = total operating cost

Note that in all formulations reviewed in Section 2.3, capital costs and capacity bounds are linear, and are the same in deterministic as well as probabilistic models. However, operating cost and reliability constraints can take very different forms. In the following two sections, the deterministic and probabilistic models to be used in this dissertation will be formulated in detail.

3.3 THE DETERMINISTIC FIRST-PHASE MODEL

3.3.1 Formulation

The problem is formulated as a nonlinear programming problem similar to the type described above in Subsection 2.3.2 or in ANDERSON, 1972. As in SHERALI and Staschus, 1985, the renewable energy contributions are modeled as depending on the time-of-day and season. For each subperiod r corresponding to a certain time-of-day and season, a renewable energy availability a_r is derived from observed renewable energy production, or from simulation results. Such subperiods repeat themselves cyclically throughout the year. For example, if five subperiods are defined for solar availability during the course of a day, as shown in the example in Figure 8, this cycle of five subperiods is repeated for each new day. Thus, the subperiod associated with nighttime hours in Figure 8 would contain the nighttime hours of all 365 days of the year. If additional seasonal variations are to be captured, ten subperiods could be formed, corresponding to the five times-of-day and two seasons. Then, the subperiod associated with summer nights would contain all the nighttime hours of days between March 21 and September 21, for example.

For each of the subperiods, load and renewable contributions can be assumed roughly independent, and this will be assumed below. The derivation process is illustrated in Figure 8.

Thus, the following multi-year expansion problem including renewable technologies results:

<u>Capacity</u> <u>Planning</u> <u>Problem</u> <u>CP</u>:

$$\min \sum_{t=1}^{T} \sum_{i=1}^{I} c_{it} x_{it} + \sum_{t=1}^{T} \sum_{j=1}^{J} c_{jt} x_{jt} + \qquad (1)$$

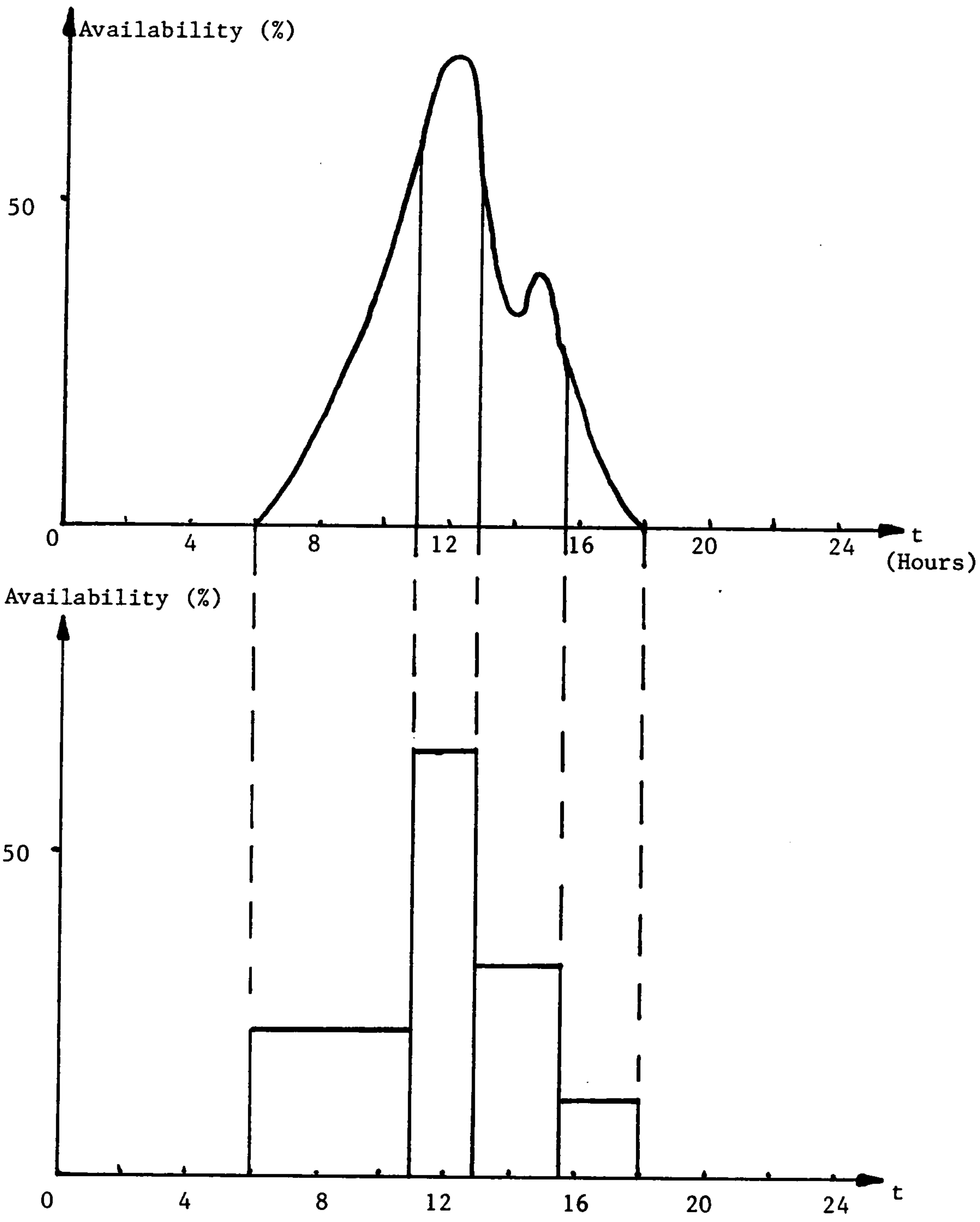


Figure 8: Varying Availability of Renewable Energy

$$\sum_{t=1}^{T} \sum_{i=1}^{I} g_{it} \sum_{r=1}^{R} \lambda_r \int_{X_{i-1,t,r}}^{X_{itr}} F_{rt}(y)dy \qquad (2)$$

$$\text{s.t.} \quad \sum_{i=1}^{I} z_{it} \geq \max_{r} (P_{rt} - \sum_{j=1}^{J} a_{rj} z_{jt}), \; t=1,..,T \qquad (3)$$

$$z_{it} \leq b_i + \sum_{\tau=1}^{t} x_{i\tau}, \; i=1,..,I, \; t=1,..,T \qquad (4a)$$

$$z_{jt} \leq b_j + \sum_{\tau=1}^{t} x_{j\tau}, \; j=1,..,J, \; t=1,..,T \qquad (4b)$$

$$z_{jt} \leq UBS_{jt}, \; j=1,..,J, \; t=1,..,T \qquad (5)$$

$$z, x \geq 0$$

where

$i=1,..,I$ = index of conventional plants in merit order

$j=1,..,J$ = index of renewable energy plants

$t=1,..,T$ = years in planning horizon

$r=1,..,R$ = index of subperiods of varying renewable energy availability

c = vector of capital costs

g = vector of operating costs

$x_{i \text{ or } j,t}$ = new capacity of type i, j, installed in t

$z_{i \text{ or } j,t}$ = total capacity of type i, j, used in t

b = vector of capacities already installed in year 0

UBS_{jt} = maximum possible usage of renewable technology j in year t

$$X_{itr} = Y_{it} + \sum_{j=1}^{J} a_{rj} z_{jt}$$

where $Y_{it} = \sum_{k=1}^{i} z_{kt}$

λ_r = length of subperiod r ($\sum_{r=1}^{R} \lambda_r = 1$)

F_{rt} = inverse load duration curve in r, t

a_{rj} = availability of renewable energy from equipment type j in subperiod r

P_{rt} = peak load in r,t (possibly including a reserve margin)

Note that Term (1) represents total system capital costs (CC in the generic model), and Term (2) total system operating costs, modeled deterministically (OC). It is assumed that for conventional equipment types, the values of c represent capital costs for derated capacity, i.e. the original capital cost per unit capacity divided by (1-forced outage rate). Merit order loading is implicitly assumed as in the models in Section 2.3.2. Constraint (3) ensures that peak demands of all subperiods in all years be met, and acts as a deterministic type of reliability constraint. Constraint (4) ensures that no more capacity be used in year t than is installed.

Finally, Constraint (5) introduces upper bounds on the usage of renewable technologies, dictated in reality by the number of houses that can be better insulated for conservation, the maximum windpower available at a certain site, or the maximum area that can be covered for solar power development. This type of constraint plays an important part in the Mexicali Project. Both Constraints (4) and (5) can be viewed as capacity bounds in the generic model.

From a modeling viewpoint, Constraint (5) can be replaced by the following restriction in terms of the x-variables by imposing a bound on installed capacity rather than on used capacity:

$$\sum_{\tau=1}^{t} x_{j\tau} \le UBS_{jt} - b_j, \quad j=1,..,J, \quad t=1,..,T \qquad (5a)$$

It can be noted that (5a) implies (5) because of (4b). However, for all realistic data structures, (5) and (5a) will lead to the same results. The only case in which it would be advantageous to buy more x-capacity of equipment type j in year t than (5a) would allow, and use only as much z-capacity as (5) allows, arises when the price c_{jt} is so much less in t than in t+k that it offsets interest, maintenance and reduced useful lifespan costs. Since the prices of renewable energy equipment can be assumed to rise no faster than the general cost of living,[5] this case will occur very rarely, and for all practical purposes, the two formulations can be assumed to lead to the same results.

However, to be able to compare the algorithms to be developed in Chapter 4, both the Lagrangian Dual and the Generalized Benders Decomposition approaches will be developed for CP with (5), i.e. we will use the less restrictive constraint (5) in our formulation, and allow the cost-minimizing nature of the problem to automatically control installed capacity via the restrictions (5) and (4b). As is shown in Chapter 7, the Generalized Benders Decomposition algorithm does not perform very well with that formulation, but works efficiently for a formulation which substitutes (5) by (5a). On the other hand, incorporation of (5a) into the Lagrangian Dual algorithm would significantly slow its convergence rate, as compared to a formulation including (5). This can be seen by examining the way in which bounds on conventional capacities are treated in this approach in Chapter 6, with the resulting increase in computation times reported in Chapter 7. Thus, in comparing the two algorithms, several options are used in the Generalized Benders Decomposition program, so that the best possible convergence rates of the two algorithms can be compared. For details,

[5] Solar cell costs, for instance, are even projected to decrease dramatically.

see Chapter 7.

For notational convenience in subsequent chapters, Term (1) may be addressed as CC(x), Term (2) as OC(z), Constraint (3) may be given in matrix notation as $Az \geq P$, and Constraint (4) may be given as $z-Bx \leq b$.

In certain applications, it may convenient to interpret $t=1,..,T$ as 'periods' rather than as 'years'. For instance, if for policy questions, only a very coarse expansion plan is needed, a 20-year planning horizon can be captured in four periods of five years each, with appropriately agglomerated load curves.

It can also be noted that life spans of equipments can be easily incorporated into this model. One can define the already installed equipment b not only for each equipment type i, but also for each year t, setting it to zero when the old equipment's life span has expired. This type of definition would prompt some changes in summation limits in constraint (4), but would not affect any of the results developed in the following sections. Similarly, if the life span of a newly installed capacity x_{it} expired within the planning horizon, a change in the lower summation limits in (4) could account for that. Hence, for simplicity in exposition, we suppress the life span feature below. Other issues which are neglected in our formulation for the sake of simplicity in exposition are financial, environmental, and hydro dispatching constraints. The incorporation of such issues would require much added work, and it would change the conceptual structure of the algorithms developed in this dissertation.

Finally, it can be noted that the introduction of two different types of decision variables, i.e. x-variables for installed capacity and z-variables for dispatched capacity, is a rather artificial tool used to facilitate the decomposition of the program. This type of formulation proves very convenient for the Lagrangian Dual and the Generalized Benders Decomposition approaches to be described in the following chapter. However, formulating the peak load constraint (3) and the operating cost (2) in terms of the x-variables is also possible, and will be used in a direct nonlinear programming approach also to be described in Chapter 4.

3.3.2 Convexity

Theorem 1:

Problem CP is a convex program.

Proof:

First, note that Term (1) of the objective function as well as Constraints (3), (4) and (5) are linear. Hence, examining Term (2), if it can be shown that $f_{rt}(z)$ defined below is convex, then the theorem would be proven.

$$f_{rt}(z) = \sum_{i=1}^{I} g_{it} \int_{X_{i-1,t,r}}^{X_{itr}} F_{rt}(y)dy$$

$$= \sum_{i=1}^{I} (g_{it}-g_{i+1,t})\bar{F}_{rt}(X_{itr}) \quad (6)$$

where

$$\bar{F}_{rt}(\xi) = \int_{0}^{\xi} F_{rt}(y)dy$$

Now note that $(g_{it}-g_{i+1,t}) \leq 0$ from the merit order loading assumption, and that $\bar{F}_{rt}(.)$ is concave since $F(.)$ is assumed to be monotone non-increasing. Since X_{itr} is a linear function of z and since a concave function composed with a linear function is concave, it follows from (6) that $f_{rt}(z)$ is convex and the proof is complete.

3.4 THE PROBABILISTIC SECOND-PHASE MODEL

In addition to the linear capital cost expression and capacity bounding constraints, the model contains an operating cost expression and reliability constraints that use the concept of the Equivalent Load Duration Curve introduced in Section 2.2.1. The impact of renewable energy contributions on operating cost and reliability is modeled through hour-by-hour simulation. Because of the numerical nature of these terms, operating cost and unserved energy are only given in generic form below:

Probabilistic Program PP

$$\min \sum_{t=1}^{T} \sum_{i=1}^{I} c_{it}x_{it} + \sum_{t=1}^{T} \sum_{j=1}^{J} c_{jt}x_{jt} + \sum_{t=1}^{T} EG_t(z) \qquad (7)$$

$$\text{s.t. } UE_t(z) \le e \quad , \; t=1,..,T \qquad (8)$$

$$z_{it} - \sum_{\tau=1}^{t} x_{i\tau} \le b_i \; , \; i=1,..,I, \; t=1,..,T \qquad (4a)$$

$$z_{jt} - \sum_{\tau=1}^{t} x_{j\tau} \le b_j \; , \; j=1,..,I, \; t=1,..,T \qquad (4b)$$

$$z_{jt} \le UBS_{jt}, \; j=1,..,J, \; t=1,..,T \qquad (5)$$

$$x,z \ge 0$$

where

EG_t = probabilistic production cost in t,

UE_t = loss-of-energy probability in t,

and where all other terms are as defined in Section 3.3. Life span issues can also be incorporated into this program in the same way as described for the deterministic model. Solution approaches for this model are given in Chapter 5.

Convexity of Program PP without renewable energy options was proven by BLOOM, 1983. By interpreting each hour of the year as a separate subperiod with respect to the calculation of operating cost and unserved energy, this convexity result can be extended to include renewable energy options if modeled through hour-by-hour simulation.

Chapter IV

ALGORITHMS FOR THE DETERMINISTIC MODEL

In this chapter, three different approaches for solving Problem CP are introduced. These approaches include a Lagrangian Dual Decomposition, a Generalized Benders Decomposition, and the application of a standard nonlinear programming algorithm as programmed and marketed in the package VMCON.

4.1 A LAGRANGIAN DUAL DECOMPOSITION

In order to re-formulate Problem CP in such a way that it can be conveniently decomposed using the concept of Lagrangian Duality, first some modeling issues regarding the renewable energy contributions have to be addressed.

4.1.1 Interpretation of Renewable Energy as a Negative Load

As is standard in the simulation approaches described in Section 2.5.2, renewable energy contributions can be interpreted as a negative load, i.e. can be modeled by subtracting them from the original load. Given the assumption stated above that renewable energy contributions remain constant during certain times-of-day, this amounts to simply sliding the load duration curve downward by the derated renewable energy capacities. This is shown in Figure 9, for an example with only two subperiods, corresponding to daytime and nighttime. The result of this procedure are load duration curves net of renewable contributions for each subperiod of a given year. These subperiod-load duration curves can then be added horizontally to obtain the yearly load duration curve net of renewable contributions, as described, e.g., in SHERALI et al, 1983, as also illustrated in Figure 9.

SHERALI and Staschus, 1985, use this approach for one-year plantmix problems. For this simplified case, once the renewable capacities are fixed, the resulting problem with the load duration curve net of renewable contributions, can be solved very efficiently with the Breakeven Method described in Subsection 2.3.1. Thus, to obtain the overall optimal solution, it only remains to minimize the total yearly cost function over the renewable energy capacities without any constraints, since at each combination of renewable energy capacities, the optimal conventional capacities are determined implicitly. This total yearly cost function is proven convex in SHERALI and Staschus, 1985. For its minimization, a tangential approximation method is chosen, which usually converges to within one percent of the optimal value within two to five iterations.

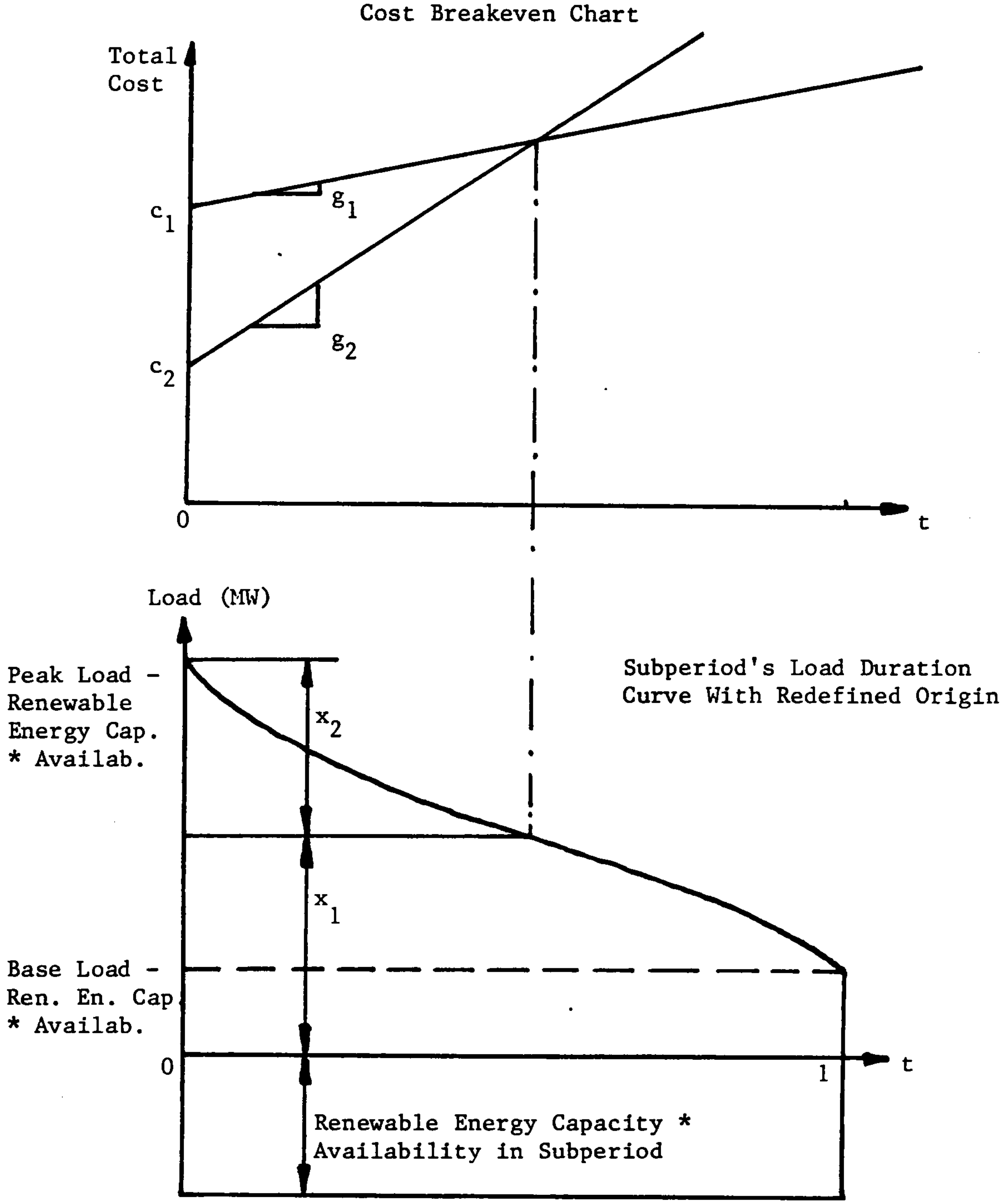


Figure 9: Plant Mix Problem Solution With Renewable Energy

For the multi-year expansion problem under examination here, this plantmix procedure cannot be applied immediately, but using a Lagrangian Dual Decomposition, the problem can be broken up resulting in plantmix-type subproblems. This decomposition is described in the following sections.

4.1.2 Formulation of the Lagrangian Dual Program

To begin with, let us re-formulate Problem CP as follows by using a suitable transformation on the integral involving the operating cost term. This transformation is motivated by the work of SHERALI and Staschus, 1985, reported on in the previous section.

$$\min \sum_{t=1}^{T}\sum_{i=1}^{I} c_{it}x_{it} + \sum_{t=1}^{T}\sum_{j=1}^{J} c_{jt}x_{jt} + \qquad (1)$$

$$\sum_{t=1}^{T}\sum_{i=1}^{I} g_{it} \int_{Y_{i-1,t}}^{Y_{it}} \{ \sum_{r=1}^{R} \lambda_r F_{rt}(y + \sum_{j=1}^{J} a_{rj}z_{jt})\}dy \qquad (9)$$

$$\text{s.t.} \quad \sum_{i=1}^{I} z_{it} \geq \max_{r} (P_{rt} - \sum_{j=1}^{J} a_{rj}z_{jt}),\ t=1,..,T \quad (3)$$

$$z_{it} \leq b_i + \sum_{\tau=1}^{t} x_{i\tau},\ i=1,..,I,\ t=1,..,T \qquad (4a)$$

$$z_{jt} \leq b_j + \sum_{\tau=1}^{t} x_{j\tau},\ j=1,..,J,\ t=1,..,T \qquad (4b)$$

$$z_{jt} \leq UBS_{jt},\ j=1,..,J,\ t=1,..,T \qquad (5)$$

Dualizing constraints (4) leads to the following Lagrangian Dual formulation:

$\max \{\vartheta(u):\ u \geq 0\}$

where

$$\vartheta(u) = \inf\{\ CC(x) + OC(z) + \tag{10a}$$

$$\sum_{t=1}^{T}\sum_{i=1}^{I} u_{it}(z_{it} - \sum_{\tau=1}^{t} x_{i\tau} - b_i) + \sum_{t=1}^{T}\sum_{j=1}^{J} u_{jt}(z_{jt} - \sum_{\tau=1}^{t} x_{j\tau} - b_j) \tag{10b}$$

$$\text{s.t. } Az \geq P \tag{3}$$

$$z_{jt} \leq UBS_{jt},\ j=1,..,J,\ t=1,..,T \tag{5}$$

$$x, z \geq 0\ \}$$

where

$u_{i \text{ or } j,t}$ = dual variable associated with constraint of type (4) for equipment type i or j and year t

For future reference, Term (10b) may be addressed as $u^t(z-Bx-b)$.

Now consider solving this Lagrangian Dual Program with the Cutting Plane Method, as for instance described in BAZARAA and Shetty, 1979, Chapter 6. Noting that the dual's objective value, ϑ, being the infimum of Terms (10), has to be less than or equal to Term (10) for all feasible values of x and z, the following Master Program can be constructed:

<u>Master Program MP</u>:

$\max \sigma$

$$\text{s.t. } \sigma \leq CC(x^k) + OC(z^k) + u^t(z^k - Bx^k - b),\ k=1,..,K \tag{11}$$

$$u \geq 0,\ \sigma \text{ unrestricted}$$

where

$k=1,..,K$ = index of trial solutions of u

Note that with the number of feasible (x,z) points being infinite, there is an infinite number of constraints of type (11). However, the Cutting Plane Method uses a relaxation strategy, i.e. starting off by including few or no constraints of type (11) and relaxing the remaining majority of constraints, a trial dual solution u^k is obtained via MP and is tested for feasibility with respect to the relaxed constraints. If this solution u^k satisfies all the relaxed constraints, it is optimal. Otherwise, a most violated constraint is generated and included in the Master Program which is then resolved. This procedure continues until optimality is reached.

To test u^k for feasibility with respect to the relaxed constraints, a so-called Subproblem is solved. This Subproblem checks whether (11) is satisfied for all (x,z) points by minimizing (11) over x and z subject to Constraints (9) and (5), and comparing the resulting objective value to σ, the MP objective value. If the two lie within a pre-specified accuracy ε of each other, the algorithm terminates. Otherwise, a new constraint of type (11) is added to MP based on the current (x,z) solution, and the process is repeated.

Thus, the Subproblem takes the following form:

Subproblem $SP(u^k)$:

$$\min \sum_{t=1}^{T}\sum_{i=1}^{I} c_{it}x_{it} + \sum_{t=1}^{T}\sum_{j=1}^{J} c_{jt}x_{jt} + OC(z) + \qquad (12a)$$

$$\sum_{t=1}^{T}\sum_{i=1}^{I} u_{it}^{k}(z_{it} - \sum_{\tau=1}^{t} x_{i\tau} - b_i) + \sum_{t=1}^{T}\sum_{j=1}^{J} u_{jt}^{k}(z_{jt} - \sum_{\tau=1}^{t} x_{j\tau} - b_j) \qquad (12b)$$

$$\text{s.t. } Az \geq P \qquad (3)$$

$$z_{jt} \leq UBS_{jt},\ j=1,..,J,\ t=1,..,T \qquad (5)$$

$$z,x \geq 0$$

It should be noted that since the original problem is a convex programming problem and since Slater's constraint qualification holds,[6] no duality gap exists (see BAZARAA and Shetty, 1979, Chapter 6). Also note that MP being a linear program, it can be solved efficiently. However, especially in the beginning, it would tend to pass erratically changing values of u to SP(u), which could hurt the overall convergence rate. This problem can however be alleviated by adding control through implied constraints which can be derived using a duality analysis, as described in a subsequent section.

Now consider solving $SP(u^k)$. Note that this problem separates into T one-year problems. This may be seen by rearranging the Terms (12a) and (12b) as follows:

---

[6] An interior point to constraints (3), (4) and (5) can be found trivially by letting all conventional capacities be excessively large, while letting renewable energy capacities be slightly positive.

Re-arranged SP (RSP)

$$\min \sum_{t=1}^{T}\sum_{i=1}^{I} x_{it}(c_{it} - \sum_{\tau=t}^{T} u_{i\tau}{}^{k}) + \sum_{t=1}^{T}\sum_{j=1}^{J} x_{jt}(c_{jt} - \sum_{\tau=t}^{T} u_{j\tau}{}^{k}) \quad (13a)$$

$$+ \sum_{t=1}^{T}\sum_{i=1}^{I} u_{it}{}^{k} z_{it} + \sum_{t=1}^{T}\sum_{j=1}^{J} u_{jt}{}^{k} z_{jt} \quad (13b)$$

$$- \sum_{t=1}^{T}\sum_{i=1}^{I} u_{it}{}^{k} b_{i} - \sum_{t=1}^{T}\sum_{j=1}^{J} u_{jt}{}^{k} b_{j} + \quad (13c)$$

$$\sum_{t=1}^{T}\sum_{i=1}^{I} g_{it} \int_{Y_{i-1,t}}^{Y_{it}} \{ \sum_{r=1}^{R} \lambda_r F_{rt}(y + \sum_{j=1}^{J} a_{rj} z_{jt})\} dy \quad (13d)$$

$$\text{s.t.} \quad \sum_{i=1}^{I} z_{it} \geq \max_{r} (P_{rt} - \sum_{j=1}^{J} a_{rj} z_{jt}), \; t=1,..,T \quad (3)$$

$$z_{jt} \leq UBS_{jt}, \; j=1,..,J, \; t=1,..,T \quad (5)$$

$$z, x \geq 0$$

Since in this formulation, one year's values do not show up in the terms for any other year, it is separable in t, i.e. it can be solved by solving T one-year problems. Furthermore, it should be noted that Term (13c) solely consists of constants, and can be taken care of by adding these constants to the optimal objective value after solving the problem without Term (13c). By examining the above program further, one can observe that Term (13d) represents the operating cost of T one-year plantmix problems,[7] while Term

[7] i.e. capacity planning problems with a one-year horizon, ignoring all future load growth and past installed equipment, as described in Section 2.3.3

(13b) can be interpreted as the capital cost of T one-year plantmix problems in z. Also the constraint (3) is a plant-mix type of demand constraint.

Additionally, and independently of this plantmix problem in z, Term (13a) is the only part of RSP containing x-variables, aside from nonnegativity constraints. Since it is a linear term, the optimal solution is

$$x_{it} = \begin{cases} 0, \text{ if } c_{it} - \sum_{\tau=t}^{T} u_{i\tau} \geq 0 & (14a) \\ \infty, \text{ otherwise} & (14b) \end{cases}$$

Unboundedness of the program in the latter case can be avoided by assigning suitably large upper bounds on the x-variables. However, by adding implied constraints derived through a duality analysis on MP, which are essentially the condition in (14a), the occurence of a u^k-solution leading to case (14b) can be prevented altogether. This also enhances the computational efficiency of the procedure. This issue will be addressed in Section 4.1.4.

If such implied constraints are not used, the following algorithm can be used to solve RSP:

<u>Algorithm for solving SP (ASP)</u>

1) Separate RSP into T one-year plantmix problems in z and T*(I+J) problems in $x_{i \text{ or } j,t}$.
2) Solve the T plantmix problems in z as suggested in SHERALI and Staschus, 1985.

3) Set $x_{i \text{ or } j,t} = 0$ for all i or j,t for which case (14a) holds. Set all remaining $x_{i \text{ or } j,t}$ equal to a suitably large upper bound.

Before proceeding with the algorithmic development, the following section gives an economic interpretation of the dual variables u.

4.1.3 Economic Interpretation

As can be seen in ASP, the dual variables u function as capital values of installed equipment. This is of course exactly the function dual multipliers have in general, see, e.g., BAZARAA and Jarvis, 1977. They represent a partial rate of change of the objective value with respect to a change in the right hand side value of the constraint they are associated with. That is, in this case, u represents the cost savings of having another unit of capacity at one's disposal.

It should be noted that the Lagrangian Dual decomposition developed here ties in several earlier attempts to decompose a CP-type program into one-year plantmix problems. For example, BEGLARI and Laughton, 1975, and PHILLIPS et al, 1969, developed algorithms that vary the capital costs of installed equipment to be used in one-year plantmix subproblems. However, both these references use a heuristic that modifies these capital values, so that none of them is able to prove convergence of their procedure. Thus, the decomposition algorithm developed here, whose theoretical convergence is due to the absence of a duality gap, which in turn is due to convexity of Program CP and a suitable constraint qualification, (see BAZARAA and Shetty, 1979), is the first theoretically sound approach of this type.

4.1.4 Duality Analysis

For convenience in reading, Problem CP is re-stated below:

$$\min \sum_{t=1}^{T}\sum_{i=1}^{I} c_{it}x_{it} + \sum_{t=1}^{T}\sum_{j=1}^{J} c_{jt}x_{jt} + OC(z)$$

$$\text{s.t.} \quad \sum_{i=1}^{I} z_{it} + \sum_{j=1}^{J} a_{rj}z_{jt} \geq P_{rt}, \quad r=1,..,R, \ t=1,..,T$$

$$-z_{it} + \sum_{\tau=1}^{t} x_{i\tau} \geq -b_i, \quad i=1,..,I, t=1,..,T \qquad (4a)$$

$$-z_{jt} + \sum_{\tau=1}^{t} x_{j\tau} \geq -b_j, \quad j=1,..,J, t=1,..,T \qquad (4b)$$

$$-z_{jt} \geq -UBS_{jt}, \quad j=1,..,J, \ t=1,..,T \qquad (5)$$

$$x,z \geq 0$$

<u>Theorem 2</u>:

There exists an optimal solution to CP such that the following Condition (15) holds:

$$\sum_{\tau=t}^{T} u_{i\tau} \leq c_{it}, \quad i=1,..,I, \ t=1,..,T \qquad (15a)$$

$$\sum_{\tau=t}^{T} u_{j\tau} \le c_{jt},\ j=1,..,J,\ t=1,..,T \qquad (15b)$$

Proof:

Note that since CP has a convex objective function and linear constraints, the Kuhn-Tucker Conditions are both necessary and sufficient for CP. This optimality condition associated with the x-variables of CP is exactly (15), which completes the proof.

From this analysis it follows that for each equipment i,t and j,t, a constraint of type (15) can be added to MP. This added control enhances computational efficiency of the decomposition algorithm. Computational tests show that large savings in computing time are incurred (see Chapter 7). Furthermore, the addition of Constraints (15) to MP guarantees that in RSP, the coefficients associated with the x-variables are non-negative, which ensures boundedness of RSP.

4.1.5 Initial Cuts in the Master Program

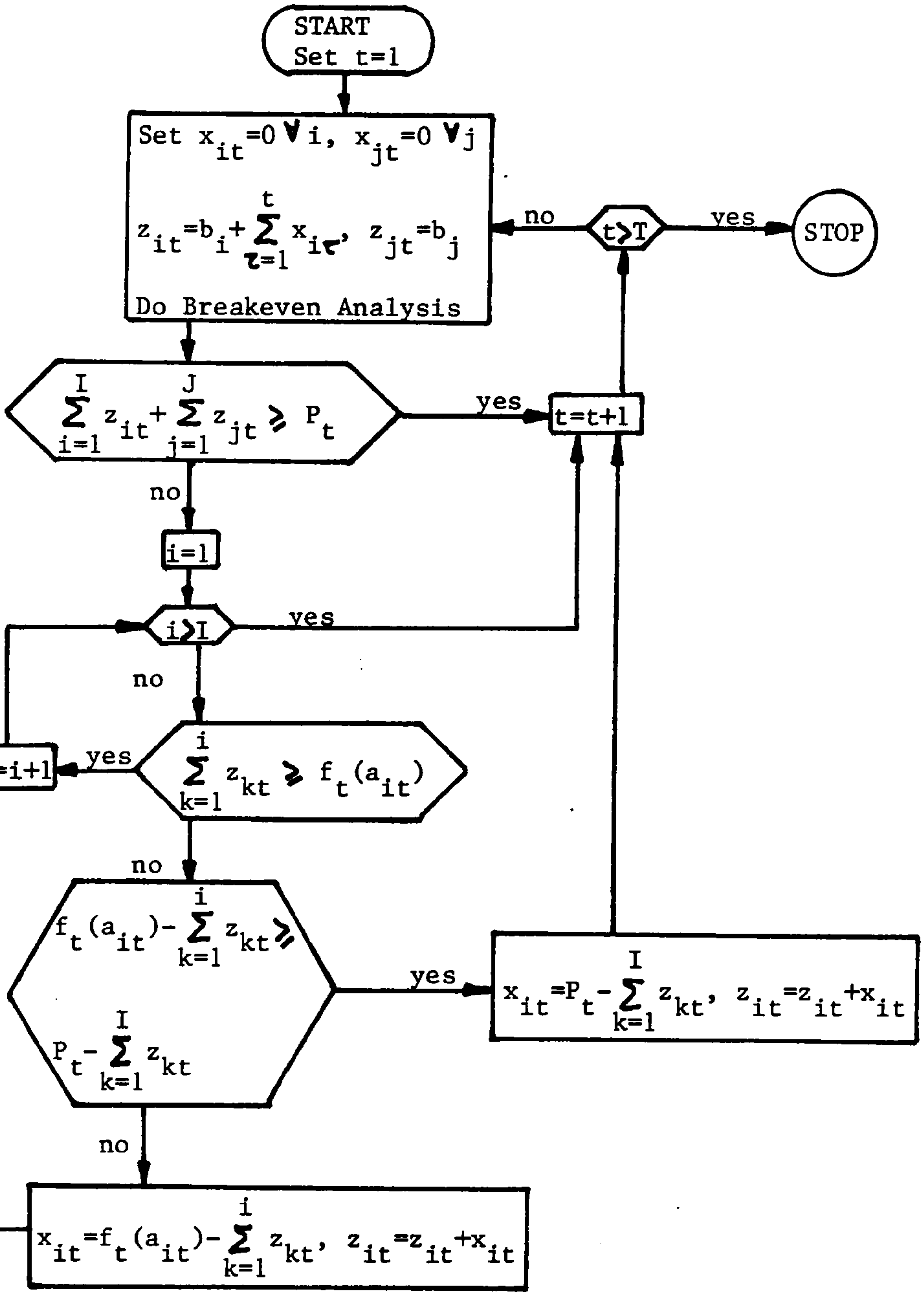
A further measure that can enhance computational efficiency of the decomposition algorithm is to initially add MP-cuts derived from heuristically obtained feasible and hopefully near-optimal CP solutions. The logic behind this is that with some constraints constructed from near-optimal solutions already present in MP, the generated values of the dual multipliers will be prevented from changing too erratically, as is typically the case in the first few iterations when no such constraints are present. Of course, to achieve an overall savings in computer time, these initial solutions have to be found as quickly as possible.

One possible quick heuristic is described by the flowchart in Figure 10. It essentially conducts a Breakeven Analysis for each year in the planning horizon, using the original capital costs. Then, starting with year one, the heuristic fills up the optimal breakeven capacities of each capacity type, either with already present equipments (z-x), or with new equipments (x). Since in reality, it is rarely optimal to scrap any old equipment before its useful lifespan is over, the heuristic never scraps old capacities. If the old capacities of some equipment type are greater than the breakeven capacities, less capacity of the next type in merit order is used. For details, see Figure 10.

4.1.6 The Lagrangian Dual Decomposition Algorithm (ALD)

We are now in a position to explicitly state the algorithm for solving Problem CP. Specializations for various steps, aimed at exploiting particular structures in the problem, are presented subsequently.

Step 1: Construct (I+J)T constraints of the form (15) and add them to the Program MP.



Here, P_t = Peak load in year t

$f_t(a_{it})$ = Value of load duration curve net of renewable energy contribution at breakeven duration between equipments i and (i+1)

Figure 10: A Capacity Expansion Planning Heuristic

Step 2: Apply a heuristic as displayed in Figure 10.

Step 3: Based on the heuristic solution, construct an MP-cut of the form (11), add it to MP, and solve MP.

Step 4: Use the optimal dual multipliers u^k obtained from MP in RSP and use Algorithm ASP to solve RSP. (Note that due to the Constraints (15), Step 3 of ASP will always assign zeroes to the x-variables, thereby avoiding difficulties associated with large penalties.)

Step 5: If the objective value of RSP plus a pre-specified desired accuracy ε is greater than or equal to the MP objective value, go to Step 6. Otherwise, use the current RSP solution to construct a new MP-cut, re-solve MP, and go to Step 4.

Step 6: For the final MP problem, find the associated dual solution, i.e. find the multipliers μ_k, k=1,..,K, associated with the K present MP-cuts. Furthermore, find the dual multipliers $\eta_{i \text{ or } j,t}$ associated with the upper bounding constraint of type (15) for each equipment i,t and j,t. Then, as the following result establishes, the final optimal solution of CP may be constructed as follows:

$$x_{it}^{o} = \eta_{it}, \quad i=1,..,I, \quad t=1,..,T \qquad (16a)$$

$$x_{jt}^{o} = \eta_{jt}, \quad j=1,..,J, \quad t=1,..,T \qquad (16b)$$

$$z_{it}^{o} = \sum_{k=1}^{K} \mu_k z_{it}^{k}, \quad i=1,..,I, \quad t=1,..,T \qquad (17a)$$

$$z_{jt}^{o} = \sum_{k=1}^{K} \mu_k z_{jt}^{k}, \quad j=1,..,J, \quad t=1,..,T \qquad (17b)$$

The following theorem shows that this solution is indeed ε-optimal.

Theorem 3:

The CP-solution given in Equations (16) and (17) is ε-optimal.

Proof:

Since each RSP solution is feasible to Constraints (3) and (5), and since Constraints (3) and (5) are linear, any convex combination of these solutions is also feasible to (3) and (5). Hence, the solution given by (16) and (17) is feasible to (3) and (5).

Furthermore, in order to show that (4a) is satisfied by the solution given by (16) and (17), we need to show that

$$\sum_{\tau=1}^{t} \eta_{i\tau} - \sum_{k=1}^{K} \mu_k z_{it}^{k} \geq -b_i \qquad (18)$$

Now, examine the dual of the final MP:

Dual of MP (DMP)

$$\min \sum_{k=1}^{K} \mu_k h^k + \sum_{t=1}^{T} \sum_{i=1}^{I} c_{it}\eta_{it} + \sum_{t=1}^{T} \sum_{j=1}^{J} c_{jt}\eta_{jt} \qquad (19)$$

$$\text{s.t.} \quad \sum_{k=1}^{K} \mu_k \Big(b_i + \sum_{\tau=1}^{t} x_{i\tau}{}^{k} - z_{it}{}^{k}\Big) + \sum_{\tau=1}^{t} \eta_{i\tau} \geq 0, \qquad i=1,..,I, \; t=1,..,T \tag{20a}$$

$$\sum_{k=1}^{K} \mu_k \Big(b_j + \sum_{\tau=1}^{t} x_{j\tau}{}^{k} - z_{jt}{}^{k}\Big) + \sum_{\tau=1}^{t} \eta_{j\tau} \geq 0, \qquad j=1,..,J, \; t=1,..,T \tag{20b}$$

$$\sum_{k=1}^{K} \mu_k = 1 \tag{21}$$

$$\mu, \eta \geq 0$$

where

$h^k = CC(x^k) + OC(z^k) = OC(z^k)$ since $x^k=0$.

Now, upon re-arranging (20a), it can be observed by noting (21) and that $x^k=0$ for all k, that (18) holds. Therefore, the solution given by (16a) and (17a) is also feasible to constraint (4a). An equivalent argument shows that (4b) holds.

It now remains to show that (16) and (17) are indeed optimal for CP. Toward this end, note that due to the convexity of the objective function of CP,

$$CC(x^o) + OC(z^o) = CC(\eta) + OC\Big(\sum_{k=1}^{K} \mu_k z^k\Big)$$

$$\leq CC(\eta) + \sum_{k=1}^{K} \mu_k OC(z^k)$$

$$= \sum_{t=1}^{T} \sum_{i=1}^{I} c_{it}\eta_{it} + \sum_{t=1}^{T} \sum_{j=1}^{J} c_{jt}\eta_{jt} + \sum_{k=1}^{K} \mu_k h$$

$$= \text{final MP objective value}$$

$$\leq \text{final RSP objective value} + \varepsilon.$$

$$= (\text{lower bound on CP}) + \varepsilon$$

Hence, (x^o,z^o) as given by (16) and (17) is ε-optimal to Problem CP, and this completes the proof.

4.1.7 Expedient for Solving the Master Program

For convenience, the Master Program MP along with the constraints of type (15) is re-stated below.

MP:

max σ

s.t. $\sigma \leq CC(x^k) + OC(z^k) + u^t(z^k - Bx^k - b)$, $k=1,..,K$ (11)

$$\sum_{\tau=t}^{T} u_{i\tau} \leq c_{it}, \quad i=1,..,I, \quad t=1,..,T \tag{15a}$$

$$\sum_{\tau=t}^{T} u_{j\tau} \leq c_{jt}, \quad j=1,..,J, \quad t=1,..,T \tag{15b}$$

$u \geq 0$, σ unrestricted

Obviously, this program displays a certain special structure, in that each of the constraints (15) only includes u-variables pertaining to one equipment type. Moreover, as will be shown later, this constraint set has an embedded network structure. One can take advantage of this special structure by decomposing MP into a master program which only includes constraints (11) (in addition to a convexity constraint), and a subproblem which only includes constraints (15). However, one also has to keep in mind that in each iteration of Algorithm ALD, a new constraint of type (11) is added to MP. For this reason, it is more convenient and efficient to apply Benders' Method on the dual of MP. Alternatively, the Dantzig-Wolfe Decomposition technique (see BAZARAA and Jarvis, 1977) may be applied directly on MP, leading to precisely the same subproblem as the Benders approach, with the two master programs simply being duals of each other.

4.1.7.1 A Benders Decomposition of MP

First, consider the application of Benders' Decomposition on DMP, the dual to MP. For convenience, DMP is re-stated below:

DMP

$$\min \sum_{k=1}^{K} \mu_k h^k + \sum_{t=1}^{T}\sum_{i=1}^{I} c_{it}\eta_{it} + \sum_{t=1}^{T}\sum_{j=1}^{J} c_{jt}\eta_{jt}$$

$$\text{s.t.} \quad \sum_{k=1}^{K} \mu_k (b+Bx^k-z^k) + B\eta \geq 0 \tag{20}$$

$$\sum_{k=1}^{K} \mu_k = 1 \tag{21}$$

$$\mu, \eta \geq 0$$

Applying Benders' Decomposition on this program yields:

MPMP:

$$\min \vartheta$$

$$\text{s.t. } \vartheta \geq \sum_{k=1}^{K} \mu_k h^k - (u^{+\ell})^t \sum_{k=1}^{K} \mu_k (b+Bx^k-z^k), \quad \ell=1,..,L \quad \text{--} w_\ell$$

$$\sum_{k=1}^{K} \mu_k = 1 \qquad \text{--} \sigma$$

$$\mu \geq 0 \text{ , } \vartheta \text{ unrestricted}$$

<u>SPMP</u>:

$$\min (u^+)^t \sum_{k=1}^{K} \mu_k^\ell (b+Bx^k-z^k)$$

$$\text{s.t. } \sum_{\tau=t}^{T} u^+_{i\tau} \leq c_{it}, \; i=1,..,I, \; t=1,..,T \quad (15a)$$

$$\sum_{\tau=t}^{T} u^+_{j\tau} \leq c_{jt}, \; j=1,..,J, \; t=1,..,T \quad (15b)$$

$$u^+ \geq 0$$

where

u^+ = vector of dual multipliers on (20) with μ-vector fixed

$\ell=1,..,L$ = index of trial solutions generated during Benders' iterations

w_ℓ = dual multiplier on MPMP constraints

Observe that both MPMP and SPMP are linear programs. MPMP can be solved with the Simplex Method. When a new MP-row is added in each iteration of ALD, this has the effect of an added variable in MPMP, which may be readily accomodated.

The linear program SPMP is separable in equipment types, yields a bounded optimum for any fixed $\mu_k^{\ell} \geq 0$ satisfying (21), and furthermore, displays a special network structure as alluded to above. The following section shows how to exploit this structure. But before that, let us investigate how to calculate the optimal u-variable values from the u^+-variable values.

4.1.7.2 Calculation of u-Variables from Benders Decomposition of DMP

First, one can note that the u^+-solution of SPMP yields the dual multipliers on constraints (20) with the μ-vector fixed (in MPMP), while the u-solution to be used in the Lagrangian Dual iterations are the dual multipliers on (20) without μ fixed. This observation leads to the following formulas for calculating u from u^+, which are shown below to be optimal in MP.

$$u_{it} = \sum_{\ell=1}^{L} w_\ell u^{+}{}_{it}^{\ell}, \quad i=1,..,I, \quad t=1,..,T \qquad (22a)$$

$$u_{jt} = \sum_{\ell=1}^{L} w_\ell u^{+}{}_{jt}^{\ell}, \quad j=1,..,J, \quad t=1,..,T \qquad (22b)$$

where w_ℓ are the optimal dual variables obtained via the final MPMP.

<u>Lemma 1</u>

Given that u^+ is optimal after the Benders' MPMP-SPMP iterations, u as given in (22) is optimal in MP.

Proof:

First note that the Benders' Decomposition Algorithm only terminates when the objective values of SPMP and MPMP are equal, which implies that this common objective value is also the optimal objective value of MP, i.e. $\sigma = \vartheta$. Thus, if u as given by (22) along with this optimal value of σ can be shown to be feasible to MP, then this u must be optimal in MP.

Now, observe by the feasibility of each u^+ in SPMP and by the linearity of constraints (15), that u is feasible to constraints (15) of MP.

Next, consider the dual to MPMP:

DMPMP

max σ

$$\text{s.t. } \sigma \le \sum_{\ell=1}^{L} h^k w_\ell - \sum_{\ell=1}^{L} (u^{+\ell})^t (b - Bx^k - z^k) w_\ell \quad k=1,..,K \qquad (23)$$

$$\sum_{\ell=1}^{L} w_\ell = 1 \qquad (24)$$

σ unrestricted, $w \ge 0$

Note that due to (24),

$$\sum_{\ell=1}^{L} h^k w_\ell = h^k,$$

and by substituting (22), one can rewrite (23) as follows:

$\sigma \leq h^k - u^t(b+Bx^k-z^k)$, $k=1,..,K$.

Observe that this is identical to Constraint (11) with $CC(x^k)+OC(z^k)$ substituted for by h^k. Thus it has been shown that u as defined by (22) is feasible to Constraints (11) and (15) in MP, which completes the proof.

4.1.7.3 Solution of the Subproblem SPMP

As observed earlier, the Problem SPMP separates into (I+J) linear programs. Each of these (I+J) separable parts of SPMP possesses an embedded network structure. This is illustrated in an example below for one such part. Let, e.g., the planning horizon consist of 4 years, i.e. T=4. Then, by dropping the index i or j, one separable part of SPMP takes the following form:

$$\min \alpha_1 u_1 + \alpha_2 u_2 + \alpha_3 u_3 + \alpha_4 u_4 \qquad (25)$$

$$\begin{aligned} \text{s.t. } u_1 + u_2 + u_3 + u_4 &\leq c_1 \qquad (26a)\\ u_2 + u_3 + u_4 &\leq c_2 \qquad (26b)\\ u_3 + u_4 &\leq c_3 \qquad (26c)\\ u_4 &\leq c_4 \qquad (26d)\\ u &\geq 0 \end{aligned}$$

where the SPMP objective function coefficients α_t are given by

$$\alpha_t = \sum_{k=1}^{K} \mu_k (b_i + \sum_{\tau=1}^{t} x_{i\tau}^{k} - z_{it}), \quad t=1,..,4.$$

It can be noted that SPMP diplays a hidden network structure, which becomes apparent through the following row operations. Add slack variables $s_1,..,s_4$, and then subtract (26b) from (26a), (26c) from (26b), (26d) from (26c), and (26a) from (26d). This gives the following program:

$$\begin{aligned}
\min\ & \alpha_1 u_1 + \alpha_2 u_2 + \alpha_3 u_3 + \alpha_4 u_4 \\
\text{s.t. } & u_1 + s_1 - s_2 = c_1 - c_2 \\
& u_2 + s_2 - s_3 = c_2 - c_3 \\
& u_3 + s_3 - s_4 = c_3 - c_4 \\
& -u_1 - u_2 - u_3 + s_4 - s_1 = c_4 - c_1 \\
& u, s \geq 0
\end{aligned}$$

The network corresponding to this program is displayed in Figure 11. Thus, the above program can be solved with the Network Simplex Method, as for instance described in BAZARAA and Jarvis, 1977.

However, a closer examination of Program (25), (26) leads to an even more efficient solution algorithm. Consider the following lemma:

<u>Lemma 2</u>

Let P_1 denote Program (25), (26), in general form, viz

$$P_1: \min \{ \sum_{t=1}^{T} \alpha_t u_t : \sum_{\tau=t}^{T} u_\tau \leq c_t,\ t=1,..,T,\ u \geq 0 \},$$

and define

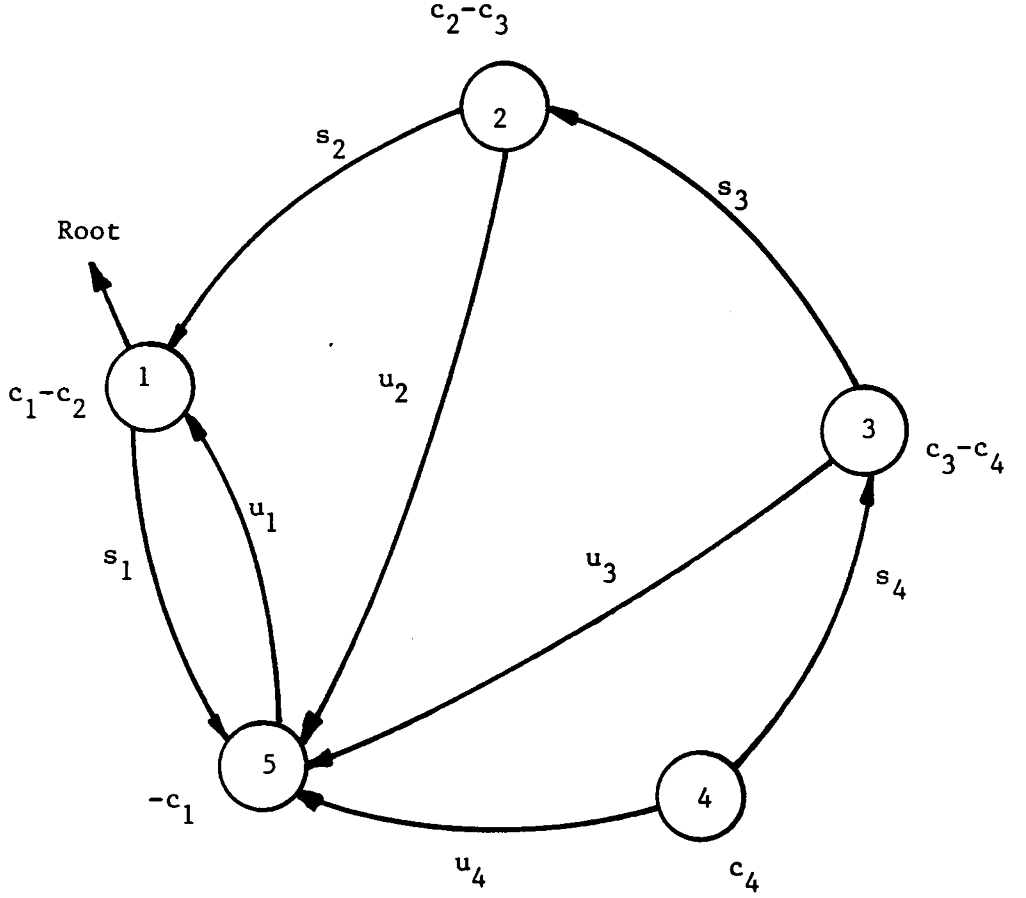


Figure 11: A Network Interpretation of SPMP

$$P_2: \min \{ \sum_{t=2}^{T} \alpha_t^{+} u_t : \sum_{\tau=t}^{T} u_\tau \le c_t^{+},\ t=2,..,T,\ u\ge 0\}$$

where

$\alpha_t^{+} = (\alpha_t - \alpha_1)$ if $\alpha_1 < 0$

$\alpha_t^{+} = \alpha_t$ if $\alpha_1 \ge 0$

$c_t^{+} = \min(c_2, c_1)$ for $t=2$

$c_t^{+} = c_t$ for $t=3,..,T$

Suppose u_t', $t=2,..,T$, solves P_2. Then an optimal solution to P_1 is given by u^{+}, where

$u_1^{+} = 0$ if $\alpha_1 \ge 0$

$u_1^{+} = c_1 - \sum_{t=2}^{T} u_t'$ if $\alpha_1 < 0$

$u_t^{+} = u_t'$, $t=2,..,T$

<u>Proof</u>:

First, note that the right hand sides c are all non-negative, since they represent capital costs. Then, note that u_1 only appears in one constraint, i.e. in our example in (26a). Two cases have to be examined to determine the optimal value of u_1.

Case 1: $\alpha_1 \ge 0$. Since u_1 only appears in (26a), and since the right hand side of the $\le$-constraint (26a) is non-negative, $u_1=0$ is optimal in this case. Furthermore, this means that the first two constraints can be replaced by one single constraint,

$$\sum_{\tau=2}^{T} u_\tau \leq \min(c_1, c_2) \qquad (27)$$

Case 2: $\alpha_1 < 0$. In this case, at optimality, we must have from (26a) that

$$u_1^+ = c_1 - \sum_{\tau=2}^{T} u_\tau^+ \geq 0. \qquad (28)$$

This implies that

$$\sum_{\tau=2}^{T} u_\tau \leq c_1$$

can be imposed, which, together with (26b), equivalently yields Constraint (27). Thus, (26a) and (26b) can be replaced by (27). Finally, by substituting (28), the objective becomes

$$\min \alpha_1 c_1 + \sum_{t=2}^{T} (\alpha_t - \alpha_1) u_t,$$

which means that as in Case 1, the problem has been reduced to Program P2 with an identical structure, but in one less variable.

This completes the proof.

Hence, one can design the following algorithm yielding a closed-form solution to every separable part of SPMP, by using Lemma 2 inductively. This algorithm is justified after its statement.

<u>Algorithm ASPMP for SPMP</u>

(This is applicable to each of the (I+J) separable portions of Program SPMP).

Step 1: Compute $c_t^+ = \min(c_1, c_2, .., c_t)$ for $t=2,..,T$.

Step 2: Construct a list $L=(0,1,2,..,T)$ and consider the ordered set of numbers $(0,\alpha_1,..,\alpha_T)$. Progressing from left to right, starting with α_1, strike out the elements not maintaining this list in strictly decreasing order. Accordingly, strike out the corresponding index from L.

Step 3: If T is not in L, then $u_T^+=0$. Otherwise, set $u_T^+=c_T^+$. Furthermore, set $u_t^+=0$ for all t not in L. Now, progressing recursively with decreasing index values, set

$$u_t^+ = c_t^+ - \sum_{\tau=t+1}^{T} u_\tau^+, \text{ for each } t \in L. \quad (29)$$

<u>Theorem</u> <u>4</u>:

Algorithm ASPMP yields an optimal solution to every separable part of SPMP.

<u>Proof</u>:

As seen by applying Lemma 2 recursively, starting with variable u_1, each u_t with t not in L at Step 3 can be set equal to zero. Furthermore, by applying Lemma 2 recursively until a one-constraint program results, it follows that one can set $u_T^+ = c_T^+$ if $T \varepsilon L$ and set it equal to zero otherwise. Now, since for each $t \varepsilon L$, the constraint

$$\sum_{\tau=t}^{T} u_\tau \le c_t^+$$

should be binding as in Case 2 of the recursively reduced program in which $u_1, .., u_{t-1}$ have been eliminated, it follows that u_t^+ may be determined as in (29). This completes the proof.

4.1.7.4 The Dual Solution to SPMP

It should be noted that Algorithm ASPMP only provides a primal solution to SPMP, which is all that is needed for the normal iterative process. For the determination of the final optimal solution as given in Section 4.2.5, however, the dual variables associated with the constraints of type (15) are needed. The dual of SPMP takes the following form:

Dual of SPMP (DSPMP)

$$\min \sum_{t=1}^{T} c_t \eta_t$$

$$\text{s.t.} \quad \sum_{\tau=1}^{t} \eta_\tau \ge -\alpha_t, \quad t=1,..,T$$

$$\eta_t \ge 0, \quad t=1,..,T$$

where η_t denotes the (negative) dual variable associated with the t^{th} constraint of type (15). Observe that the structure of DSPMP is similar to the one of SPMP itself, and hence, a similar one-pass solution algorithm may be developed as below.

Algorithm for DSPMP (ADSPMP)

Step 1: Construct a list L2=(1,2,..,T) and consider the ordered set of numbers $(c_1,..,c_T)$. Progressing from left to right, starting with c_2, strike out the elements not maintaining this list in strictly decreasing order. Accordingly, strike out the corresponding index from L2.

Step 2: Replace α_t by $\alpha_t^+ = \min(0,\alpha_1,..,\alpha_t,..,\alpha_{\tau-1})$ for each t=1,..,T, where τ denotes the first index in L2 greater than t.

Step 3: Set $\eta_1=-\alpha_1^+$. Set $\eta_t=0$ for all t not in L2. Progressing with increasing index values $t\geq 2$, set, for all t in L2,

$$\eta_t = \alpha_t^+ - \sum_{\tau=1}^{t-1} \eta_\tau$$

Lemma 3

Algorithm ADSPMP provides an optimal solution to DSPMP.

Proof:

First, note that for any t not in L2, an optimal solution with $\eta_t=0$ exists. This can be shown by contradiction: Assume that in some solution η, we have t not in L2 with $\eta_t>0$. Find the largest index $k<t$ such that $k\varepsilon L2$. Observe that $c_k \le c_t$. Since η_k appears in all constraints that η_t appears in, the solution η' with $\eta'_t=0$, $\eta'_k=\eta_k+\eta_t$ and $\eta'_j=\eta_j$ otherwise is feasible with $c\eta'-c\eta = \eta_t(c_k-c_t) \le 0$.

Thus, all η_t with t not in L2 can be discarded from the problem. Now, by feasibility, we must have $\eta_1 \ge -\alpha_1^+$. If $\eta_1 > -\alpha_1^+$ in any feasible solution to the resulting problem, then letting $r\varepsilon L2$ be the next index appearing in L2 after 1, as above, a feasible solution η' may be constructed as follows. Put $\eta'_1=-\alpha_1^+$, $\eta'_r=\eta_r+(\eta_1+\alpha_1^+)$, $\eta'_j=\eta_j$ for $j\varepsilon L2$, $j>1$. Since $c_r<c_1$, it follows that $c\eta'<c\eta$. Hence, this implies that $\eta_1=-\alpha_1^+$ at optimality. Eliminating η_1 from the problem, results in a problem of the same structure with η_r above playing the role of η_1. Repeating this inductively, we obtain the solution in Step 3 of ADSPMP, and the proof is complete.

4.1.7.5 A Dantzig-Wolfe Decomposition of MP

Alternatively to the Benders Decomposition of MP described in Section 4.1.7.1, a Dantzig-Wolfe Decomposition (see

BAZARAA and Jarvis, 1977) can be applied to MP. Since the Benders and the Dantzig-Wolfe Decomposition are exact duals of each other, the Dantzig-Wolfe master program is the dual of MPMP, while its subproblem is SPMP exactly. Therefore, only the Dantzig-Wolfe master program MPMPDW is stated below:

<u>MPMPDW</u>

max σ

$$\text{s.t. } \sigma \le CC(x^k) + OC(z^k) + \sum_{\ell=1}^{L} w_\ell (u^{+\ell})^t (z^k - Bx^k - b), \quad k=1,..,K \qquad (31)$$

$$\sum_{\ell=1}^{L} w_\ell = 1 \qquad (32)$$

$$w \ge 0$$

Note that (31) is the dual constraint associated with μ_k in MPMP, while (32) is the constraint associated with ϑ in MPMP.

The MP-solution of the u-variables is obtained from the SPMP-solutions in the u^+-variables in the way stated in (22), and the MPMPDW-SPMP iterations of the Dantzig-Wolfe Decomposition terminate when the SPMP objective value is greater than or equal to $-\vartheta'-\varepsilon$, where ϑ' is the dual variable associated with (32) and ε is a suitable tolerance. Note that this termination criterion is equivalent to the termination criterion for the Benders Decomposition, namely that the SPMP objective value minus the sum over k of $\mu_k h^k$ be greater than or equal to the negative MPMP objective value ($-\vartheta$) minus a tolerance. This follows since from (31), (32) and the optimal value ϑ of MPMP, we have

$$\vartheta' + \sum_{k=1}^{K} \mu_k h^k = \vartheta$$

The comparative computational performance of the two decomposition approaches for MP will be investigated in Chapter 7. The fact that the number of constraints of MPMP is related to the number of variables in MPMPDW and vice versa, will have an effect on this relative performance.

This completes the development of the Lagrangian Dual decomposition algorithm for solving Problem CP. The results of the application of this algorithm on the Mexicali data and computational experience are given in subsequent chapters. But first, some alternative approaches for solving Problem CP are described.

4.2 A GENERALIZED BENDERS DECOMPOSITION

Recall the formulation of Problem CP as given in Chapter 3:

CP

min $CC(x) + OC(z)$

s.t. $Az \geq P$ (3)

$z - Bx \leq b$ (4)

$z_{jt} \leq UBS_{jt}$, $j=1,..J$, $t=1,..,T$ (5)

$x, z \geq 0$

The Generalized Benders Decomposition approach (developed by GEOFFRION, 1972, and applied in a similar way as in BLOOM, 1983, for a probabilistic problem) proceeds to separate the variables that occur only linearly in the problem, from all other variables. In the above program, the x-variables occur linearly and are separated from the z-variables in the following manner:

$$\min_{x \geq 0} \; CC(x) + \begin{bmatrix} \min OC(z) & \\ \text{s.t. } Az \geq P & \\ \quad -z \geq -b - Bx & \\ \quad z_j \leq UBS_j & \\ \quad z \geq 0 & \end{bmatrix}$$

where $z_j \leq UBS_j$ represents Constraints (5).

Replacing the inner optimization problem over the z-variables by its Lagrangian Dual, one obtains

$$\min_{x \geq 0} \; CC(x) + \left[\max_{u \geq 0} \vartheta(u, x)\right],$$

where u is the vector of dual variables associated with the constraints $-z \geq -b-Bx$, and

$$\vartheta(u,x) = \min OC(z) + u^t(-b-Bx+z)$$
$$\text{s.t. } Az \geq P$$
$$z_j \leq UBS_j$$
$$z \geq 0,$$

or, $\vartheta(u,x) = -u^t(b+Bx) + \begin{bmatrix} \min OC(z) + u^t z \\ \text{s.t. } Az \geq P \\ z_j \leq UBS_j \\ z \geq 0 \end{bmatrix}$

Thus, one obtains the following decomposition into a master program and a subproblem:

<u>Generalized Benders Master Program GBMP</u>

$\min \sigma$

s.t. $\sigma \geq CC(x)+OC(z^k) + (u^k)^t z^k - (u^k)^t(b+Bx)$, $k=1,..,K$ (33)

$x \geq 0$

<u>Generalized Benders Subproblem GBSP</u>

$\min OC(z)$

s.t. $Az \geq P$ (3)

$z_j \leq UBS_j$ (5)

$z \leq b + Bx^k$ -- $(-u)$ (34)

$z \geq 0$

where $k=1,..,K$ = index of trial solutions.

Note that GBSP represents an operating subproblem as in Section 2.3.5, but in a deterministic formulation. As long as it is feasible, it can be solved in one pass by applying merit-order loading.

A possible way to ensure feasibility of GBSP would be to impose additional constraints on the x-variables in GBMP. The constraints needed to ensure feasiblity of GBSP can be derived from (3), (4) and (5), which together imply that

$$P_{rt} \leq \sum_{i=1}^{I} z_{it} + \sum_{j=1}^{J} a_{rj} z_{jt}, \quad r=1,..,R, \ t=1,..,T$$

$$\leq \sum_{i=1}^{I} (b_i + \sum_{\tau=1}^{t} x_{i\tau}) + \sum_{j=1}^{J} a_{rj} [\min\{b_j + \sum_{\tau=1}^{t} x_{j\tau}, UBS_{jt}\}],$$
$$r=1,..,R, \ t=1,..,T \quad (35)$$

where the min is taken separately for each equipment type j.

However, (35) consists of (T*R) constraints, i.e. one for each subperiod in each year. Furthermore, in each subperiod r and each year t, all 2^J possible combinations for the min in the renewable equipment part have to be accounted for. Adding all these constraints to GBMP would increase its size and the computational effort required for its solution dramatically. Therefore, it may be advantageous to initially include in GBMP only those T constraints of (35) corresponding to the subperiod in each year which contain that year's overall peak load, using the b+Bx-part of the min in the renewable energy equipment portion of Constraint (35). Then, the remaining constraints of type (35) can be generated if and when needed, i.e. when GBSP is infeasible in a given year and subperiod. Including only T constraints (35) in GBMP initially, saves up to 50 percent in computation time, as will be shown in Chapter 7.

Thus, with the added constraints and with (33) re-arranged, the Master Program GBMP takes the following form:

<u>GBMP</u>

min σ

s.t. $\sigma \geq CC(x) + OC(z^k) + (u^k)^t B(x^k - x)$, $k=1,..,K$ (36)

$X'_{Irt} \geq P_{rt}$, $t=1,..,T, r=\rho$ or from infeasible GBSPs (35)

$x \geq 0$

where ρ = subperiod containing yearly peak load, and

$$X'_{Irt} = \sum_{i=1}^{I} (b_i + \sum_{\tau=1}^{t} x_{i\tau}) + \sum_{j=1}^{J} a_{rj}[\min\{b_j + \sum_{\tau=1}^{t} x_{j\tau}, UBS_{jt}\}].$$

Here, the yearly peak loads $P_{\rho t}$ are assumed to include a reserve margin, which is a common deterministic reliability planning tool as described in Section 2.3. The new form of (36) can be derived by noting that due to complementary slackness,

$(u^k)^t(-b-Bx^k) = -(u^k)^t z^k$, i.e. $(u^k)^t z^k - (u^k)^t b = (u^k)^t Bx^k$.

When few constraints of type (36) are present and with certain u^k-values for conventional equipments, Program GBMP can be unbounded. However, this can be prevented by assigning suitable large upper bounds on all conventional capacities.

The algorithm for the Generalized Benders Decomposition approach takes the following form:

<u>Generalized Benders Decomposition Algorithm GBDA</u>

Step 1: Incorporate T peak load constraints into GBMP.

Step 2: Find a starting solution with the heuristic displayed in Figure 10.

Step 3: Evaluate GBSP for the current solution. If the GBMP objective $\geq$ the GBSP objective - ε, stop. Otherwise, go to Step 4.

Step 4: Based on the subproblem evaluation, add a new constraint (36) or (35) to GBMP.[8] Solve GBMP to find a new trial solution and go to Step 3.

Thus, the Generalized Benders Decomposition Master Program can be interpreted to construct a convex envelope for the convex total cost function of Program CP. Each constraint of type (36) is a tangential approximation to the convex total cost function of CP. The accumulated tangential approximations in GBMP provide a lower bound on the optimal objective value, while in each iteration with a feasible GBSP, the GBSP objective value provides an upper bound. This justifies the stopping criterion in Step 3 of GBDA.

It can be noted that Algorithm GBDA converges finitely, since for convex programs, finite, ε-optimal convergence of the Generalized Benders Decomposition algorithm is proven in GEOFFRION, 1972.

To complete the description of the Generalized Benders Decomposition approach, it remains to show how to calculate the dual variables u. As dual variables associated with the GBSP constraints (34), i.e. the constraints that limit the available capacities, they represent the negative rate of

[8] If (5a) is used in CP instead of (5), constraints (36), (35) with only the Bx+b-part possible in the min, or violated constraints (5a) are added to GBMP.

change of the GBSP objective, i.e. the operating cost, with respect to the available capacities. Thus, the following formulas for u_{it}, $i=1,..,I$, $t=1,..,T$, and u_{jt}, $j=1,..,J$, $t=1,..,T$, can be derived from Expression (2):

$$-u_{it} = \sum_{r=1}^{R} \sum_{\iota=i}^{I} \lambda_r (g_{\iota\tau} - g_{\iota+1,\tau}) F_{rt}(X_{\iota r\tau}) \quad (37a)$$

$$-u_{jt} = \sum_{r=1}^{R} \sum_{\iota=0}^{I} \lambda_r (g_{\iota\tau} - g_{\iota+1,\tau}) F_{rt}(X_{\iota r\tau}) \quad (37b)$$

where X is as defined in Section 3.3.1, and undefined quantities are taken as zero.

Note that if for a given capacity solution which leads to a feasible GBSP, it turns out that (5) is binding and the corresponding constraint in (34) is non-binding, i.e.

$$UBS_{jt} < \sum_{\tau=1}^{t} x_{j\tau} + b_j,$$

then one selects $u_{jt}=0$ in generating the GBMP cut (36).

4.3 THE VMCON PACKAGE

4.3.1 Theoretical Background

The FORTRAN subroutine VMCON for solving general nonlinear programming problems, developed by CRANE et al, 1980, is based on a successive quadratic programming algorithm due to POWELL, 1978. At each iteration of that algorithm, a positive definite quadratic programming problem is solved and a one-dimensional minimization is performed. The quadratic programming problem comes about by approximating the Lagrangian function associated with the original nonlinear programming problem with a quadratic function, and by linearizing its constraints about the current solution estimate. If one lets f(.) denote the original objective function, δ denote the search direction resulting from the quadratic program, B denote an approximation to the Hessian of the Lagrangian function with respect to the primal variables, λ denote the Lagrange multipliers, superscripts denote iteration numbers, and $c_i(.)$ denote the equality constraints for $i=1,..,k$ and the inequality constraints for $i=k+1,..,m$ in the original problem, then the quadratic programming problem QPP takes the following form:

<u>QPP</u>

$$\min Q(\delta) = f(x^{j-1}) + \delta^T \nabla f(x^{j-1}) + (1/2)\delta^T B(x^{j-1},\lambda^{j-1})\delta$$

$$\text{s.t. } \nabla c_i^T(x^{j-1})\delta + c_i(x^{j-1}) = 0, \quad i=1,..,k$$

$$\nabla c_i^T(x^{j-1})\delta + c_i(x^{j-1}) \geq 0, \quad i=k+1,..,m$$

Then a line search is conducted along the direction δ^j resulting from the above program by minimizing the following penalty function in the single variable α:

<u>Line Search Problem LS</u>

$$\min f(x) + \sum_{i=1}^{k} \mu_i \text{abs}(c_i(x)) + \sum_{i=k+1}^{m} \mu_i \text{abs}(\min(0,c_i(x)))$$

where $x = x^{j-1} + \alpha\delta^j$ and $\mu_i \geq 0$.

Note that the latter two terms are penalty terms associated with the absolute constraint violations. The penalty weights are defined as

$\mu_i = abs(\lambda_i^{\,1})$ for the first iteration and

$\mu_i = max(abs(\lambda_i^{\,j}) \; , \; .5(\mu_i^{\,j-1} + abs(\lambda_i^{\,j})))$

for subsequent iterations. With the new solution x^j resulting from the line search, the Hessian estimate B is revised in the following manner, using the rank-two BFGS update formula:

$$B^{new} = B - \frac{B\xi\xi^T B}{\xi^T B\xi} + \frac{\gamma\gamma^T}{\xi^T\xi}$$

where $\xi = x^j - x^{j-1}$,

$$\gamma = \nabla_x L(x^j, \lambda^j) - \nabla_x L(x^{j-1}, \lambda^j).$$

Starting with an arbitrary starting solution x^1 and a Hessian estimate B equal to the identity matrix, the algorithm iterates through the quadratic programming problem and the line search until the convergence criterion

$$abs(\nabla f(x^{j-1})^T \delta^j) + \sum_{i=1}^{m} abs(\lambda_i^{\,j} c_i(x^{j-1})) < \varepsilon$$

is satisfied.

4.3.2 Solution of the Expansion Problem with VMCON

For convenience in using VMCON to solve the deterministic capacity expansion problem with renewable energy sources, the problem is defined as follows:

Capacity Planning Problem for VMCON (CPVMCON)

$$\min CC(x) + \sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{r=1}^{R} \int_{X_{i-1,r,t}}^{X_{irt}} \lambda_r g_{it} F_{rt}(y)dy \quad (38)$$

$$\text{s.t. } X_{Irt} \geq P_{rt}\ , \ r=1,..,R,\ t=1,..,T \quad (39)$$

$$Bx_j \leq UBS_j \quad (5a)$$

$$x \geq 0 \quad (40)$$

where a_i = 1 - forced outage rate of equipment i, and all other variables as defined above.

It can be noted that as alluded to in Chapter 3, the above formulation uses only x-variables. This is feasible since all costs, constraints and derivatives can be calculated in terms of the x-variables, too, even though the formulas are more complicated than when z-variables are used.

In order to solve CPVMCON with VMCON, the derivatives of (38) and (39) with respect to all variables have to be determined. (The derivatives of (5a) and (40) are obtained trivially.) Let the acronyms TC and PK_{rt} respectively denote total cost and the left hand side of Constraint (39) for subperiod r in year t. Then,

$$\frac{\delta PK_{rt}}{\delta x_{it}} = a_i,\ t=1,..,T,\ r=1,..,R,\ i=1,..,I$$

$$\frac{\delta PK_{rt}}{\delta x_{jt}} = a_{rj}, \quad t=1,..,T, \quad r=1,..,R, \quad j=1,..,J$$

$$\frac{\delta TC}{\delta x_{it}} = c_{it} + \sum_{\tau=t}^{T} \frac{\delta OC_{\tau}}{\delta x_{i\tau}}$$

$$\frac{\delta TC}{\delta x_{jt}} = c_{jt} + \sum_{\tau=t}^{T} \frac{\delta OC_{\tau}}{\delta x_{j\tau}}$$

$$\frac{\delta OC_{\tau}}{\delta x_{i\tau}} = \sum_{r=1}^{R} \sum_{\iota=i}^{I} \delta_{r}(g_{\iota\tau}-g_{\iota+1,\tau})F_{rt}(X_{\iota r\tau})$$

$$\frac{\delta OC_{\tau}}{\delta x_{j\tau}} = \sum_{r=1}^{R} \sum_{\iota=0}^{I} \delta_{r}(g_{\iota\tau}-g_{\iota+1,\tau})F_{rt}(X_{\iota r\tau})$$

where undefined quantities are taken as zero.

The algorithm for applying VMCON to the electric utility capacity expansion problem can be stated as follows:

Step 1: Find a starting solution with the heuristic displayed in Figure 10.

Step 2: Solve Problem CPVMCON with the package VMCON, i.e. by repeatedly solving QPP and LS. Stop when the convergence criterion is satisfied.

This completes the description of the package VMCON and its application on the electric utility capacity expansion problem. It also completes the description of the alternative approaches for solving the deterministic first-phase problem. The following chapters address the probabilistic second-phase problem as well as some integrality issues.

Chapter V

ALGORITHMS FOR THE PROBABILISTIC SECOND PHASE

5.1 INTRODUCTION

Having found an optimal solution to Problem CP, i.e. the deterministic optimum, the two-phase algorithm enters the probabilistic phase. Here, the deterministic solution is to be perturbed toward the probabilistic optimum. As will be shown in Chapter 7, using a deterministic phase before entering the probabilistic algorithm can save up to 85 percent of computation time, as compared to a purely probabilistic algorithm. This can be attributed to the fact that in most cases, the deterministic optimum lies very close to the probabilistic one.

Before several possible solution approaches for the probabilistic Problem PP are outlined in the following sections, first recall the formulation of Problem PP as given in Chapter 3:

<u>Probabilistic Program PP</u>

$$\min CC(x) + \sum_{t=1}^{T} EG_t \qquad (7)$$

$$\text{s.t. } UE_t \le e \quad , \ t=1,..,T \qquad (8)$$

$$z - Bx \le b \qquad (4)$$

$$z_j \le UBS_j \qquad (5)$$

$$x,z \ge 0$$

where

EG_t = probabilistic production cost in year t

UE_t = loss-of-energy probability in year t

For future reference, OC(z) may again be used to represent the total operating cost, which here consists of the EG-terms.

5.2 SOLUTION APPROACHES FOR THE PROBABILISTIC PROBLEM

Three possible solution approaches for Problem PP will be outlined in this section. These three approaches include successive linear programming, a feasible directions algorithm, and Generalized Benders Decomposition. The investigation of the former two approaches can be motivated by noting that in most cases, the deterministic optimum lies very close to the probabilistic optimum. Therefore, an approach in which a current solution is perturbed slightly in an improving feasible direction could be preferable, i.e. could require less time-consuming probabilistic iterations, than a decomposition approach. Such a case could arise in a situation as depicted in Figure 12, where a decomposition algorithm's master program moves far away from a near-optimal point, only to slowly re-approach the optimum in later iterations.

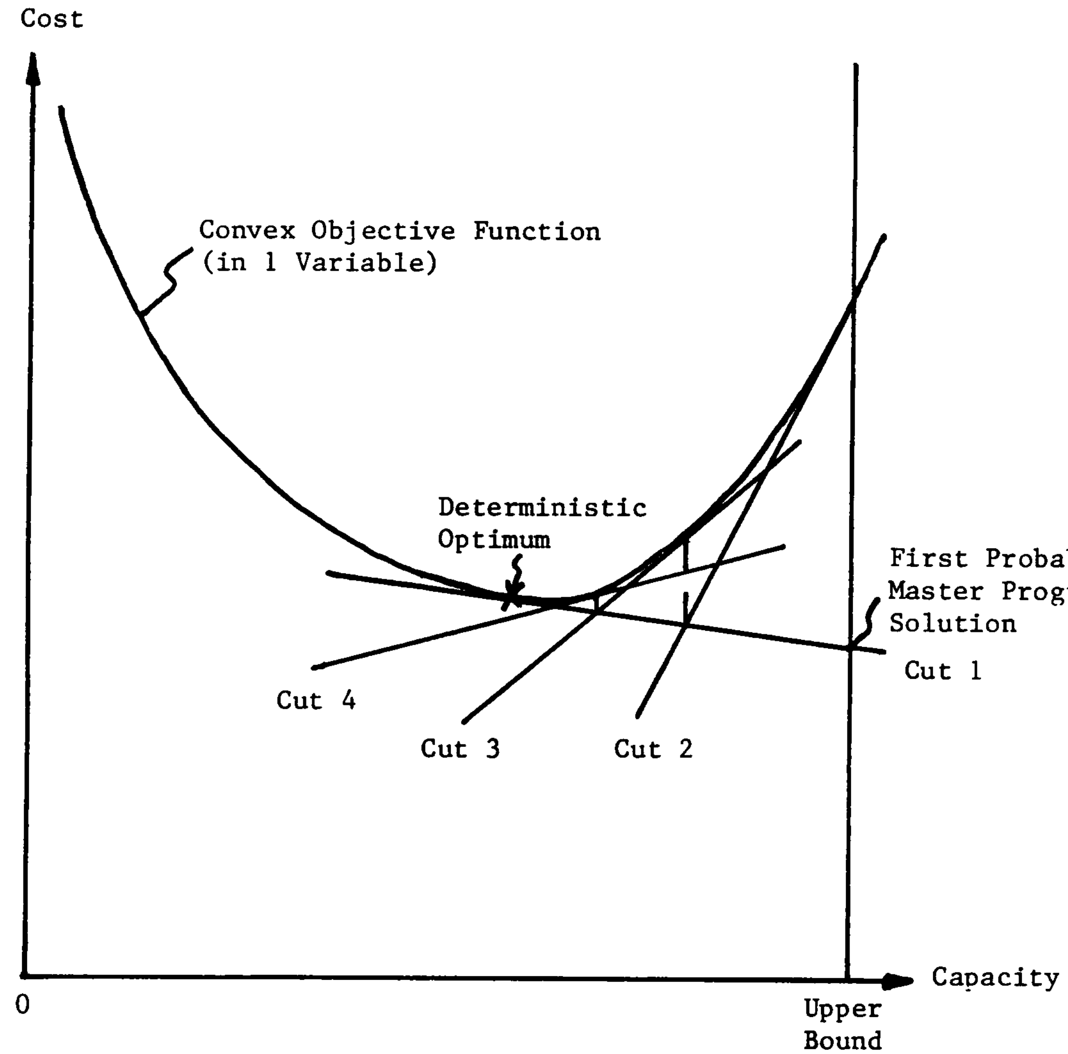


Figure 12: Example of Poor Performance of a Decomposition Algorithm

However, the need to perform a line search along the feasible direction in order to find an improved solution, can quickly offset that possible advantage of a direction-based algorithm. Thus, because of its greater reliability, a Generalized Benders Decomposition algorithm is chosen for implementation, and is described in Section 5.2.3. The other two possible approaches are described in the following sections.

5.2.1 A Successive Linear Programming Approach

Given a current point (z_k, x_k), the linear program used for a successive linear programming approach takes the following form (see PALACIOS-GOMEZ et al, 1982):

$LP(z_k, s_k)$:

$$\min CC(x) + \nabla OC(z_k)^t d$$

$$\begin{aligned} \text{s.t. } & \nabla UE_t(z_k)^t d \le e - UE(z_k) \\ & d - Bx \le b - z_k \\ & \max(-z_k, -s_k) \le d \le s_k \\ & \max(-(z_k)_j, -(s_k)_j) \le d_j \le \min(UBS_j, (s_k)_j) \\ & x \ge 0 \end{aligned}$$

The following successive linear programming algorithm is quoted from PALACIOS-GOMEZ et al, 1982:

1) Solve $LP(z_k, s_k)$, yielding a solution $(d_k, x_{k\ new})$.
2) If $\|d_k\|_\infty < \varepsilon_2$, stop.
3) If $(z_k + d_k, x_{k\ new})$ is ε_f-feasible, phase = 2.

4) If $LP(z_k, s_k)$ is infeasible, go to 6.

5) If phase=2, go to 8.

6) If $sinf(z_k+d_k, x_{k\ new}) < sinf(z_k, x_k)$, then

   a) set $z_{k+1} = z_k+d_k$, $x_{k+1} = x_{k\ new}$,

   b) (possibly) increase some step bounds obtaining s_{k+1},

   c) k=k+1 and go to 1.

7) If $\|s_k\|_\infty < \varepsilon_2$, stop. Else, set $z_{k+1}=z_k$, $x_{k+1}=x_k$, $s_{k+1}=r*s_k$, k=k+1 and go to 1.

8) If $comp(z_k+d_k, x_{k\ new}) \geq comp(z_k, x_k)$, go to 7. Else set $z_{k+1}=z_k+d_k$, $x_{k+1}=x_{k\ new}$ and (possibly) increase some step bounds obtaining s_{k+1}.

9) If the change in the objective value is small enough, stop. Else k=k+1 and go to 1.

where

ε_f = feasibility tolerance

$\varepsilon_{1,2}$ = stopping tolerances

s = step bounds

r = step bound reduction factor

sinf(x,z) = the sum of infeasibilities function, and

comp(x,z) = the composite objective function

= CC(x) + OC(z) + βsinf(x,z),

β = a positive scalar,

as defined in PALACIOS-GOMEZ et al, 1982.

It can be noted that although explicitly, no line search along the direction d is performed in the above algorithm, Steps 7 and 8 in effect perform an inexact line search (see ARMIJO, 1966) until an improved solution is found. Thus, in most cases, some five to ten probabilistic evaluations of unserved energy and production costing would have to be conducted before an improved solution is found (according to the computational experience of the author). This together with the fact that with the presence of nonlinear constraints, theoretical convergence of the algorithm cannot be proven, leads us to prefer the Generalized Benders Decomposition approach described below for solving PP.

5.2.2 A Feasible Directions Approach

A feasible directions algorithm (BAZARAA and Shetty, 1979, TOPKIS and Veinot, 1967, ZOUTENDIJK, 1960) is an alternative choice for modifying the deterministic optimum in small perturbations towards the probabilistic optimum. Because its convergence to a Fritz-John Point can be proven, a Topkis-Veinot-type algorithm is investigated here. It consists of the following steps:

Initialization: Put $k=0$. If the deterministic solution (x_k, z_k) is feasible, continue with Step 1. Otherwise, increase the conventional capacity with the most negative or least positive current total cost derivative until feasibility is reached, call this solution (x_k, z_k), and proceed with Step 1.

Step 1: Solve the linear program

$$
\begin{aligned}
&\min \sigma \\
&\text{s.t. } \sigma \geq CC(d_x) + \nabla OC(z_k)^t d \qquad (41) \\
&\qquad \nabla UE_t(z_k)^t d \leq e - UE_t(z_k), \; t=1,..,T \\
&\qquad d - Bd_x \leq \sigma + b - z_k + Bx_k \\
&\qquad d_j \leq \sigma + UBS_j - (z_k)_j \\
&\qquad -d_x \leq \sigma + x_k \\
&\qquad -d \leq \sigma + z_k \\
&\qquad -s \leq d_x \leq s, \; -s \leq d \leq s
\end{aligned}
$$

where
s = step bounds
d_x = feasible directions for x-variables
d = feasible directions for z-variables

Step 2: If $\sigma=0$, the last solution is a Fritz-John-Point, stop. Otherwise, continue with Step 3.

Step 3: Search along the feasible direction (d, d_x) resulting from Step 1, to find an improved solution (z_{k+1}, x_{k+1}). Increment k by 1 and return to Step 1.

Here, an inexact line search as in ARMIJO, 1966, can be applied in Step 3. However, a difficult problem is what termination tolerance should be assigned to the optimality test in Step 2. Since σ appears not only in the objective function expression (41), but also in the other constraints, it is not a measure of the possible improvement in the objective value, and only $\sigma=0$ can indicate optimality. A termination tolerance could be imposed on the possible objective value improvement, based on the total cost gradient and the maximum possible variation in the decision variables. But apart from being quite a cumbersome approach, this would ignore all feasibility considerations.

The two problems of the relatively large number of probabilistic evaluations of unserved energy and production costing in the line search, and the problem of imposing an adequate termination tolerance, make this feasible directions approach a less desirable option than the decomposition approach to be described in the following section.

5.2.3 A Generalized Benders Decomposition Approach

Because of its reliability, a Generalized Benders Decomposition approach as developed in BLOOM, 1983, is chosen in our implementation for solving Problem PP. The key difference is that as opposed to initializing this algorithm from scratch, we have instead opted to use an advanced start deterministic solution to accelerate the overall convergence. The derivation of the master program and the subproblem of this decomposition has been given in Sections 2.3.5 and 4.2. Here, only the master program and the subproblem themselves are displayed for the probabilistic problem:

Probabilistic Generalized Benders Master Program PGBMP

$$\min \sigma$$

$$\text{s.t. } \sigma \geq CC(x) + \sum_{t=1}^{T} EG_t(z^k) + (u^k)^t B(x^k - x), \quad k=1,..,K_1 \quad (42)$$

$$\sum_{t\varepsilon\Gamma_{1k}} [UE_t{}^k + \mu_t{}^k B(x^k - x)] \leq \sum_{t\varepsilon\Gamma_{1k}} e_t, \quad k=1,..,K_2 \quad (43)$$

$$x \geq 0$$

<u>Probabilistic Generalized Benders Subproblem PGBSP</u>

$$\min EG_t(z), \quad t=1,..,T$$

$$\text{s.t. } UE_t(z) \leq e \quad (44)$$

$$z \leq b + Bx^k \quad (45)$$

$$z_j \leq UBS_j \quad (5)$$

$$z \geq 0$$

where $k=1,..,K_1$ = index of feasible trial solutions

$k=1,..,K_2$ = index of infeasible trail solutions

u = vector of dual multipliers associated with PGBSP Constraint (45)

= derivatives of operating cost EG with respect to capacities

μ = derivatives of unserved energy UE with respect to capacities

Γ_k = set of years for which (44) is not satisfied for trial solution k

Thus, in the linear Master Program, Constraints (42) form a convex envelope to the convex total cost function of Problem PP, while Constraints (43) bound PGBMP away from infeasible solutions.

As in Section 2.3.5, Problem PGBSP is an operating subproblem, and can be solved by the Balerieaux-Booth probabilistic production costing method with hour-by-hour simulation of the renewable energy contributions. Formulas for the derivatives of EG and UE with respect to conventional capacities are given in BLOOM, 1983:

$$\mu_{it} = H_{I+1,i,t}(Y_{It})$$

$$u_{it} = g_{it}p_i ELDC_{it}(Y_{it}) - g_{It}H_{I+1,i,t}(Y_{It}) + \sum_{k=i+1}^{I} g_{kt}p_k(H_{kit}(Y_{kt})-H_{kit}(Y_{k-1,t}))$$

$$H_{kit}(U) = \sum_{\ell=0}^{m} \left(\frac{-q_i}{p_i}\right)^{\ell} ELDC_{kt}(U-\ell z_{it})+p_i\left(\frac{-q_i}{p_i}\right)^{m+1},\ z_{it}>0$$

$$= p_i ELDC_{kt}(U),\ z_{it}=0$$ [9]

where m is an integer satisfying $mz_{jt} < U \leq (m+1)z_{jt}$

$ELDC_{it}$ = equivalent load duration curve faced by equipment i in year t

For renewable energy capacities, these derivatives can be determined by finite differences.[10] First, one finds the probabilistic total cost and the unserved energy for all years with the current renewable capacities z_j. Then, one increases these renewable capacities slightly, one at a time, and obtains cost and UE-values for each of the slightly changed capacities. The cost and UE differences between

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[9] Erroneously, BLOOM, 1983, gives $p_i ELDC_{it}(U)$ here.

[10] As in the deterministic model, μ_{jt} and u_{jt} are set to zero if (45) is non-binding and (5) is binding in PGBSP.

the original case and one renewable capacity being slightly increased, appropriately scaled, are approximations to the derivatives of cost and unserved energy with respect to that renewable capacity.

This concludes the theoretical development of the probabilistic phase algorithm using Generalized Benders Decomposition. However, before stating the algorithm explicitly, some issues concerning the interface of the deterministic with the probabilistic phase have to be addressed.

5.2.3.1 The Deterministic-Probabilistic Interface

It has been noted above that in most cases, the deterministic optimum lies very close to the probabilistic optimum. However, it was mentioned as a disadvantage of the Generalized Benders Decomposition approach that it can be expected to depart far from the near-optimal first-phase solution in its initial probabilistic iterations.

One possible way to avoid this is to bound the variation of all decision variables in PGBMP within a certain range close to the deterministic optimum. Given a certain percentage deviation PD (PD=0.5 works well in our computational experience), this is achieved by imposing the following restriction on the x-variables in PGBMP, for all $i=1,..,I$, $t=1,..,T$ and $j=1,..,J$, $t=1,..,T$:

$$x^*_{it}(1-PD) \le x_{it} \le x^*_{it}(1+PD) \qquad (46)$$

where x^* = deterministic optimal x-solution.

In many runs in our computational experience, reported on in Chapter 7, the deterministic solution is actually probabilistically optimal, too. Such a case is detected by PGBMP, if the resulting PGBMP objective value is greater than or equal to the probabilistic evaluation of the total cost of the deterministic optimum plus some termination tolerance ε. If this is not the case, the probabilistic algorithm PA stated below continues with its normal Master Program-Subproblem iterations with (46) included in PGBMP, until ε-optimality is reached. Then, a test is performed to find out if any of the Constraints (46) is binding at optimality. If that is the case, the binding constraints are relaxed, and further iterations are conducted until an optimum is found with (46) non-binding for all equipments.

Another issue of interest in examining the interface of the two phases is that many power companies, including the Mexican national utility, use both a reserve requirement, usually 20 percent, and an LOLP-goal for capacity planning, i.e. they mix deterministic with probabilistic reliability planning goals. Such an approach can be easily accomodated in the Generalized Benders Decomposition algorithm by initially including in PGBMP a deterministic peak load constraint, with the peak load modified to include the required reserve margin. These constraints have the exact same form as in (35) in Section 4.2.

Thus, the Master Program PGBMP takes the following complete form:

<u>PGBMP</u>

min σ

$$\text{s.t. } X_{I\rho t} \geq P_{\rho t}, \; t=1,..,T \tag{35}$$

$$\sigma \geq CC(x) + \sum_{t=1}^{T} EG_t(z^k) + (u^k)^t B(x^k - x) \quad k=1,..,K_1 \tag{42}$$

$$\sum_{t\varepsilon\Gamma_k} [UE_t^{\,k} + \mu_t^{\,k} B(x^k - x)] \leq \sum_{t\varepsilon\Gamma_k} e_t, \; k=1,..,K_2 \tag{43}$$

$$x^*(1-PD) \leq x \leq x^*(1+PD) \tag{46}$$

5.2.3.2 The Probabilistic Generalized Benders Decomposition Algorithm

<u>Probabilistic Algorithm PA</u>

Step 1) Incorporate Constraints (35) and (46) in PGBMP. Evaluate PGBSP for the deterministic optimum. If PGBSP is infeasible, go to Step 3. If PGBSP is feasible, add a constraint of type (42) to PGBMP and solve PGBMP. If the PGBMP objective value is within ε of the PGBSP objective value, stop. Otherwise, go to Step 2.

Step 2) Evaluate PGBSP for the current solution. If the PGBMP objective value < PGBSP objective value - ε, go to Step 3. Otherwise, determine if any of the

Constraints (46) in the last PGBMP are binding. If that is the case, relax the binding constraints and go to Step 3. Otherwise, stop.

Step 3) Based on the PGBSP evaluation, add a new constraint of type (42) if PGBSP is feasible, or of type (43)[11] if PGBSP is infeasible, to PGBMP. Solve PGBMP to obtain a new trial solution and go to Step 2.

For convex programs (recall that BLOOM, 1983, addresses convexity of Program PP), the Generalized Benders Decomposition algorithm converges finitely using the ε-termination criterion (see GEOFFRION, 1972). Computational experience with the algorithm is given in Chapter 7. This chapter also investigates the comparative performance of a pure probabilistic algorithm versus the two-phase algorithm developed in this dissertation.

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[11] If (5a) is used instead of (5) in PP, violated constraints of type (5a) may have to be added to PGBMP.

Chapter VI

THE MODEL WITH INTEGER VARIABLES

6.1 MOTIVATION

Even though the models and algorithms developed in the previous two chapters solve the electric utility capacity expansion problem, they neglect one very important constraint. The algorithms could for instance lead to an optimal capacity of 191.785 MW for a new nuclear power plant to be installed, while in the real world, nuclear plants may only be available in capacities of 600, 900 or 1200 MW. Utility managers, from CFE and other utilities, keep emphasizing that a prescribed optimal capacity of 191.785 MW is not very helpful in their decision-making process. They cannot tell whether it would be better to install the nuclear plant as soon as any positive nuclear capacity appears as part of the optimal expansion plan, or if they should wait until such time when the required nuclear capacities have accumulated to at least 600 MW. In the latter case, the question arises about what other plants to substitute in the meanwhile.

Thus it seems essential to impose a type of integrality or discrete capacity constraint on the conventional capacity decision variables. But such constraints are cumbersome and place an overwhelming burden on computational performance, which is the reason why most researchers in the field choose to ignore this integrality issue.

Because of its importance to CFE-planners, however, this issue had to be addressed in the Mexicali Project. Hence, a Branch and Bound approach was developed as described below (see SALKIN, 1975, for material on Branch and Bound as well as other integer programming approaches).

To begin with, the root node or node zero evaluation amounts to solving the capacity expansion problem without any bounds or integrality constraints on the conventional capacities. If the resulting solution happens to include only capacities available in the market, then it is optimal. (Let the available capacities be called integer capacities for convenience, although one would have feasible values of 600, 900 and 1200 only for nuclear plants, and similar discrete feasible availabilities for the other plant types.) Otherwise, one of the non-integer variables is restricted to be either less than or equal to the next lowest, or greater than or equal to the next highest feasible capacity. In this way two nodes branching from node 0 are formed, and both these node problems are solved with modified deterministic and probabilistic algorithms taking into account the added bound on a conventional capacity.

Each node's objective value provides a lower bound on the optimal integer objective value, since each node's problem is a relaxation of the integer problem. Each feasible integer solution found during the process provides an upper bound on the optimal integer objective value, and can be used to fathom nodes with non-integer, higher-objective value solutions. To more quickly obtain an upper bound, i.e. to increase the chance of fathoming non-optimal nodes early, it may be advantageous to construct a feasible integer solution from the continuous node 0 solution heuristically. This could be done by increasing all non-integer capacities to the nearest greater integer capacity. The branching and bounding, together with the fathoming of nodes based on their objective values, continues until all nodes are fathomed, yielding the incumbent solution as an optimal solution.

The following sections show how the deterministic and probabilistic algorithms can be modified so that they take into account upper and lower bounds on conventional capacities. Because the VMCON program proved orders of magnitude slower than either the Lagrangian Dual or the Generalized Benders Decomposition program for the continuous deterministic problem, it is not considered here for the solution of the integer problem.

It should be noted that only the conventional capacities need integer bounding, since for renewable energy and conservation equipment, availability in any desired size can be safely assumed. This can be seen clearly with solar cells, for instance, which can be installed in modules of any capacity. And although wind machines or home insulation would not be available in any size, the different available sizes are sufficiently small so that integrality does not play a very crucial role with those resources.

6.2 THE LAGRANGIAN DUAL APPROACH IN THE BRANCH AND BOUND ALGORITHM

At each node inside the Branch and Bound routine, a problem of the type CP has to be re-solved, with some added bounds on conventional capacities. But neither upper nor lower bounds can be easily incorporated into the Breakeven Analysis which forms the kernel of the Lagrangian Dual Subproblem. Thus, in order to preserve the basic Lagrangian Dual approach, it is necessary to dualize these bounding constraints in the same way as constraints (4) are dualized. This does not affect the structure of the Subproblem, and the structure of the Master Program also remains intact, except that dual variables associated with the bounding constraints get added.

In the following sections the various components of Algorithm ALD are modified to incorporate the added bounding constraints.

6.2.1 The Lagrangian Dual Program with Bounding Constraints

The bounding constraints are formulated in the following manner:

$$x_{it} \le UB_{it}, \quad i,t \in SUB \quad \text{--} \ \beta_{it} \quad (47)$$

$$-x_{it} \le -LB_{it}, \quad i,t \in SLB \quad \text{--} \ \gamma_{it} \quad (48)$$

where

SUB = set of variables with upper bounds

SLB = set of variables with lower bounds

β_{it} = dual variable associated with (47)

γ_{it} = dual variable associated with (48)

Of course, if some $(i,t) \in$ SUB and SLB with $LB_{it} > UB_{it}$, then the current node problem is infeasible and may be fathomed. Even if this is not the case, the problem may still be infeasible if the renewable energy contributions in some subperiod are all zero and the upper bounds on conventional capacities prevent a sufficient installation of conventional equipments. The heuristic shown in Figure 10 can be modified to test for such a case. If such a case is detected, the node can be fathomed. Otherwise, the problem is feasible and is readily seen to have an optimum.

It can be noted that Constraints (47) and (48) are linear. Therefore Program CP remains convex when they are added to it, and since Slater's constraint qualification continues to hold, theoretical convergence of the Lagrangian Dual algorithm with no duality gap is still guaranteed.

Dualizing Constraints (47) and (48) along with the Constraints (4), one obtains the following Lagrangian Dual program:

max $\vartheta(u,\beta,\gamma)$

where

$$\vartheta(u,\beta,\gamma) = \inf \{ CC(x) + OC(z) + u^t(z-Bx-b)$$

$$+ \sum_{i,t\varepsilon SUB} \beta_{it}(x_{it}-UB_{it}) + \sum_{i,t\varepsilon SLB} \gamma_{it}(LB_{it}-x_{it}) \quad (49)$$

$$\text{s.t. } Az \geq P$$

$$z_j \leq UBS_j$$

$$x,z \geq 0 \}$$

The Master Program MP retains the same form as given in (11), with (49) added as above in the tangential approximation cuts. The Re-arranged Subproblem RSP takes the following form:

<u>Re-arranged</u> <u>SP</u> (<u>RSP</u>)

$$\min \sum_{t=1}^{T}\sum_{i=1}^{I} x_{it}(c_{it}- \sum_{\tau=t}^{T} u_{i\tau}^{k} + \beta_{it}^{k} - \gamma_{it}^{k})$$

$$+ \sum_{t=1}^{T}\sum_{i=1}^{J} x_{jt}(c_{jt}- \sum_{\tau=t}^{T} u_{j\tau}^{k}) \quad (50a)$$

$$+ \sum_{t=1}^{T} \sum_{i=1}^{I} u_{it}^{k} z_{it} + \sum_{t=1}^{T} \sum_{j=1}^{J} u_{jt}^{k} z_{jt} \tag{50b}$$

$$- \sum_{t=1}^{T} \sum_{i=1}^{I} (u_{it}^{k} b_i - \beta_{it}^{k} UB_{it} + \gamma_{it}^{k} LB_{it}) - \sum_{t=1}^{T} \sum_{j=1}^{J} u_{jt}^{k} b_j \tag{50c}$$

$$+ \sum_{t=1}^{T} \sum_{i=1}^{I} g_{it} \int_{Y_{i-1,t}}^{Y_{it}} \{ \sum_{r=1}^{R} \lambda_r F_{rt}(y + \sum_{j=1}^{J} a_{rj} z_{jt})\} dy \tag{50d}$$

$$\text{s.t.} \quad \sum_{i=1}^{I} z_{it} \geq \max_{r} \, (P_{rt} - \sum_{j=1}^{J} a_{rj} z_{jt}), \; t=1,..,T \tag{3}$$

$$z_{jt} \leq UBS_{jt}, \; j=1,..,J, \; t=1,..,T \tag{5}$$

$$z, x \geq 0$$

where for notational convenience, UB_{it} for (i,t) not in SUB as well as LB_{it} for (i,t) not in SLB are taken as zeroes in (50c).

Note that RSP is still separable in t. Therefore, Algorithm ASP does not change, except that in Step 3, one checks whether

$$c_{it} - \sum_{\tau=t}^{T} u_{i\tau}^{k} + \beta_{it}^{k} - \gamma_{it}^{k} < 0, \tag{51}$$

where β_{it}^{k} and γ_{it}^{k} are taken as zeroes if (i,t) is not in SUB or SLB, respectively.

If (51) holds, Program RSP would be unbounded if no suitable artificial upper bounds were imposed on the x-variables. However, as in Section 4.1.4, implied constraints derived through a duality analysis and added to the Master Program can guarantee that (51) does not hold, and thus one can ensure feasibility of RSP. For the integer case and a given conventional equipment (i,t), these constraints take the following form:

$$\sum_{\tau=t}^{T} u_{i\tau} - \beta_{it} + \gamma_{it} \leq c_{it} \qquad (52)$$

(If (i,t) is not in SLB or not in SUB, the appropriate term has to be omitted from (52).) This constraint takes the place of Constraint (15) for conventional equipments within Algorithm ALD.

It has to be noted here that due to possibly negative coefficients of the β-variables in the Master Program in (49), this Master Program may be unbounded. This issue, together with its cause and its solution, will be addressed in a subsequent section.

6.2.2 Efficient Solution of the Master Program with Bounds

As in Section 4.1.7, Benders Decomposition as well as Dantzig-Wolfe Decomposition can be applied to solve the Master Program. Below, the application of Benders Decomposition is developed first.

Due to the addition of (49) and the new form of (52) in MP, MPMP and SPMP change their structure. In order to develop their new structure, consider first the dual DMP of MP:

DMP

$$\min \sum_{k=1}^{K} \mu_k h^k + \sum_{t=1}^{T} \sum_{i=1}^{I} c_{it}\eta_{it} + \sum_{t=1}^{T} \sum_{j=1}^{J} c_{jt}\eta_{jt}$$

$$\text{s.t.} \quad \sum_{k=1}^{K} \mu_k (b + Bx^k - z^k) + B\eta \geq 0$$

$$\sum_{k=1}^{K} \mu_k (UB_{it} - x_{it}^k) - \eta_{it} \geq 0 \;, \quad i,t \varepsilon SUB$$

$$\sum_{k=1}^{K} \mu_k (x_{it}^k - LB_{it}) + \eta_{it} \geq 0 \;, \quad i,t \varepsilon SLB$$

$$\sum_{k=1}^{K} \mu_k = 1$$

$$\mu \; \varepsilon \; \Phi \tag{53}$$

$$\mu, \eta \geq 0$$

Here, Constraint (53) is added to ensure feasibility of DMP, i.e. ensure boundedness of MP. The structure of the set Φ will be investigated below.

Applying Benders' Decomposition on DMP yields:

MPMP:

$$\min \vartheta$$

$$\text{s.t.} \quad \vartheta \geq \sum_{k=1}^{K} \mu_k h^k - (u^{+\ell})^t \sum_{k=1}^{K} \mu_k (b + Bx^k - z^k)$$

$$- \sum_{i,t \varepsilon SUB} \beta^{+}{}_{it}{}^{\ell} \sum_{k=1}^{K} \mu_k (UB_{it} - x_{it}^k)$$

$$- \sum_{i,t\varepsilon SLB} \gamma^{+}{}_{it}{}^{\ell} \sum_{k=1}^{K} \mu_k (x_{it}{}^{k} - LB_{it}), \; \ell=1,..,L \quad -- \; w_\ell$$

$$\mu \; \varepsilon \; \Phi$$

$$\sum_{k=1}^{K} \mu_k = 1 \qquad\qquad -- \; \sigma$$

$$\mu \geq 0 \; , \; \vartheta \text{ unrestricted}$$

<u>SPMP</u>:

$$\min \; (u^{+})^{t} \sum_{k=1}^{K} \mu_k{}^{\ell} (b + Bx^k - z^k)$$

$$+ \sum_{i,t\varepsilon SUB} \beta^{+}{}_{it} \sum_{k=1}^{K} \mu_k{}^{\ell} (UB_{it} - x_{it}{}^{k})$$

$$+ \sum_{i,t\varepsilon SLB} \gamma^{+}{}_{it} \sum_{k=1}^{K} \mu_k{}^{\ell} (x_{it}{}^{k} - LB_{it})$$

$$\text{s.t.} \; \sum_{\tau=t}^{T} u^{+}{}_{i\tau} - \beta^{+}{}_{it} + \gamma^{+}{}_{it} \leq c_{it}, \; i=1,..,I, \; t=1,..,T \quad (52)$$

$$\sum_{\tau=t}^{T} u^{+}{}_{j\tau} \leq c_{jt}, \; j=1,..,J, \; t=1,..,T \qquad (15b)$$

$$u^{+}, \beta^{+}, \gamma^{+} \geq 0$$

where $u^{+}, \beta^{+}, \gamma^{+}$ = dual multipliers with μ fixed. Again, for (i,t) not in SUB or SLB, β_{it} or γ_{it} has to be removed from Constraint (52).

Note that MPMP not only maintains its linear structure, but also the same number of variables μ as in Section 4.1.7.

Thus it can be solved very efficiently with the Simplex Method. SPMP for the conventional equipment types, however, has more decision variables than before, and Algorithm ASPMP can no longer be applied. But SPMP still displays a network structure, as can be seen from the following example with T=4 for a given conventional equipment type i, with all (i,t), t=1,..,4 assumed to be in SUB and SLB in the example).

$$\min \alpha_1 u_1 + \alpha_2 u_2 + \alpha_3 u_3 + \alpha_4 u_4 + \zeta_1 \beta_1 + \zeta_2 \beta_2 + \zeta_3 \beta_3 + \zeta_4 \beta_4 + \nu_1 \gamma_1 + \nu_2 \gamma_2 + \nu_3 \gamma_3 + \nu_4 \gamma_4 \qquad (54)$$

$$\text{s.t. } u_1 + u_2 + u_3 + u_4 - \beta_1 + \gamma_1 \le c_1 \qquad (55a)$$

$$u_2 + u_3 + u_4 - \beta_2 + \gamma_2 \le c_2 \qquad (55b)$$

$$u_3 + u_4 - \beta_3 + \gamma_3 \le c_3 \qquad (55c)$$

$$u_4 - \beta_4 + \gamma_4 \le c_4 \qquad (55d)$$

$$u, \beta, \gamma \ge 0$$

where the SPMP objective function coefficients are given by the following expressions:

$$\alpha_t = \sum_{k=1}^{K} \mu_k (b_i + \sum_{\tau=1}^{t-1} x_{i\tau}^{k} - z_{it}^{k})$$

$$\zeta_t = \sum_{k=1}^{K} \mu_k (UB_{it} - x_{it}^{k})$$

$$\nu_t = \sum_{k=1}^{K} \mu_k (x_{it}^{k} - LB_{it})$$

Adding slacks to Constraints (55) and performing appropriate row operations, one obtains the following network constraints:

$$u_1 - \beta_1 + \beta_2 + \gamma_1 - \gamma_2 + s_1 - s_2 = c_1 - c_2$$
$$u_2 - \beta_2 + \beta_3 + \gamma_2 - \gamma_3 + s_2 - s_3 = c_2 - c_3$$
$$u_3 - \beta_3 + \beta_4 + \gamma_3 - \gamma_4 + s_3 - s_4 = c_3 - c_4$$
$$u_4 - \beta_4 + \gamma_4 + s_4 = c_4$$
$$-u_1 - u_2 - u_3 - u_4 + \beta_1 - \gamma_1 - s_1 = -c_1$$

The corresponding network is shown in Figure 13.
Even though Algorithm ASPMP is no longer applicable, one can still solve SPMP with an efficient network based algorithm (see BAZARAA and Jarvis, 1977). Computational speed can be further enhanced by using ASPMP to obtain an advanced feasible starting solution.

Examining (54) and (55), one can note that this program can be unbounded if certain combinations of ζ and α occur. This is related to the possibility of MP being unbounded, viz, DMP being infeasible. For example, if ζ_4=-3, the optimal value of β_4 is infinite and the program is unbounded. Thus, the task of the set Φ in DMP and MPMP is to prevent the occurence of such coefficients. Let us therefore examine the necessary structure of Φ.

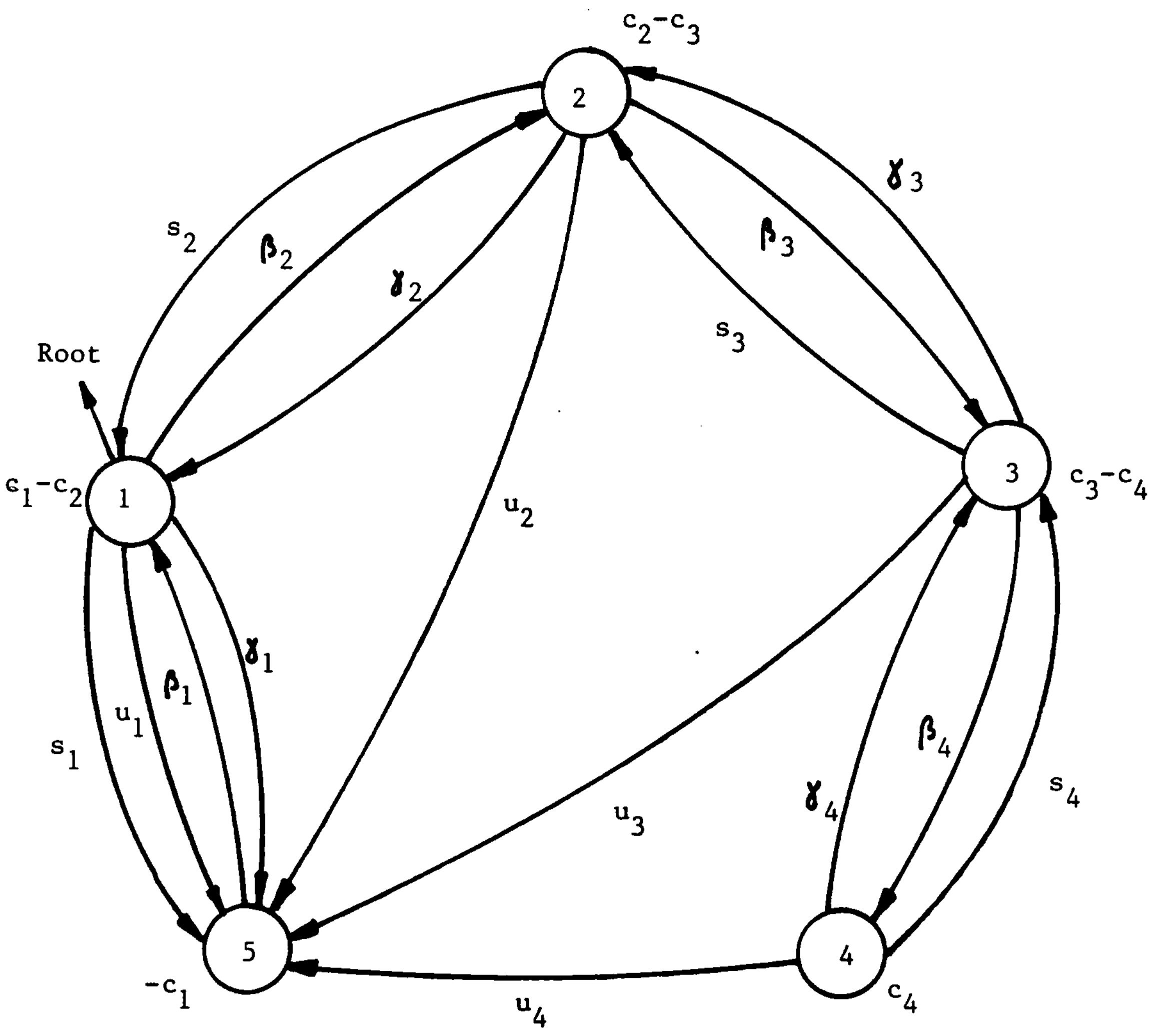

Figure 13: A Network Interpretation of SPMP with Bounds

The cause of the problem can be found by examining the dual DSPMP of Program SPMP for a given conventional equipment type i:

$$\max \sum_{t=1}^{T} c_{it}\eta_{it} \qquad (56)$$

$$\text{s.t.} \quad \sum_{\tau=1}^{t} \eta_{i\tau} \le \sum_{k=1}^{K} \mu_k(b_i + \sum_{\tau=1}^{t} x_{i\tau}{}^{k} - z_{it}{}^{k}) \quad \text{--}\ u_{it} \qquad (57)$$

$$-\eta_{it} \le \sum_{k=1}^{K} \mu_k(UB_{it} - x_{it}{}^{k}) \quad \text{--}\ \beta_{it} \quad i,t \varepsilon SUB \qquad (58)$$

$$\eta_{it} \le \sum_{k=1}^{K} \mu_k(x_{it}{}^{k} - LB_{it}) \quad \text{--}\ \gamma_{it} \quad i,t \varepsilon SLB \qquad (59)$$

$$\eta \le 0 \qquad (60)$$

In order for the primal to be unbounded, the dual of SPMP must be infeasible. Thus, to avoid unboundedness for SPMP, one has to guarantee feasibility for its dual.

From (56) to (60), the following necessary conditions for feasibility can be derived. From (60) and (58), it follows that

$$\sum_{k=1}^{K} \mu_k(UB_{it} - x_{it}{}^{k}) \ge 0 \qquad (61)$$

has to hold for all $i,t \ \varepsilon$ SUB.

Furthermore, from (58) and (57),

$$\sum_{k=1}^{K} \mu_k(b_i + \sum_{\tau=1}^{t} x_{i\tau}{}^{k} - z_{it}{}^{k}) \ge \sum_{\tau=1}^{t} \sum_{k=1}^{K} \mu_k(x_{i\tau}{}^{k} - UB_{i\tau}) \qquad (62a)$$

has to hold for all equipment types i and all years $t=1,..,t_0$, where $1+t_0 = \min\{t:(i,t) \text{ not in SUB}\}$. (If SUB = $\{(i,t),t=1,..,T\}$, then set $t_0=T$.) This is equivalent to

$$\sum_{k=1}^{K} \mu_k z_{it}^{k} \leq \sum_{\tau=1}^{t} UB_{i\tau} + b_i \qquad (62)$$

having to hold for all i and all $t=1,..,t_0$.

<u>Lemma 4</u>

Conditions (61) and (62) guarantee feasibility of DSPMP.

<u>Proof</u>:

For a given index i, which is suppressed below for convenience, DSPMP is feasible if and only if the solution η given by

$$\eta_t = \sum_{k=1}^{K} \mu_k (x_t^{k} - UB_t) \text{ for all } t \varepsilon \text{SUB}, \qquad (63)$$

and η_t=-BIGM (a large number) for all other t gives a feasible solution. Hence, by (60) and (58) or (63), we must have (61). In addition, if $t_0=0$ in the above definition of t_0, then clearly the η defined above is feasible since η_1=-BIGM. If $t_0>0$, η is feasible if and only if (62) holds for all $t=1,..,t_0$. To prove this, assume that for some t, $1<t<t_0$,

$$\sum_{k=1}^{K} \mu_k z_t^{k} > \sum_{\tau=1}^{t} UB_\tau + b. \qquad (64)$$

Then, from (63) and (64),

$$\sum_{\tau=1}^{t} \eta_\tau = \sum_{\tau=1}^{t}\sum_{k=1}^{K} \mu_k(x_t^k - UB_t) > \sum_{k=1}^{K} \mu_k(b + \sum_{\tau=1}^{t} x_\tau - z_t),$$

which means that η is infeasible to (57). Thus, (62) has to hold for feasibility of DSPMP. Conversely, if (62) holds, it is readily seen that the above solution η is feasible to DSPMP, and this completes the proof.

Recall that the set Φ was defined above to ensure feasibility of DMP and hence boundedness of MP. We are now in a position to define Φ based on (61) and (62). Thus, replacing containment in Φ by (61) and (62), MPMP takes the following form:

MPMP:

min ϑ

$$\text{s.t. } \vartheta \ge \sum_{k=1}^{K} \mu_k h^k - (u^{+\ell})^t \sum_{k=1}^{K} \mu_k(b + Bx^k - z^k)$$

$$- \sum_{i,t\varepsilon SUB} \beta^{+\ \ell}_{it} \sum_{k=1}^{K} \mu_k(UB_{it} - x_{it}^k)$$

$$- \sum_{i,t\varepsilon SLB} \gamma^{+\ \ell}_{it} \sum_{k=1}^{K} \mu_k(x_{it}^k - LB_{it}) \quad \ell=1,..,L \qquad \text{-- } w_\ell$$

$$\sum_{k=1}^{K} \mu_k = 1 \qquad \text{-- } \sigma^0$$

$$\sum_{k=1}^{K} \mu_k(UB_{it} - x_{it}^k) \ge 0 \qquad \text{-- } \xi_{it} \quad i,t\varepsilon SUB \qquad (61)$$

$$-\sum_{k=1}^{K} \mu_k z_{it}^k \ge -\sum_{\tau=1}^{t} UB_{i\tau} - b_i \quad i,t=1,..,t_0 \ \varepsilon\ SUB \text{ -- } \rho_{it} \quad (62)$$

$\mu \geq 0$, ϑ unrestricted

Here, ξ and ρ are the vectors of dual variables associated with (61) and (62), respectively.

It has to be noted that as in Section 4.1.7.1, the solution vector resulting from MPSP and SPSP, (u^+, β^+, γ^+), is not equal to the solution vector needed in Algorithm ALD, namely (u, β, γ). But in an analogous way as in Section 4.1.7.1, the following formulas state how (u, β, γ) can be obtained from (u^+, β^+, γ^+):

$$u_{it} = \sum_{\ell=1}^{L} w_\ell {u^+}_{it}^{\ell} + \rho_{it}, \quad i=1,..,I, \ t=1,..,T \qquad (65)$$

$$u_{jt} = \sum_{\ell=1}^{L} w_\ell {u^+}_{jt}^{\ell}, \qquad j=1,..,J, \ t=1,..,T \qquad (66)$$

$$\gamma_{it} = \sum_{\ell=1}^{L} w_\ell {\gamma^+}_{it}^{\ell}, \qquad i,t\varepsilon SLB \qquad (67)$$

$$\beta_{it} = \sum_{l=1}^{L} w_\ell {\beta^+}_{it}^{\ell} + \xi_{it} + \sum_{\tau=t}^{T} \rho_{i\tau}, \quad i,t\varepsilon SUB \qquad (68)$$

where for notational convenience, $\rho_{i\tau}$ is to be taken as zero wherever $\tau > t_0$ for the given i.

Lemma 5

Given that (u^+, β^+, γ^+) is optimal after the Benders' MPMP-SPMP iterations, (u, β, γ) as given in (65) to (68) is optimal in MP.

Proof:

First note that the Benders' Decomposition Algorithm only terminates when the objective values of SPMP and MPMP are equal, which implies that this is also the optimal objective value of MP, i.e. $\sigma = \vartheta$. Thus, if feasibility of the solution given by (65) to (68) in MP can be shown, it must be optimal.

Next note that by feasibility of each (u^+, β^+, γ^+) in SPMP and by linearity of (52), (u, β, γ) is feasible to Constraints (52) of MP.

Now, consider the dual to MPMP:

<u>Dual</u> <u>of</u> <u>MPMP</u> (<u>DMPMP</u>)

$$\max \sigma^0 - \sum_{i,t=1,..,t_0 \varepsilon SUB} \rho_{it}\left(\sum_{\tau=1}^{t} UB_{i\tau} + b_i\right)$$

$$\begin{aligned} \text{s.t. } \sigma^0 \le & \sum_{\ell=1}^{L} h^k w_\ell - \sum_{\ell=1}^{L} (u^{+\ell})^t (b + Bx^k - z^k) w_\ell \\ & - \sum_{\ell=1}^{L} \sum_{i,t \varepsilon SUB} \beta^{+}{}_{it}{}^{\ell} (UB_{it} - x_{it}{}^k) w_\ell \\ & - \sum_{\ell=1}^{L} \sum_{i,t \varepsilon SLB} \gamma^{+}{}_{jt}{}^{\ell} (x_{it}{}^k - LB_{it}) w_\ell \\ & - \sum_{i,t \varepsilon SUB} \xi_{it} (UB_{it} - x_{it}{}^k) \\ & + \sum_{i,t=1,..,t_0 \varepsilon SUB} \rho_{jt} z_{it}{}^k, \qquad k=1,..,K \end{aligned} \tag{69}$$

$$\sum_{\ell=1}^{L} w_\ell = 1 \tag{70}$$

σ^0 unrestricted, $w, \rho, \xi \ge 0$

Note that due to (70),

$$\sum_{\ell=1}^{L} h^k w_\ell = h^k.$$

Next, let

$$\sigma = \sigma^0 - \sum_{i,t=1,..,t_0 \varepsilon SUB} \rho_{it}\left(\sum_{\tau=1}^{t} UB_{i\tau}+b_i\right),$$

which for the proof can be written as

$$\sigma = \sigma^0 - \sum_{i,t=1,..,t_0 \varepsilon SUB} \rho_{it}\left[\sum_{\tau=1}^{t} (UB_{i\tau}-x_{i\tau}+x_{i\tau})+b_i\right]. \quad (71)$$

Then, by substituting (71) and (65) to (68) into (69), (69) can be rewritten as follows:

$$\sigma \le h^k - u^t(b+Bx^k-z^k)$$
$$+ \sum_{i,t\varepsilon SUB} \beta_{it}(x_{it}-UB_{it}) + \sum_{i,t\varepsilon SLB} \gamma_{it}(LB_{it}-x_{it}),\ k=1,..,K$$

with all other terms of (69) cancelling out. (Here, the x- and z-terms for $u^t(b+Bx^k-z^k)$ are collected from (71) as well as the last term of (69).) This is identical to Constraint (11) with Term (49) added. Thus it has been shown that (u,β,γ) as defined by (65) to (68) is feasible to Constraints (11) with the term (49), and to (52), in MP, which completes the proof.

6.2.3 MP Dantzig-Wolfe Decomposition in the Branch and Bound Algorithm

As noted above, the Dantzig-Wolfe Master Program is the exact dual of the Benders Master Program. Thus, incorporating the (dual) variables associated with Constraints (61) and (62) in MPMPDW, M[illegible]MPDW takes the same form as DMPMP given above. The termination criterion for the decomposition algorithm as well as the calculation of the final (u,β,γ)-solution are equivalent to the respective parts of the Benders Decomposition algorithm as stated above.

6.2.4 Initial MP-Constraints Based on Heuristics

As in Section 4.1.5, heuristically obtained solutions to the capacity planning problem with bounds on the conventional capacities, can be used to derive initial MP-cuts. It is shown in Section 7.3 that it is advantageous to include more than one such initial cuts if upper bounds on conventional capacities are present.

One possible heuristic is equivalent to the one shown in Figure 10, but does not allow any conventional capacity below its lower or above its upper bound. Thus, a solution feasible to the peak load constraints as well as to all bounds is obtained. It may be more desirable, however, to also include cuts based on heuristic solutions which are infeasible to some or all upper bounds, in order to force the master program to take into account such infeasible solutions earlier than it would otherwise, and to possibly avoid the generation of subproblem solutions infeasible to these bounds.

To achieve this, a first heuristic solution can be obtained using the procedure illustrated in Figure 10. This solution may be infeasible to some bounds. Then, in order to obtain further heuristic solutions, the upper bounds on one, two, and up to all equipment types with upper bounds can be enforced, thus creating solutions feasible to an increasingly large number of upper bounds. This can be done starting with the equipment type with the least operating cost and proceeding in merit order, or starting with the type with the highest operating cost and proceeding in reverse merit order. If such an approach is chosen, (NUB+1) heuristic cuts have to be included, where NUB denotes the number of upper bounds on conventional capacities. This is necessary in order to ensure that with at least one heuristic solution, i.e. with the last one which has all conventional capacities with non-infinite upper bounds no larger than these upper bounds, a feasible solution to the first master program can be found.

As shown in Section 7.3, such an approach can save 25 percent in computation time, as compared to the inclusion of only one heuristic resulting in a solution feasible to all bounds.

6.3 THE GENERALIZED BENDERS ALGORITHMS IN THE BRANCH AND BOUND ALGORITHM

The incorporation of upper and lower bounds on the decision variables into Algorithms GBDA and PA is a trivial task. Note that the initial solution with which the algorithm is entered is feasible to the bounds, since it is the final solution of the deterministic phase. Hence, one simply needs to impose upper and lower bounds on the capacity variables in Program PGBMP, and solve the resulting linear program using the upper and lower bounded Simplex Method (see BAZARAA and Jarvis, 1977).

6.4 THE COMPLETE BRANCH AND BOUND ALGORITHM

With the theory of the deterministic, probabilistic and integer phases developed sufficiently above, the complete algorithm for solving electric utility capacity expansion problems involving renewable energy sources can now be stated. Here, the DAKIN, 1965, variation of the original LAND and Doig, 1960, Branch and Bound algorithm is used with a LIFO (depth-first) node selection strategy.

First, however, some Branch and Bound notation has to be introduced. Let n denote the level under investigation, i.e. the number of active bounds on variables. Furthermore, let d be a 4xn matrix whose four row-vectors are defined as follows:

d_1 = vector containing the years of the n branching variables. If $d_1(k)>0$, the branching variable at the k^{th} level is ≤ constrained. Otherwise, it is ≥ constrained.

d_2 = vector containing the conventional equipment type numbers of the n branching variables.

d_3 = vector containing the bounds on the branching variables.

d_4 = vector containing a 0 or 1 for each level k, where a 0 indicates that the node at that level is still dangling, i.e. has only one node branching from it, while a 1 indicates that the node is not active.

In the following algorithm, let 'integer' denote a solution of conventional capacities that are available in the market. Let xs_i denote the standard capacity size in which conventional equipment type i is available. That is, feasible integer values of x_{it} are $xs_i^{\,k}$, $k=0,1,..,K_i$. Also, let z(n) denote the continuous objective value found at the node under investigation at level n, and z* the objective value of the incumbent integer solution.

<u>Complete Algorithm CA</u>

Initialization: n=0. Solve the continuous node-0 problem, using Algorithms ALD or GBDA and PGBDA, to obtain a solution x^0. From x^0, obtain an integer incumbent solution heuristically. Initialize d empty.

Step 1 (Depth branching): If x^n is integer or if $z(n) \geq z^{*}+\varepsilon$, where ε is a suitable tolerance, go to Step 2. Otherwise, determine the conventional capacity variable x_{it} and the factor k' for which the product of total cost derivative and $\min(\mathrm{abs}(x_{it}-xs_i^{k}), k=0,1,..K_i)$ is greatest. Set $n=n+1$, $d_3(n)=xs_i^{k'}$, and $d_2(n)=i$, $d_1(n)=t$ if $x_{it}>d_3(n)$, and $d_1(n)=-t$ otherwise. Set $d_4(n)=0$ and proceed with Step 3.

Step 2 (Breadth branching): Scanning d_4 backwards, starting from level n, determine the highest level ℓ with $d_4(\ell)=0$. If $\ell=0$, stop, the incumbent is optimal. Otherwise, delete all levels $m>\ell$ from d. Set $d_4(\ell)=1$ and $n=\ell$. If $d_1(\ell)>0$, set $d_3(\ell)=xs_i^{k'+1}$, otherwise, set $d_3(\ell)=xs_i^{k'-1}$. Set $d_1(\ell)=-d_1(\ell)$.

Step 3 (Bounding): Solve the capacity planning problem with bounds as indicated in matrix d, using Algorithms ALD or GBDA, and PGBDA,[12] to obtain a solution x^n. Go to Step 1.

This completes the theoretical development of the integer programming algorithm for solving electric utility capacity expansion problems. In the following chapters, computation-

[12] Here, the cuts generated during the algorithms for previous nodes can be used in the first iteration of the solution for the current node. After the first iteration, slack cuts can be discarded.

al experience as well as the implementation on the Mexicali Project are given.

Chapter VII

COMPUTATIONAL EXPERIENCE

In order to be able to judge the speed and accuracy of the algorithms described above, several programs implementing the various approaches developed, were run on the same test data. All programs are written in FORTRAN 77, and all runs were performed on Viginia Tech's IBM 3084. In the following sections, implementation particulars of these programs will be displayed, followed by tables describing their comparative speed and accuracy.

7.1 THE DETERMINISTIC ALGORITHMS

7.1.1 Implementation Particulars

7.1.1.1 The Lagrangian Dual Decomposition Program LDD

The LDD program, including probabilistic and integer analysis features, contains over 5000 lines of code, and occupies roughly 3000 kilobytes of storage in order to be able to handle a 20-year, six conventional and four non-dispatchable equipment type expansion problem.

For all linear programming problems occuring within Algorithm ALD, be it primal or dual or bounded linear programs, the Revised Simplex Method is used as programmed by the author. The implementation includes user-set tolerances for detecting optimal solutions and numerical stability problems, backtracking features for the case when a linear program terminates due to numerical instability, as well as a basis re-inversion routine called at a user-supplied frequency. A regression routine programmed by the author derives fifth-order polynomials for the inverse load duration curves from hourly data. Monotonicity of the load duration curve fits is verified before the algorithm is begun. If Benders or Dantzig-Wolfe Decomposition is used on the Master Program, the cuts or extreme points, respectively, generated during the previous MP-SP iteration are kept for the first Benders or Dantzig-Wolfe iteration in the current MP-SP iteration. After the first iteration, non-binding cuts are then discarded.

For the benefit of the Mexican users in the Instituto de Investigaciones Electricas and the Comision Federal de Electricidad, in order to facilitate the generation of the input data file for LDD, a 1000-line FORTRAN program was written that prompts the user in Spanish for all input data and creates the data file in the correct format.

Part of the input data are options that let the user control whether or not he wants to use the heuristic for creating a starting solution (H), hour-by-hour load data input, the initial upper bounding constraints developed in Section

4.1.4 (U), Benders Decomposition on the Master Program MP (B), or alternatively, Dantzig-Wolfe Decomposition on MP (D). Furthermore, various output options control how many intermediate results are printed out. The acronyms H, U, B and D will be used in the tables below to indicate which options are in effect during each run.

Of course, the user supplies the number of years in the planning horizon as well as the number of subperiods of varying renewable energy availabilities. In order to do so, the user has to determine which parts of the year can be suitably aggregated in the same subperiod with the same renewable energy availability factors.

The user can also control the termination tolerances for the numerous linear programs that form part of LDD with the variable EPSL, for the MP decomposition with EPSB, for the Subproblem's tangential approximation with EPSS, and for the overall Lagrangian Dual Decomposition with EPSM. The recommended values for these tolerances lie between one and ten percent of the overall objective value for EPSM, EPSS and EPSB, and at 0.01 for EPSL. Computational tests were performed to determine with which options and tolerances the fastest and most stable convergence rates could be obtained.

7.1.1.2 The Generalized Benders Decomposition Program GBD

The GBD program, including probabilistic and integer analysis features, contains over 3000 lines of code, and occupies roughly 1500 kilobytes of storage in order to be able to handle a 20-year, six conventional and four non-dispatchable equipment type expansion problem. The primal bounded linear programming subroutine needed to solve GBMP was programmed by the author, and uses the Revised Simplex Method with the same termination and numerical stability features as in the program LDD described above. The regression routine for processing hourly input data is also included.

The user can control the Generalized Benders termination tolerance EPSM, the linear programming tolerance EPSL, whether T*P (option P=1) or only T (P=0) constraints of the type (35) are to be included initially in GBMP, and whether the renewable energy equipment upper bounds (5) are to be handled as described in Section 4.2 (option U=3), or whether they are to be approximated in one of the following ways. Instead of (5), the Constraint (5a) in the x-variables can be included directly in GBMP either initially (U=1), or they can be generated if and when needed (U=2). Finally, they can be replaced in an approximating fashion by simple upper bounds on the individual x_{jt}-variables (U=0). These U-options are used below to investigate the sensitivity of the

Generalized Benders Decomposition algorithm with respect to the enforcement of Constraints (5)/(5a).

7.1.1.3 The VMCON Package

The FORTRAN package VMCON for solving general nonlinear programming problems by CRANE et al, 1980, was supplemented by the appropriate subroutines to solve the deterministic capacity expansion problem. These subroutines include the regression routine for processing hourly load input data as well as routines for the calculation of derivatives as stated in Section 4.3.2. The termination tolerance, which in this case does not represent the maximum allowed deviation from the optimal objective value as in Programs LDD and GBD, but rather is a limit on the norm of the penalty function gradient, is user-supplied.

7.1.2 Computational Performance

Before the computational performance of Programs LDD, GBD and VMCON is compared for various test problems, the options and tolerances with which program LDD performs best are first explored. This is necessary because of the complexity of Algorithm ALD, which involves two nested decompositions.

7.1.2.1 Options and Tolerances in LDD

Test runs were performed with data derived from the Mexicali Project, in order to determine the combination of options and tolerances with which the program LDD performs best. An initial goal of one percent of objective function value was set for EPSM, the tolerated difference between Master Program and Subproblem objective values.

For the testing of the various options mentioned in Section 7.1.1.1, first a small deterministic problem with a two-year planning horizon, 21 subperiods, and with four conventional and two renewable energy equipment types was solved. The results are reported in the first part of Table 1.

Comparing Runs 1 and 2, it is seen that the addition of constraints (15) to MP reduces computing time drastically (Option U). Comparing Runs 2 and 3, it is seen that exploiting the special structure of those constraints through the application of Benders Decomposition on MP also saves considerable amounts of computing time (Option B). Comparing Run 3 with Run 5, it can be seen that the incorporation of the heuristic developed in Section 3.2.6 for an advanced starting solution does not seem to save any computing time (Option H). However, this conclusion has to be revised after examining Runs 6 through 9, where it becomes clear that with increasing problem complexity (reflected through an increase in the number of years Y), the incorporation of such a heuristic saves computing time (up to 65 percent). Finally, comparing Runs 3 and 4, it does not seem to affect computing time significantly, whether MP is decomposed with the Benders (Option B) or the Dantzig-Wolfe Decomposition (Option D) method. This is verified in Runs 6, 8, 10 and 11 for larger problem sizes.

All runs in the second part of Table 1 were made for four conventional and two renewable energy equipment types. Up to 20-year planning horizons were used. Runs 12 through 19 address the choice of tolerances. To obtain convergence with a 20-year horizon, an EPSL linear programming termination tolerance of 0.001 had to be used, as compared with an EPSL of 0.01 being sufficient for smaller problem sizes. However, for all runs, a re-inversion frequency of 10 was sufficient.

It can be seen from Run 8 and Runs 12 through 15, that with growing complexity of the problem, i.e. with growing planning horizon, the final convergence tolerance EPSM has a growing impact on the computing time and the number of iterations. Since EPSS is the tolerance associated with a single-year plantmix problem, it is equal to EPSM, percentage-wise. The choice of EPSB can be addressed by comparing Runs

3 and Runs 16 through 19, from which EPSB = EPSM can be recommended. (For Runs 18 and 19, 4 renewable energy equipment types were included.)

It should be noted that even in cases when a run has to be aborted due to the excessive number of iterations needed or due to numerical stability problems, the program still constructs the best feasible solution possible with the accumulated information. And finally, the application of a complicated algorithm like LDD rather than a simple heuristic, is justified by the large improvements realized between the heuristic and the final objective values.

7.1.2.2 Comparative Performance of LDD, GBD and VMCON

The comparative computational performance of the three programs LDD, GBD and VMCON on deterministic problems is addressed in Tables 2 and 3. Table 2 includes runs with Mexicali Project data for planning horizons varying from two to 20 years (i.e. they are run for four conventional and two renewable energy equipment types). The runs in Table 3 investigate the sensitivity of Programs LDD and GBD to the number of subperiods and to the number and cost characteristics of conventional and renewable energy equipment types. All runs in both tables start with the heuristic. Therefore, only the pure CPU-time PCPU = FCPU - HCPU is reported.

TABLE 1

Options and Tolerances in LDD

Run	H	U	B	D	EPSM	EPSS	EPSB	HObj	FObj	HCPU	FCPU	PCPU	Its
1	1	0	0	0	.01	.01	-	2.39	2.39	1.57	>18.	>16.	>50
2	1	1	0	0	.01	.01	-	2.39	1.78	1.57	4.17	2.60	14
3	1	1	1	0	.01	.01	.01	2.39	1.78	1.57	2.76	1.19	12
4	1	1	0	1	.01	.01	.01	2.39	1.78	1.57	2.80	1.23	12
5	0	1	1	0	.01	.01	.01	-	-	1.78	2.56	-	10

Run	H	B	D	Y	P	EPSM	EPSS	EPSB	FObj	HObj	HCPU	FCPU	PCPU	Its
6	1	1	0	5	21	.01	.01	.01	5.57	7.01	3.63	5.49	1.86	9
7	0	1	0	5	21	.01	.01	.01	5.57	-	-	5.64	-	10
8	1	1	0	10	21	.01	.01	.01	13.6	22.1	7.08	10.9	3.82	10
9	0	1	0	10	21	.01	.01	.01	13.6	-	-	34.4	-	46
10	1	0	1	5	21	.01	.01	.01	5.57	7.01	3.65	5.50	1.85	9
11	1	0	1	10	21	.01	.01	.01	13.6	22.1	7.08	10.9	3.80	10
12	1	1	0	10	21	.1	.1	.1	14.3	22.1	7.08	8.41	1.33	6
13	1	1	0	20	21	.01	.01	.01	40.0	71.6	13.9	>61.	>47.	>50
14	1	1	0	20	21	.02	.02	.02	39.0	71.6	13.8	48.0	34.1	42
15	1	1	0	20	21	.1	.1	.1	41.3	71.6	13.9	16.6	2.70	6
16	1	1	0	2	21	.01	.01	.03	1.81	2.39	1.57	2.05	.48	6
17	1	1	0	2	21	.01	.01	.005	1.78	2.39	1.57	2.61	1.04	11
18	1	1	0	10	21	.1	.1	.1	10.9	22.1	7.08	14.0	6.96	16
19	1	1	0	10	21	.1	.05	.05	10.3	22.1	7.08	24.9	17.9	30

H,U,B,D = Options explained in text
FObj = final objective value
HObj = heuristic objective value
FCPU = total cpu seconds
HCPU = cpu seconds through the heuristic (includes CPU-time for regression on hourly load data)
PCPU = pure cpu seconds (=FCPU-HCPU)
Its = number of MP-SP iterations
Y = number of years
P = number of subperiods

All tolerances are given as fractions of the appropriate objective values.

From the runs in Table 2, it can be concluded that for all problem sizes (here represented as the sizes of the planning horizon), Program LDD performs fastest, with Program GBD performing slightly slower and Program VMCON orders of magnitude slower. The performance of GBD gets close to or even better than the LDD performance only when Constraint (5), the upper bounds on the renewable energy capacities, is approximated through simple upper bounds on the individual x_{jt}-variables (U=0). It must be noted, however, that this approximation can lead to unrealistic results quite different from the results obtained with the other U-options.

Among these other options of U=1, U=2 and U=3, the only theoretically correct option for CP under restriction (5) is U=3, as described in Section 4.2. This option is seen to perform quite poorly in Runs 4, 5, 10, 11, 19 and 20. This is due to the generation of a large number of constraints of the type (35), for many subperiods in many years, for the 21-subperiod runs. But even in the two-subperiod runs, where not as many Constraints (35) are generated, performance is poor (see Runs 4 and 10). This can be explained with the necessity to finetune the renewable energy capacities close to the bounds, not directly (as with the other options), but indirectly via cost-based cuts.

The preferable option appears to be U=2, which uses (5a) instead of (5),[13] and shows good convergence rates. Therefore, for future runs, U=2 is taken as the default.

Comparing Runs 16 and 17, it can furthermore be seen that including only T constraints of type (35) initially in GBD saves roughly 50 percent in computing time. Similarly, comparing Runs 2 and 3, 8 and 9, 17 and 18, 21 and 22, and 29 and 30, it can be seen that generating Constraints (5a) only if and when needed (U=2) saves up to 60 percent of computing time as compared to including all Constraints (5a) in GBMP initially (U=1).

For the sensitivity analysis runs in Table 3, a data set with 21 subperiods per year and a planning horizon of 10 years (for most runs) was chosen. Comparing the runs in Table 3 for 21 subperiods with the appropriate runs in Table 2 for 2 subperiods, it can be seen that a lower number of subperiods reduces computing effort in both GBD and LDD, but that the general advantage of LDD is maintained, except for very short planning horizons.

Both algorithms are remarkably stable on all data sets. As expected, increasing the number of conventional equipment types increases computing time, although in a much more pro-

[13] Since (5a) implies (5), the program with option U=2 (or U=1) is slightly more restrictive than with U=3. With any realistic cost structures, however, the two will lead to the same results, as explained in Chapter 3.

TABLE 2

Computational Performance of LDD, GBD and VMCON

Run	Program	Y	P	Tol	Its	PCPU	FObj	Note
1	VMCON	2	2	.1	4	.55	1.88	
2	GBD	2	2	.01	9	.22	1.68	U=1
3	GBD	2	2	.01	10	.20	1.68	
4	GBD	2	2	.01	13	.41	1.68	U=3
5	GBD	2	21	.01	12	.58	1.79	U=3
6	LDD	2	2	.01	9	.17	1.68	
7	VMCON	5	2	.05	6	8.35	5.80	
8	GBD	5	2	.01	14	2.37	5.23	U=1
9	GBD	5	2	.01	15	1.65	5.23	
10	GBD	5	2	.01	20	4.10	5.25	U=3
11	GBD	5	21	.01	17	6.64	5.57	U=3
12	LDD	5	2	.01	9	.34	5.23	
13	VMCON	10	2	.5	3	33.79	15.20	
14	VMCON	10	2	.1	8	80.43	12.50	
15	GBD	10	2	.1	5	1.07	12.71	U=0
16	GBD	10	2	.1	5	9.66	12.71	P=1,U=1
17	GBD	10	2	.1	5	5.05	12.71	U=1
18	GBD	10	2	.1	6	2.42	12.71	
19	GBD	10	2	.1	5	3.89	12.99	U=3
20	GBD	10	21	.1	8	238.6	14.14	U=3
21	GBD	10	2	.01	14	7.28	12.66	
22	GBD	10	2	.01	13	14.02	12.66	U=1
23	GBD	10	2	.01	13	3.44	12.66	U=0
24	LDD	10	2	.1	7	.31	13.56	
25	LDD	10	2	.01	28	3.60	12.75	
26	VMCON	20	2	4.	3	246.8	41.60	
27	GBD	20	2	.1	6	9.53	36.94	U=0
28	GBD	20	2	.1	7	27.38	36.91	
29	GBD	20	21	.1	8	35.01	39.66	
30	GBD	20	21	.1	7	87.38	39.67	U=1
31	GBD	20	21	.1	7	12.19	39.58	U=0
32	LDD	20	21	.1	6	2.70	41.30	

Note that the default for GBD runs is U=2 and P=0.
All abbreviations are as defined in Table 1, except for
Tol = EPSM (fraction of objective value) for GBD and LDD runs, and
Tol = gradient norm limit for VMCON runs,
i.e., the same tolerance value is actually looser for VMCON than for LDD or GBD.

nounced way in GBD than in LDD. This is due to the fact that in GBD, additional conventional equipments are additional decision variables in the linear program GBMP, with quite some effect on its solution effort, while in LDD, they only affect the Breakeven Analysis part of the Subproblem, where they do not cause much additional effort.

For an increase in the number of renewable energy equipment types, the opposite effect takes place. In GBD, an increase in that number affects computational effort roughly as much as an increase in the number of conventional equipments. In LDD, however, where the Subproblem optimizes the capacities of renewable energy equipments with a tangential approximation algorithm, which is far more complex than the Breakeven Analysis for conventional equipments, an increase in the number of renewable energy equipments has a marked effect on computational effort. In all cases, however, LDD still performs faster than GBD.

7.2 THE PROBABILISTIC ALGORITHM

7.2.1 Implementation Particulars

In our implementation of Algorithm PGBDA, the features concerning the interface of the deterministic with the probabilistic phase, addressed in Section 5.2.3.1, are incorporated in the program. As in the deterministic Generalized

TABLE 3

Sensitivity of LDD and GBD to Problem Structure

Run	Y	P	E	S	EPSM	GBD Its	GBD PCPU	GBD FObj	LDD Its	LDD PCPU	LDD FObj
1	2	21	4	2	.01	10	.37	1.78	12	1.19	1.78
2	5	21	4	2	.01	12	1.70	5.57	9	1.68	5.57
3	10	21	4	2	.01	16	10.32	13.51	10	3.82	13.61
4	10	21	4	4	.1	5	8.64	9.64	16	6.96	10.91
5	10	21	4	1	.1	7	3.98	15.20	5	.80	15.86
6	10	21	6A	2	.1	7	5.20	13.69	6	1.47	14.24
7	10	21	6B	2	.1	6	3.80	13.64	6	1.52	15.96
8	10	21	6C	2	.1	7	4.55	13.63	6	1.65	15.38
9	10	21	5A	2	.1	6	3.44	13.63	6	1.47	15.96
10	10	21	5B	2	.1	6	3.49	13.59	6	1.40	14.27
11	10	21	3	2	.1	8	4.50	13.98	4	.69	14.18
12	10	21	2	2	.1	4	1.25	35.42	4	.53	35.01
13	10	21	1	2	.1	3	.71	58.55	3	.14	59.47
14	10	21	1	4	.1	7	14.51	18.09	3	.30	17.86

where all abbreviations are as defined in Table 1, except

E = number of conventional equipment types
S = number of renewable energy equipment types

6A,B,C and 5A,B differ in the conventional plant cost characteristics.

Again, the default for the GBD runs was U=2 and P=0. As a matter of interest, below the PCPU-times for GBD runs with U=1 are given:

Run	1	2	3	4	5	6	7	8
PCPU	.40	2.23	18.31	15.62	4.06	9.65	6.78	7.91

Run	9	10	11	12	13	14
PCPU	6.41	6.50	9.13	2.60	1.15	15.04

Benders Decomposition program, the user has the choice of how to incorporate Constraints (5) in the master program (with U = 3, 2, 1 or 0).

Probabilistic production costing and reliability analysis are conducted with numerical convolution for obtaining the equivalent load duration curves (ELDCs), and with hour-by-hour simulation of renewable energy generation (which is treated as a negative load and subtracted from the original load curve before a load duration curve and the ELDCs are obtained).

The convolution process that accounts for conventional plant forced outages and generates the ELDCs, is conducted by individual generator, where the standard generator size for each conventional equipment type is assumed to be xs_i as defined in Section 6.4. Each generator's production as well as the final unserved energy are calculated with the energy balance method (CARAMANIS et al, 1983), which was chosen because of its accuracy and reliability. The loss-of-energy probability (LOEP) is adopted as the reliability criterion.

For the calculation of the cost and unserved energy derivatives with respect to renewable energy capacities, finite differences are used. Here, the user supplies the size of this finite difference. The user also controls the maximum number of grid points at which the ELDCs are evaluated, the size of the interval between grid points, and a tolerance on the LOEP-goal within which reliability is still considered to be at an acceptable level. Two more user supplied input data determine whether or not a deterministic phase is used before the prbabilistic phase, and if so, which value of PD (as defined in (46) in Section 5.2.3.1) is to be used to restrict the capacities within a PD-neighborhood of the deterministic optimum.

Before the first iteration of a purely probabilistic run, a heuristic as pictured in Figure 10 provides a starting solution. If this solution is infeasible to the probabilistic reliability constraint, the capacities are increased in user-controlled steps until feasibility is reached. The same procedure is conducted if the deterministic optimum is probabilistically infeasible in a two-phase run. This procedure serves to obtain an upper bound on the optimal objective value quickly. If such a procedure is not included, convergence can become slow as the algorithm inches toward feasibility from an infeasible starting solution (see BLOOM et al, 1984).

7.2.2 Computational Performance of the Two-Phase Algorithm

For all runs reported on in this section, data derived from the original Mexicali Project data are used.[14] Because of the large computer time requirements of the probabilistic phase, planning horizons of only up to five years were used. However, this duration is sufficiently long so as to claim that the results obtained can be assumed to be valid for longer planning horizons as well.

From the runs reported in Table 4, it can be seen that the two-phase approach consistently saves between 14 and 80 percent, and sometimes more, of computation time, as compared to purely probabilistic runs. (This would be amplified further by using LDD in-lieu of GBD for the deterministic phase.) For the Mexicali data, characterized by highly structured renewable energy availabilities and low forced outage rates for conventional equipments, the deterministic phase often finds the probabilistic optimum (to the specified tolerance). This can be observed from Runs 2, 3, 5, 6, 8, 10, 13 and 14. Here, in Runs 3, 9, 13 and 14, the early probabilistic iterations actually move away from the deterministic and probabilistic optimum, only to approach it

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[14] Because of the easier interface of the deterministic and probabilistic phases, program GBD is used here rather than LDD. Usage of LDD would not alter the results to be exposed, since it performs faster than GBD on the deterministic model.

again after much computer time has been wasted. Nevertheless, comparing Runs 13 and 14, a PD-value of 0.5 appears preferable over a tighter value of 0.1 that would restrict the solution unduly (if the deterministic solution is not detected to be the probabilistic optimum, as in Run 14).

Comparing Runs 1 through 3 with Runs 15 through 17, it can furthermore be seen that the use of the option U does not affect the advantage of the two-phase over the purely probabilistic algorithm.

Comparing Runs 7 through 11, the complexity added through two additional renewable energy equipments with less structured availabilities (the availabilities were random-generated for these two equipments), does appear to have a definite impact on computational effort, and increases computing time twofold. Similarly, when going from very low forced outage rates for conventional equipments to very high ones, i.e. comparing Runs 1 through 3 with Runs 12 through 14, computational effort increases up to fivefold. However, the two-phase method performs significantly faster than a purely probabilistic algorithm in these cases as well.

TABLE 4

Two Phases Versus a Single Probabilistic Phase

Run	U	PD	Y	P	E	S	EPSM	DCPU	FPObj	LPObj	PIts	FCPU
1	1	P	2	21	4	2	.01	-	-	1.78	9	36.42
2	1	.1	2	21	4	2	.01	1.89	1.78	1.78	1	5.23
3	1	.5	2	21	4	2	.01	1.91	1.78	1.78	7	24.94
4	1	P	5	21	4	2	.1	-	-	5.66	6	67.90
5	1	.5	5	21	4	2	.1	4.61	5.69	5.69	1	13.13
6	1	1.	5	21	4	2	.1	4.56	5.69	5.62	4,3	38.27
7	1	P	3	21	4	4	.1	-	-	2.25	11	98.15
8	1	.5	3	21	4	4	.1	2.97	2.28	2.28	1	17.49
9	1	1.	3	21	4	4	.1	3.00	2.28	2.30	5,4,3	49.13
10	1	P	3	21	4	2	.1	-	-	3.05	7	44.81
11	1	.5	3	21	4	2	.1	2.70	3.04	2.98	6,5,4,3	32.63
12	1	P	2	21	4F	2	.01	-	-	2.64	31	150.98
13	1	.5	2	21	4F	2	.01	1.94	2.53	2.59	16,15,13	90.64
14	1	.1	2	21	4F	2	.01	1.95	2.53	2.63	25,20,7,2	131.43
15	2	P	2	21	4	2	.01	-	-	1.78	10	37.52
16	2	.1	2	21	4	2	.01	1.93	1.78	1.78	1	5.33
17	2	.5	2	21	4	2	.01	1.93	1.78	1.78	8	26.05

where acronyms are as defined in previous tables, and
DCPU = cpu-seconds through the deterministic phase
FPObj = objective value in first probabilistic iteration
LPObj = final probabilistic objective value
* PIts = number of probabilistic iterations
FCPU = total cpu-seconds used
U=2 is used as the default in all runs.

4F in the E-column indicates four conventional equipment types with drastically changed forced outage rates.

PD=P indicates a purely probabilistic run, while a number indicates a two-phase run with the PD given.

* In two-phase runs, more than one number in the iteration column shows the final iteration number first, followed by the iteration numbers at which an optimum constrained by Constraints (46) was found.

7.3 COMPUTATIONAL PERFORMANCE OF THE INTEGER ALGORITHMS

Since the performance of the Branch and Bound Algorithm CA is not to be compared to any alternative integer programming techniques, the only computational experience reported on it is given in Chapter 8 for the Mexicali Project. In this section, we investigate the comparative performance of the Generalized Benders versus the Lagrangian Dual Decomposition Algorithm when incorporated in Algorithm CA.

In the runs given in Table 5, varying numbers of upper and lower bounds were imposed on various conventional capacity variables x_{it}. All runs were performed on Mexicali Project data with 21 subperiods, four conventional and two renewable energy equipment types. Since all runs use the heuristic, only the pure CPU-time PCPU is reported here.

As noted in Section 7.1.2.2, Program LDD implementing the Lagrangian Dual Decomposition algorithm performs faster than Program GBD implementing the Generalized Benders Decomposition algorithm, for almost all data sets. However, this result is reversed in the runs of Table 5 with bounds on conventional capacities. In Runs 1 through 9, for a two-year planning horizon, GBD uses only three to four percent of the CPU-time LDD needs.

Here, the Dantzig-Wolfe Decomposition of MP in LDD appears to work better if a large number of upper bounds is present, while for smaller numbers of upper bounds, Benders Decomposition of MP appears to be preferable. This is due to the fact that for each upper-bounded capacity, MPMP has at least one constraint of type (61) and (62), which increases the size of the basis matrix and thus affects computational effort directly. In MPMPDW, however, these constraints appear as additional variables, and do not affect computational effort in as direct a manner.

For a longer planning horizon, LDD encounters massive numerical stability problems, and has to be aborted prematurely. This strikingly different performance in the presence of bounds as compared to without bounds on the conventional capacities, may be explained as follows. As shown in Section 6.3, bounds on the conventional capacities can be incorporated very easily in GBMP through the use of the Bounded Simplex Method. They restrict the feasible region and thus speed convergence of Algorithm GBDA. In Algorithm ALD, however, bounds on the conventional capacities have to be dualized as shown in Section 6.2, with the result that Program MP (or Program SPMP if MP is decomposed) has up to three times as many dual variables as decision variables as there are without bounds. Thus, the complexity of MP increases greatly, especially considering the necessary inclusion of the set Φ, represented by Constraints (61) and (62) in MPMP.

This interpretation is verified through Runs 13 and 14, which correspond to a data set including very large upper bounds that are non-binding at optimality. Here, one obtains convergence within a small number of iterations comparable to the numbers of iterations in the LDD-runs in Tables 1 and 2.[15] The large number of iterations necessary in Runs 2, 3, 5, 6, 8 and 9 of Table 5, are apparently needed to finetune the dual variables such that optimal capacities result that are at or near the tight bounds used in these runs.

Runs 17 through 21 address the choice of heuristics to be used to generate initial cuts for the master program, as described in Section 6.2.4. Run 17 was performed with the same heuristic used in all the runs 1 through 16, which provides a solution feasible to all bounds. Run 18 was performed with a set of three heuristics, which first use the heuristic illustrated in Figure 10 to generate a solution possibly infeasible to some bounds, and then enforce such bounds in later heuristic solutions, increasing the number of enforced upper bounds by one in each additional solution. The last heuristic solution generated under this option is feasible to all upper bounds. As can be seen by comparing Runs 17 and 18, the second option with three heuristic cuts (in these runs with two upper bounds, three heuristic solu-

[15] The impression that not decomposing MP might speed convergence here, is dispelled through Runs 15 and 16.

tions are necessary to guarantee feasibility of the first master program) results in some savings (25 percent) in computation time. From Runs 20 and 21, it can be seen that proceeding in merit order when enforcing upper bounds on conventional capacities is to be preferred over using the reverse merit order.

But with no combination of options and numbers of initial heuristic cuts does the program LDD perform nearly as fast as the program GBD (see Run 19 as compared with Run 18). Thus, in the Branch and Bound context, Algorithm GBDA and Program GBD are preferred over Algorithm ALD and Program LDD, although for the case without bounds on conventional capacities, ALD and LDD perform faster than GBDA and GBD.

TABLE 5

Branch and Bound Iterations in LDD and GBD

Run	Program	B	D	Y	UB	LB	EPSM	Its	PCPU	FObj	Note
1	GBD	-	-	2	8	2	.01	3	.08	1.83	
2	LDD	1	0	2	8	2	.01	22	3.15	1.83	
3	LDD	0	1	2	8	2	.01	18	1.76	1.83	
4	GBD	-	-	2	2	8	.01	3	.09	2.26	
5	LDD	1	0	2	2	8	.01	22	2.19	2.26	
6	LDD	0	1	2	2	8	.01	27	3.93	2.26	
7	GBD	-	-	2	5	1	.01	3	.09	1.83	
8	LDD	1	0	2	5	1	.01	25	2.43	1.83	
9	LDD	0	1	2	5	1	.01	26	3.13	1.83	
10	GBD	-	-	5	14	0	.01	6	1.02	5.61	
11	LDD	1	0	5	14	0	.01	>9	>9.07	6.75	a
12	LDD	0	1	5	14	0	.01	>50	>38.0	5.66	b
13	LDD	1	0	2	8L	0	.01	12	2.24	1.78	
14	LDD	0	0	2	8L	0	.01	10	1.79	1.78	c
15	LDD	1	0	2	8	0	.01	24	9.75	1.83	
16	LDD	0	0	2	8	0	.01	18	40.26	1.83	c
17	LDD	1	0	2	2	0	.01	20	1.63	1.83	d
18	LDD	1	0	2	2	0	.01	14	1.28	1.87	e
19	GBD	-	-	2	2	0	.01	3	.08	1.83	
20	LDD	1	0	2	8	0	.01	30	5.26	2.25	e
21	LDD	1	0	2	8	0	.01	33	5.73	2.25	f

where acronyms are as defined in previous tables, and

B=1 = Benders Decomposition used on MP
D=1 = Dantzig-Wolfe Decomposition used on MP
UB = number of upper bounds on conventional equipments
LB = number of lower bounds on conventional equipments
8L = 8 very large upper bounds non-binding at optimality

U=1 was used here for the GBD runs.

Notes: a) aborted because of numerical instability in MP.
b) aborted because of limit of 50 iterations.
c) MP was not decomposed.
d) one heuristic solution feasible to all bounds.
e) (UB+1) heuristic solutions with merit order. PCPU includes computation time for the two added heuristics.
f) (UB+1) heuristics with reverse merit order. PCPU as in e.

Chapter VIII

THE MEXICALI PROJECT: AN IMPLEMENTATION

8.1 BACKGROUND

The approach developed for this dissertation has been applied to a project in Mexicali, Baja California, Mexico.[16] HUACUZ, 1982, describes the Mexicali project. The city of Mexicali is situated in a desert on the California border. The climate features few cloud-cover periods and very little rain, with very hot summers and mild winters. To serve the electricity demand of primarily the three cities in the area, Mexicali, Tijuana and Ensenada, the local branch of the national Comision Federal de la Electricidad (CFE) operates three power plants of a combined capacity of 677 MW, including a geothermal complex of 180 MW capacity. Details of the generating system are given in a following table.

Due to the hot temperatures in the summer, and helped by the relative prosperity of the region and the closeness of the U.S., more and more people in Mexicali are installing air conditioners. This not only causes peak demand projections to rise steeply, but also creates the undesirable si-

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[16] The author has been working on that project with the Mexican Instituto de Investigaciones Electricas (IIE) in Cuernavaca, Morelos, Mexico, for the academic year 1983/84.

tuation that a large part of the capacity is needed only for the summer months, remaining idle for most of the rest of the year.

Speaking in general terms, Mexico has enough oil to fulfil its energy needs, and for instance, EIBENSCHUTZ, 1981, does not believe that renewable energy technologies are either ready or necessary for application in Mexico. However, for the special Mexicali dilemma, one possible solution lies in solar cooling. If several customers adopted solar cooling systems instead of purely electrical systems, this could hold down the demand projections and help avoid construction of new power plants, for which capital is scarce. The author's task at IIE was to examine the effect of programs to promote solar cooling and perhaps other conservation measures, on the region's capacity expansion plan.

The following sections address the data procurement and the results for an application of the algorithms developed in this dissertation, to the Mexicali Project.

8.2 DATA PROCUREMENT

The main purpose of the Mexicali Project was to develop a cost-minimizing capacity expansion plan possibly including conservation and solar cooling, for the electrical subsystem Tijuana-Mexicali of CFE (Comision Federal de Electricidad, the Mexican national utility). For implementation purposes, four types of data were specifically needed for the Tijuana-Mexicali subsystem, namely, the load data, the plant data, the solar cooling and the conservation data, along with general economic indices used in CFE planning.

8.2.1 Load Data

Load forecasts for the Tijuana-Mexicali subsystem can be found in the documents CFE, 1981, and CFE, 1983a. CFE, 1983a, describes the anticipated load growth until 1992. The forecasting takes into account large industrial loads, such as the loads of the Tecate Brewery, of the Fertimex and Cementos California Companies, and of the Mexicali-Tijuana aqueduct. For the residential, commercial and small industrial loads, 1981 is taken as a base year, from which a certain percentage growth dependent on regional economic development is assumed for the remaining years.

While CFE, 1983a, describes the anticipated peak load growth over the coming ten years, CFE, 1981, provides the load shapes for one typical week out of every month of a year, as well as detailed load duration curve data. From the two documents in conjunction, load curve forecasts for the coming ten years can be deduced. (If 20-year forecasts are desired, the last year's percentage growth rate can be applied to obtain forecasts until 2002.) Table 6 depicts projected peak and base loads for the Tijuana-Mexicali subsystem for twenty years starting in 1983.

8.2.2 Conventional Plant Data

The plants currently (December 31,1983) on-line in the Tijuana-Mexicali subsystem (CFE, 1984a), as well as the conventional expansion options, are given in Table 7.
Additions in the planning or construction stages are described in CFE, 1984b. Forced outage rates were obtained through personal communication with the CFE Engineer Mr. Lara Nunez, but are not to be disclosed. Capital, operation and maintenance costs of the different plant types can be found in TALAVERA, 1984, which is based on CFE, 1983b.

8.2.3 Renewable Resource Data

Two types of renewable resources were to be included as options in the capacity plan for the Tijuana-Mexicali subsystem. First, because it would most directly alleviate the peak load problem caused by summer cooling loads, solar cooling systems of the type described in Section 2.8, were included. They are, however, quite expensive, about 2,000,000 Pesos per unit of 2 tons cooling capacity, saving 6 kW during operation compared to a 2 ton conventional air conditioner (HUACUZ, 1984).

TABLE 6

Twenty-Year Load Forecast for the Tijuana-Mexicali System

Year	Base Load (MW)	Peak Load (MW)
1983	183	556
1984	261	793
1985	274	833
1986	288	874
1987	303	918
1988	318	964
1989	334	1012
1990	350	1063
1991	368	1116
1992	386	1172
1993	405	1230
1994	426	1292
1995	447	1356
1996	469	1424
1997	493	1496
1998	517	1570
1999	543	1649
2000	570	1731
2001	599	1818
2002	629	1909

TABLE 7

Conventional Plants in the Tijuana-Mexicali Subsystem

Installed Plants

Plant Type	Location	MW	$/MWyear
Oil	Tijuana Rosarito	307	63.5
Gas	Mexicali	75	112.3
Gas	Rosarito	55	112.3
Gas	Ensenada	60	112.3
Geothermal	Cerro Prieto	180	13.3
Total		677	

Expansion Options

Plant Type	Standard Size (MW)	$/MW	$/MWyear
Oil	88	6.3	63.5
Oil	160	5.4	60.4
Gas	30	3.3	112.3
Geothermal	110	13.0	13.3

Note:

The heading $/MW represents 10^7 Mexican Pesos capital cost per MW; the heading $/MWyear represents 10^7 Mexican Pesos operating and maintenance costs per MW capacity per year.
All capital costs are annualized over the economic plant lives.
All costs are given in 1984 Mexican Pesos.

Thus, for purposes of comparison, a conservation alternative was also included, in the form of added roof insulation and storm doors and windows, at a cost of 130,000 Pesos per average house, and with a power savings of 3.4 kW during operation of the air conditioner (GUIZA, 1984).

Through personal communication with Dr. Huacuz of IIE and other engineers having lived in Mexicali, it was determined that air conditioning equipments typically run 24 hours a day during the hottest summer months, due to the forbidding heat in Mexicali in that period from June through September. From the latter part of October through April, virtually no air conditioning is necessary, while in May and the first days in October, air conditioners will typically have to be run all day long, but not at night. Thus, only two subperiods of varying renewable energy availability are necessary: one summer period including the day-times of May and early October with solar cooling savings of 6 kW and conservation savings of 3.4 kW per unit, and one winter period including the night-times of May and early October with zero contributions of both solar cooling and conservation. Here it is assumed that the solar cooling devices can keep running during summer nights because of storage systems.[17]

However, to accomodate different typical load patterns in different months and on weekdays vs. on Saturdays and Sun-

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[17] Here, the diversity factors of conventional air conditioning devices as well as possible transmission and distribution credits for the renewable energy installations are ignored. However, they could be incorporated easily if the necessary data were available.

days, the year is broken up into 21 subperiods in our implementation. These renewable energy contributions, together with the periods into which the year is divided because of data availability and varying resource availability, are shown in Table 8.

Currently, 35000 Mexicali houses use electrical air conditioning. Thus, the upper bound UBS_1 for the first year in the planning horizon, and for both the solar cooling and the conservation option, is set at 35000 units. This limit, i.e. the number of air conditioned houses, is assumed to grow three percent per year throughout the planning horizon (personal communication with Dr. Huacuz).

8.2.4 General Indices

Through personal communication with CFE's Mr. Zendejas and from the document TALAVERA, 1984, it was learned that CFE uses a 20-year horizon for long-range planning purposes, together with a reliability goal of three days in ten years loss-of-load probability, a reserve margin of 20 Percent and a real internal discount rate of 10 Percent.

The optimal expansion plan for the Tijuana-Mexicali subsystem obtained with the data input described above, is given in the following section.

TABLE 8

Renewable Resource Availabilities over the Year

r = subperiod number
λ = fractional length of subperiod
s = solar cooling availability in MW per 1000 residences
c = conservation availability in MW per 1000 residences
P = subperiod peak load in MW in 1983

The year is divided into 21 subperiods for reasons of differences between typical loads in different months and seasons, between typical loads on weekdays vs. Saturdays and Sundays, and between renewable resource availabilities in different seasons.

r	λ	s	c	P	Part of the Year
1	.2381	0	0	361	weekdays Jan/Feb/Mar/Dec
2	.0476	0	0	339	Sat Jan/Feb/Mar/Dec
3	.0476	0	0	306	Sun Jan/Feb/Mar/Dec
4	.1190	0	0	379	weekdays Apr/Nov
5	.0238	0	0	366	Sat Apr/Nov
6	.0238	0	0	334	Sun Apr/Nov
7	.0793	0	0	334	wkday (nights, May + Oct 1-10), Oct 11-31
8	.0159	0	0	395	Sat (nights, May + Oct 1-10), Oct 11-31
9	.0159	0	0	381	Sun (nights, May + Oct 1-10), Oct 11-31
10	.0400	6	3.4	352	weekdays (days, May + Oct 1-10)
11	.0079	6	3.4	404	Sat (days, May + Oct 1-10)
12	.0079	6	3.4	391	Sun (days, May + Oct 1-10)
13	.0595	6	3.4	502	weekdays June
14	.0119	6	3.4	465	Sat June
15	.0119	6	3.4	406	Sun June
16	.0595	6	3.4	556	weekdays July
17	.0119	6	3.4	508	Sat July
18	.0119	6	3.4	466	Sun July
19	.1190	6	3.4	539	weekdays Aug/Sep
20	.0238	6	3.4	512	Sat Aug/Sep
21	.0238	6	3.4	452	Sun Aug/Sep

8.3 OPTIMAL EXPANSION PLAN

To illustrate the effect of the integrality restrictions on conventional capacities, two expansion plans are given in this section. First, no integrality restrictions are considered, and results for a twenty-year planning horizon for the Tijuana-Mexicali subsystem are given in Table 9 and can be visualized in Figure 14.

Program GBD,[18] as implemented on Virginia Tech's IBM 3084 computer, needed 79.26 seconds of CPU time to solve that problem to within a five percent accuracy, of which 40.27 seconds were used in the deterministic phase with 6 iterations, while 38.99 seconds were used for one single probabilistic iteration that verified probabilistic optimality of the deterministic optimum. (Here, the option U=2 was used.)

The sensitivity of the results in Table 9 with respect to the forced outage rate data for conventional plants was investigated by re-running the 20-year expansion planning problem without enforcement of integrality, for a data set with drastically changed forced outage rates. The results are reported in Table 10. Due to the greater probabilities of forced outages, more conventional plants are installed in this expansion plan than in the one illustrated in Table 9. The conservation option is at its upper bound in every year,

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[18] chosen over LDD because of the initial bounds on geothermal capacities mentioned in the table.

TABLE 9

20-Year Expansion Path without Enforcement of Integrality

		New MW			Residences	
Year	Peak Load	Geothermal	Coal	Gas	Solar	Conservation
1983	556	110	0	0	0	35000
1984	793	110	0	0	0	1050
1985	833	0	0	0	0	1070
1986	874	0	0	39	0	1080
1987	918	0	0	51	0	1100
1988	964	110	0	0	0	1100
1989	1012	0	0	0	0	1200
1990	1063	52	0	0	0	1300
1991	1116	60	0	0	0	1300
1992	1172	62	0	0	0	1400
1993	1230	66	0	0	0	1400
1994	1292	69	0	0	0	1400
1995	1356	73	0	0	0	1500
1996	1424	77	0	0	0	1500
1997	1496	80	0	0	0	1600
1998	1570	281	0	0	0	1600
1999	1649	0	0	0	0	1600
2000	1731	0	0	0	0	1700
2001	1818	0	0	88	0	1700
2002	1909	103	0	0	0	1800

The total discounted cost of this expansion plan is 39274 Million Mexican Pesos (1984 Pesos).

Because of the long lead times for construction of geothermal plants at the Cerro Prieto site, upper bounds on the geothermal capacities were imposed for the first 7 years. (as given in Table 12). For these years, the optimal expansion plan shown above has the geothermal capacities at their upper bounds.

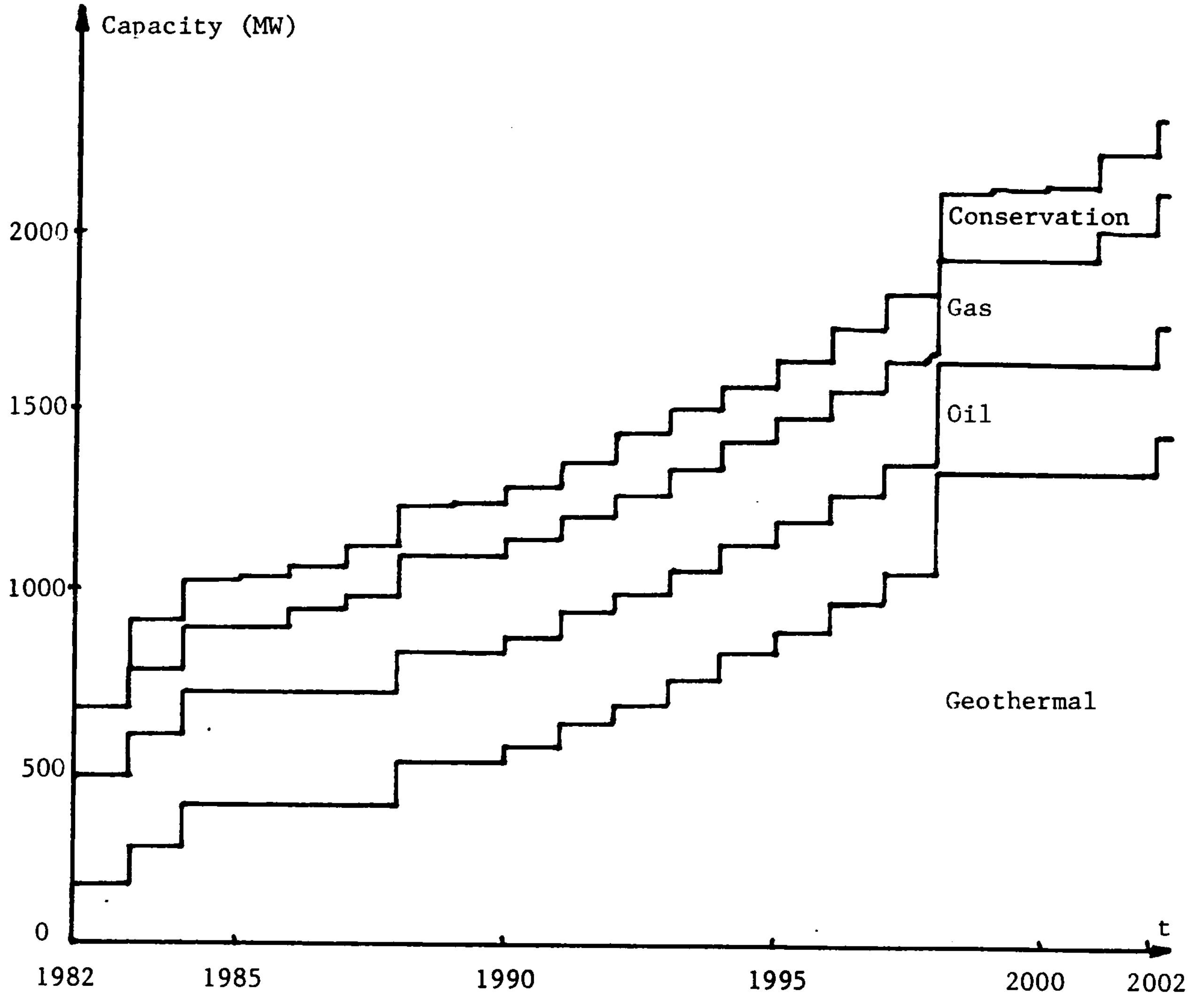

Figure 14: 20-Year Expansion Plan Without Enforcement of Integrality

as in Table 9, and the solar cooling option is not included in the optimal plan. The total cost is higher than in Table 9, due to the additional installation of conventional capacities necessary to offset the higher forced outage rates. Program GBD, as implemented on Virginia Tech's IBM 3084, needed 329.06 CPU-seconds to solve that problem to within a five percent accuracy, of which 36.11 seconds were used in five deterministic iterations, and 292.95 seconds were used in five probabilistic iterations to find a probabilistically feasible solution close to the deterministic optimum, which was then found optimal to within the five percent tolerance.

For the results in Table 11, integrality restrictions were imposed for all conventional equipment types, and a twenty year planning horizon was used. The original forced outage rate data provided by the Mexican authorities were used for this run. At each node of the Branch and Bound program, both the deterministic and the probabilistic phases were used. The resulting expansion plan is illustrated in Figure 15, while the progress of the Branch and Bound algorithm is illustrated in Table 12. Total computation time on the IBM 3084 was 1413.04 seconds for 26 nodes.

It can be seen from these results that the promotion of conservation would be a cost-effective tool for the Tijuana-Mexicali subsystem of CFE, even if CFE had to carry the

TABLE 10

20-Year Expansion Path with Changed Forced Outage Rates

		New MW			Residences	
Year	Peak Load	Geothermal	Coal	Gas	Solar	Conservation
1983	556	110	163	344	0	35000
1984	793	110	306	220	0	1050
1985	833	0	68	0	0	1070
1986	874	0	0	66	0	1080
1987	918	0	0	70	0	1100
1988	964	110	0	0	0	1100
1989	1012	110	0	0	0	1200
1990	1063	74	0	0	0	1300
1991	1116	0	0	0	0	1300
1992	1172	83	0	0	0	1400
1993	1230	7	0	86	0	1400
1994	1292	92	0	0	0	1400
1995	1356	97	0	0	0	1500
1996	1424	102	0	0	0	1500
1997	1496	107	0	0	0	1600
1998	1570	112	0	0	0	1600
1999	1649	118	0	0	0	1600
2000	1731	124	0	0	0	1700
2001	1818	131	0	0	0	1700
2002	1909	137	0	0	0	1800

The total discounted cost of this expansion plan is 57195 Million Mexican Pesos (1984 Pesos).

Here, forced outage rates of 0.25 for geothermal plants, 0.35 and 0.4 for new and old oil-fired plants, respectively, and 0.3 for gas turbines were used.

The upper bounds on geothermal capacities given in Table 12 were also included here.

TABLE 11

20-Year Expansion Path with Integrality Restrictions

Year	Peak Load	Geothermal	New MW Coal	Gas	Residences Solar	Conservation
1983	556	110	0	0	0	35000
1984	793	110	0	0	0	1050
1985	833	0	0	0	0	1070
1986	874	0	0	30	1480	1080
1987	918	0	0	60	0	1100
1988	964	110	0	0	0	1100
1989	1012	110	0	0	0	1200
1990	1063	0	0	0	0	1300
1991	1116	110	0	0	0	1300
1992	1172	110	0	0	0	1400
1993	1230	0	0	0	0	1400
1994	1292	110	0	0	0	1400
1995	1356	110	0	0	0	1500
1996	1424	0	0	0	0	1500
1997	1496	0	0	0	0	1600
1998	1570	110	0	0	0	1600
1999	1649	0	0	60	0	1600
2000	1731	220	0	0	0	1700
2001	1818	110	0	0	0	1700
2002	1909	0	0	0	0	1800

The total discounted cost of this expansion plan is 39996 Million Mexican Pesos (1984 Pesos).

Because of the long lead times for geothermal plants at Cerro Prieto, upper bounds on the geothermal capacities were included in node 0. The optimal expansion plan shown above has the geothermal capacity at its upper bound in all years with such initial upper bounds.
These bounds are given in Table 12.

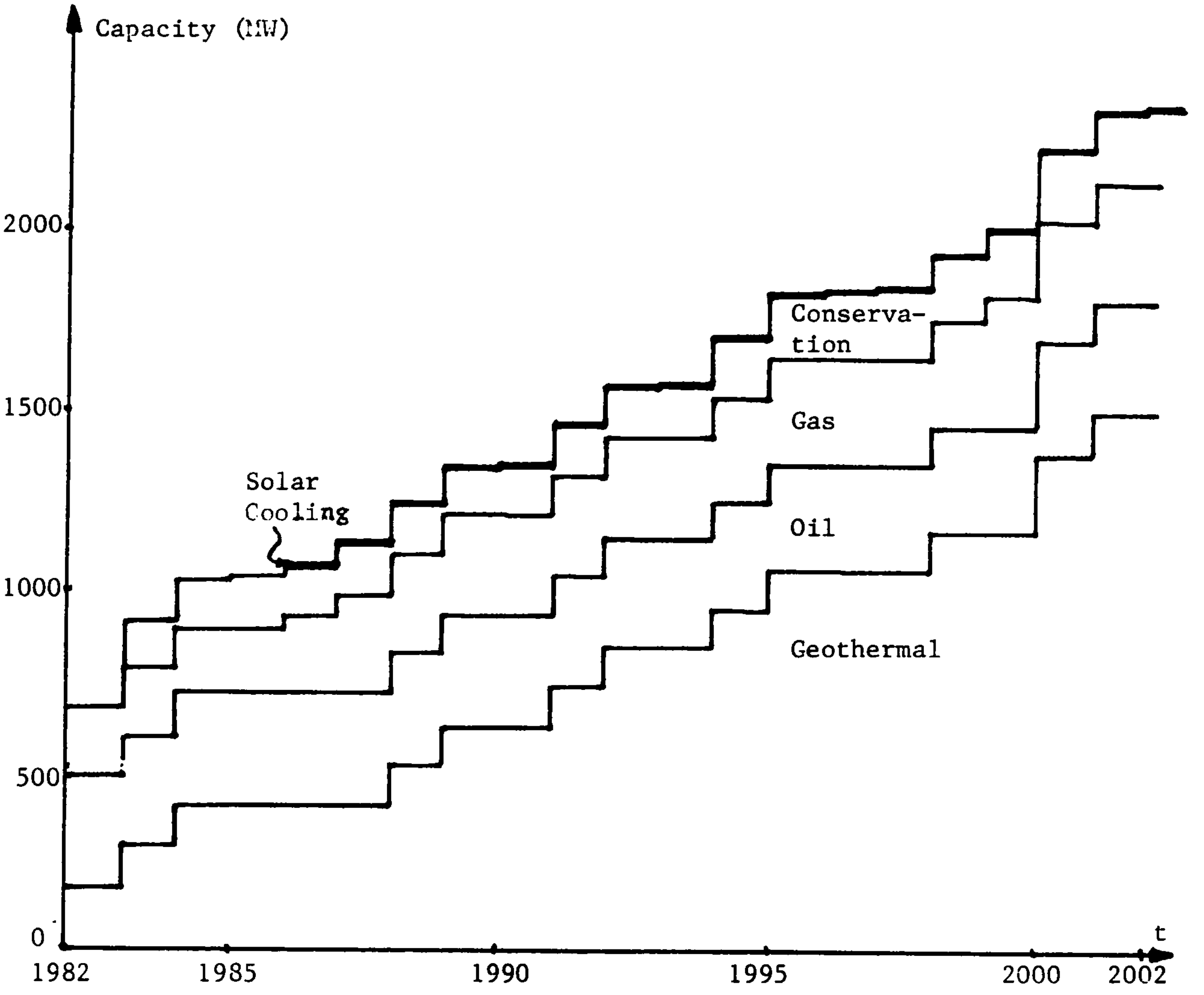

Figure 15: 20-Year Expansion Plan With Integrality Restrictions

TABLE 12

Progress of the Branch and Bound Routine

node	obj value	cpu sec	DIts	PIts	new bound eq type	new bound year	bound
0	39274	79.26	6	1	geothermal	1990	≤0
0	42910	90.92	-	1	heuristic integer soln.		
1	39114	158.89	6	1	geothermal	1992	≥110
2	39231	223.88	6	1	geothermal	1995	≥110
3	39277	287.80	6	1	geothermal	1994	≥110
4	39164	347.95	5	1	oil	1987	≤0
5	39102	410.26	5	1	oil	1986	≤0
6	39069	471.36	5	1	geothermal	1991	≥110
7	39454	527.49	4	1	oil	1997	≤0
8	39482	582.76	3	1	geothermal	1998	≥110
9	39132	632.55	3	1	geothermal	1989	≥110
10	39166	681.24	3	1	gas	1986	≤30
11	39167	730.56	3	1	gas	1985	≤0
12	39170	779.79	3	1	gas	1984	≤0
13	39173	818.87	3	1	gas	1983	≤0
14	39179	882.32	3	1	oil	1985	≤0
15	39182	936.06	3	1	oil	1984	≤0
16	39186	990.15	3	1	oil	1983	≤0
17	39600	1039.99	3	1	gas	1987	≥60
18	39638	1089.40	3	1	geothermal	2001	≥110
19	39973	1134.99	2	1	geothermal	1999	≤0
20	40008	1181.14	2	1	geothermal	1998	≤110
21	40037	1227.23	2	1	geothermal	1997	≤0
22	40074	1273.72	2	1	geothermal	1996	≤0
23	39877	1320.94	2	1	geothermal	2000	≥220
24	39977	1368.06	2	1	gas	1999	≥60
25	39996	1412.96	2	1	integer solution, all other nodes fathomed since their objective values are within ε=5 percent of 39996.		

DIts = number of deterministic iterations
PIts = number of probabilistic iterations
The cpu seconds are counted cumulatively.
The objective values are given in Millions of Mexican Pesos.
Some nodes may have lower objective values than lower-numbered nodes due to the ε-termination tolerance in Program GBD (ε=5 percent = 2000 here).

Initial bounds on the geothermal capacities:

Year	1983	1983	1984	1984	1985	1986	1987	1988	1989
Bound	≤110	≥110	≤110	≥110	≤0	≤0	≤0	≤110	≤110

whole cost of conservation.[19] In fact, the number of houses to be insulated in the optimal solution, is consistently the largest number feasible to the upper bounds mentioned in Section 8.2.3. However, the solar cooling option does not emerge as a cost-effective option in our analysis, mainly due to its high capital requirements. (In Table 11, the solar capacity is positive only in one year.)

As noted in Section 7.1.2.1, for the test runs conducted with the Mexicali data, the large savings realized by going from a purely conventional expansion plan, arrived at with the heuristic displayed in Figure 10, to the optimal expansion plan including conservation equipment, is remarkable. For the runs in Tables 9 and 10, the heuristic objective value was 71600 Million Pesos, i.e. 75 percent higher than the optimal objective value.

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[19] The issue of incorporating into our algorithms the possibility that the utility only carries part of the conservation cost, say through cash rebates or zero-interest loans, is addressed in Chapter 9.

Chapter IX

EXTENSIONS AND CONCLUSIONS

In this concluding chapter, first some possible extensions of the models described in this disseration will be suggested. These include the incorporation of a model of consumer response to utility promotion programs for renewable energy and conservation, the incorporation of hydro plants into the algorithms presented in this dissertation, and a possible modification of the models' objective functions to minimize per kWh-cost rather than total cost. Thereafter, the contributions of this research effort will be summarized.

9.1 CONSUMER RESPONSE TO UTILITY PROGRAMS

9.1.1 The Demand for Conservation and Renewable Energy Equipment

As noted in the literature review, models of the market penetration of solar energy products still leave much to be desired in terms of accuracy and explanatory strength (SHAMA, 1981). However, some such models representing the state of the art exist, and are for instance described in SHAMA, 1981, and SCHIFFEL, 1978b.

On the other hand, federal, state and local governments as well as utilities are already engaging in many programs designed to promote the use of conservation and renewable resources (see, e.g., RANDOLPH, 1980a, 1981). With this research concentrating on electric utility planning, it should be noted that for instance the Pacific Northwest Region plans to rely on conservation and renewable energy sources for serving a major part of its electricity demand growth (NWPPC, 1983). However, even when such major commitments are made, no attempt has been made to optimize the measures that are to bring about such large amounts of conservation and usage of renewable energy sources, in conjunction with the optimization of the actual power system (NWPPC 1983).

Thus, one can hardly lose accuracy, but only gain insight and economic efficiency, by including a model of consumer response to utility promotion of conservation and renewable energy into the capacity planning process. For this purpose, one needs an expression for consumer demand for conservation and renewable energy equipment. This demand has to be expressed as a function of prices, the possible financial incentive programs promoted by the utility, the intensity of information campaigns conducted by the utility, and the ease of obtaining information from other sources. In particular, if the level of financial incentives and the intensity of information campaigns are to be included in a capacity expansion planning algorithm as decision variables, demand has to be modeled as a function of these parameters.

However, as appropriately noted in SHAMA, 1981 (p 66),

> evidence from the early solar marketplace suggests that solar systems are purchased even if they are not the lowest-cost option, and that cost-competetiveness does not guarantee adoption. According to this premise, to be useful in explaining the solar diffusion process, models must incorporate the major noncost variables associated with solar penetration of early markets.

LEONARD-BARTON, 1978 and 1981, reports on a statewide survey of California homeowners on attitudes toward solar energy. (For an overview on similar studies, see UNSELD and Crews, 1979). It is found that the best predictors of intention to purchase solar equipment are the number of solar owners known by the homeowner, his general attitude toward solar equipment, his score on an index of voluntary simplicity behaviors (i.e. do-it-yourself attitudes motivated by environmental concerns), and the perceived paypack period of solar equipment. Other explanatory variables that failed to be significant were awareness of tax credit, socioeconomic status, age, probability of moving, perceived effect of solar equipment on house resale value, mechanical ability, energy cost expectations, utility bill, and attitude toward the energy crisis.

These findings underscore the statements made above that for early adopters, non-monetary issues such as the voluntary simplicity attitude, and personal communication with solar owners are very important. When constructing any model on consumer acceptance of solar equipment, such factors will have to be included, especially if the general model to be developed is to be applied in different areas with differing consumer characteristics. On the other hand, the two other significant factors mentioned by LEONARD-BARTON, 1981, namely, general attitude and perceived payback, can be influenced by information campaigns, and can thus be directly related to potential decision variables representing the intenseness of such campaigns.

Combining this information with the approach taken in the market penetration models reviewed in SCHIFFEL, 1978b, a possible approach for incorporating consumer acceptance in capacity planning models emerges, which is described in the following subsection. This subsection also addresses the problems of estimating consumer acceptance particularly for the Mexicali project.

9.1.2 A Model of Consumer Response to Utility Programs

If only financial incentive programs were to be considered by the utility, a straightforward economic demand curve for solar equipment would suffice as a model of consumer response to the utility program, since the incentives could be interpreted as simply a reduction in price. However, two factors make this approach impossible to apply on the Mexicali project.

First, possible information campaigns, which are potentially very helpful in the early stages of adoption, are also to be considered. Second and more importantly, demand curve information is not available. The market for solar cooling systems is in its infancy even in the U.S. (VENHUIZEN, 1982). In Mexico, not even a well-developed market for solar collectors exist, and absolutely no market for solar cooling systems (HUACUZ, 1982). Thus, there exists no information whatsoever on Mexican demand for solar cooling systems.

Therefore, one has to resort to estimating demand curves either from non-market data, i.e. from surveys, or from market data available in the U.S. If surveys are used, it is desirable to be able to validate the information given by survey respondents. Otherwise, one has no guarantee that the respondents would actually behave as they indicated in the survey, when faced with a real world decision. If for any reason they see an advantage in doing so, they might even behave strategically, i.e. give biased answers in the hope of influencing decisions that are made based on survey results (FREEMAN, 1979).

Since there is no Mexican market for solar cooling systems, there is no way of validating any information survey respondents may give concerning their intent to acquire such a system. Indeed, the greater part of the population would probably be so unfamiliar with solar equipment that questions on such equipment would be meaningless.

One possible approach is to use a regression similar to the one LEONARD-BARTON, 1981, reports on, and calculate regression coefficients for the factors influencing purchase decisions from U.S. data. By plugging Mexican data into the regression, Mexican demand for solar equipment can be estimated. If general attitude toward solar energy and perceived payback can be expressed as functions of utility activity, demand can be expressed as a function of that activity. These Mexican data could be obtained from surveys, and since they only concern attitudes rather than purchase intentions themselves, one can hope for rather accurate responses.

However, this approach amounts to applying regression data found from U.S. data in Mexico, a procedure that at least has to be validated sufficiently. One possible validation approach is to apply the exact same procedure on a commodity that is available both in the U.S. and in Mexico, for instance electric air conditioners. Then, the demand obtained from the regression can be compared with the actual Mexican demand for air conditioners, and the regression approach can be considered validated if results compare closely. If results do not compare closely, the actual data could be used to derive a scaling factor with which all coefficients may be multiplied when the regression equation is applied to Mexico.

One should also consider a logit or probit analysis, instead of applying the standard regression formulas, i.e. ordinary least squares or generalized least squares. This type of analysis has been suggested in the agricultural economics literature for modeling the aggregate of individual decisions on adoption of some behaviour or innovation. Such decisions can be explained using a threshold theory of decision in which adoption occurs only after certain influences on the decision grow past the individual's threshold. See, e.g., HILL and Kau, 1973, and MILLER and Hay, 1981, for applications of such models.

Once a function relating the amount of utility expenditure with the consumer response, i.e. with a certain investment in conservation and a resulting expected energy savings is obtained, it has to be incorporated into the capacity planning models. In most cases, it can be expected to be a convex function, since the more conservation investment a utility tries to induce, the more incentives it would have to provide marginally. Thus, convexity of Problems CP and PP would still be given, the only change being that the capital cost for renewable energy and conservation equipment becomes convex rather than linear. This would trigger some non-trivial changes in the Generalized Benders Decomposition approach, since that approach is based on the x-variables appearing only in linear expressions.

The Lagrangian Dual Decomposition approach, however, could incorporate convex capital cost functions for renewable equipments very easily. These capital costs affect the algorithm within the Subproblem RSP, in which a convex total yearly cost function is optimized with respect to the renewable equipment capacities, and without any constraints except bounding constraints. Convexity rather than linearity of the capital cost part of that cost function would not affect its structure nor the algorithm suggested for the solution of RSP in SHERALI and Staschus, 1985.

9.2 INCORPORATING HYDRO PLANTS IN CAPACITY PLANNING

CARAMANIS et al, 1982b, include a state of the art method for accomodating hydro plants and pumped-storage plants in a probabilistic capacity planning algorithm and in their program EGEAS. This method is based on the dispatching policy which can be directly proven to be optimal only in the deterministic case.

The optimal policy is to dispatch the near-zero operating cost stored energy at the time when it replaces most expensive conventionally generated energy, i.e. during times of high loads. Therefore, hydro plants with storage reservoirs are dispatched such that the stored energy is equal to the integral of the inverse load duration curve between the load at which the hydro plant is loaded, and this load plus the plant's capacity. In this way, both the full capacity and all the stored energy are used. This dispatching rule is proven optimal for the deterministic case in STASCHUS, 1982, for instance.

In a probabilistic model, uncertainties about the river flow, the actual load at any time, and about conventional plant outages have to be considered, and the above rule cannot be applied directly. As reported in Section 2.3.6, hydro-thermal system scheduling algorithms are mostly of the dynamic programming type. An incorporation of hydro plant modeling into the algorithms described in this dissertation could therefore be very cumbersome, although for the deterministic models, it would not present any theoretical difficulties.

9.3 ELECTRICITY PRICE MINIMIZATION

As mentioned in Section 2.5.3, a utility embarking on conservation promotion programs has to be careful to ensure that none of its customers becomes worse off through such programs. A decision rule based on the utility's marginal cost can be used to guarantee this. However, a more rigorous treatment of the problem would require that the utility's expansion plan can be shown to minimize the per-kWh cost for every customer.

If a utility's conservation and renewable energy usage promotion programs are to play a major role in its resource plan, its capacity planning objective should therefore be the minimization of per-kWh cost rather than total cost. Thus, an objective function of the following type results:

$$\min \frac{CC(x) + OC(z)}{TG(z_j)},$$

where $TG(z_j)$ = total generation, which is a function of the renewable energy usage z_j, as exemplified in the following total generation expression for one year only

$$= \int_0^P \sum_{r=1}^{R} \lambda_r F_r(y + \sum_{j=1}^{J} a_{rj} z_j)dy$$

where P = yearly peak load.

Here, discount factors have to be appropriately taken into account in formulating a total generation expression for the entire planning horizon.

In the above objective function expression, both the denominator and the numerator are functions in the decision variables. All constraints would remain the same as in Problem CP. It should be noted that the above formulation represents the deterministic case, and that in a probabilistic formulation, the total generation would have to be arrived at by using hour-by-hour simulation of the renewable energy contributions.

Problems that contain functions in the decision variables in both the denominator and the numerator of an objective function, can be solved with the tools of Fractional Programming. SCHAIBLE and Ibaraki, 1983, give an overview of available Fractional Programming algorithms. The application of a parametric approach, as outlined in Section 3.4 of SCHAIBLE and Ibaraki, 1983, would seem most promising for the problem at hand, given that the necessary convexity properties could be proven.

9.4 CONCLUSION

In this dissertation, the electric utility capacity expansion planning problem, including renewable energy options, has been examined. Several decomposition algorithms have been developed and applied to a Mexican electric utility's expansion planning problem.

Although there are many methods available for the capacity planning problem in the literature and in the form of computer codes, to our knowledge only the Electric Power Research Institute's EGEAS code (CARAMANIS et al, 1982b) includes renewable energy options on an equal footing with conventional expansion options in its methodology. Chapter 3 lists some restrictions on the application of that methodology, namely, that it can only be applied on large systems, and that its Gram-Schmidt orthogonalization of load and renewable energy contributions does not always yield proper results. Different approaches in the literature, i.e. hour-by-hour simulation and probabilistic production costing methods, that can avoid these difficulties, consume far too much computing time to even be considered in a capacity planning context. Finally, the literature also shows a number of previous attempts to decompose the multi-year planning problem into single-year plantmix problems, without being able to give convergence proofs.

In this research, both these issues of devising a probabilistic algorithm not subject to the above mentioned restrictions, and of proving convergence of a decomposition algorithm that has single-year plantmix problems as its subproblems, are addressed and resolved. The two-phase algorithmic approach, with a fast deterministic phase followed by few probabilistic iterations, has been shown to be able to save up to 80 percent in computing time as compared to a purely probabilistic algorithm. Renewable energy contributions are modeled in the deterministic phase through histogram approximations, with their availabilities varying in different subperiods of the year and the day. Several decomposition approaches for the deterministic model have been investigated. Of these, the theoretically convergent Lagrangian Dual Decomposition approach, which has single-year plantmix problems as subproblems, proved to be the fastest. In extensive computational tests, both decomposition approaches that were investigated proved orders of magnitude faster than a standard nonlinear programming package applied on the same data.

A Branch and Bound routine was superimposed on the two-phase algorithm, so that a solution consisting only of integer plant numbers for conventional plants could be obtained. This integrality issue is often ignored in the literature. The fast solution of each node's restricted expansion problem becomes even more inportant in this context, when a large number of nodes may need to be evaluated in order to arrive at the optimal integer solution. Thus, the computer time savings realized through the application of the two-phase method are crucial here.

Finally, the methods developed were applied in the real-world Mexicali Project of the Mexican Institute of Electrical Research (IIE). Data were collected, and the optimal expansion plan including conservation options for the Tijuana-Mexicali subsystem of the Mexican utility system was determined through the application of the deterministic, probabilistic and integer algorithms, using the computer programs developed for this dissertation.

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Abbreviations:

AER = American Economic Review
Bell = Bell Journal of Economics
EJOR = European Journal of Operations Research
EPSR = Electric Power Systems Research
JLE = Journal of Law and Economics
JPE = Journal of Political Economy
MS = Management Science
OR = Operations Research
ORNL = Oak Ridge National Laboratory Report
PAS = IEEE Transactions on Power Apparatus and Systems
PICA = Power Industry Computer Applications
PSCC = Power Systems Computation Conference
QJE = Quarterly Journal of Economics
SE = Solar Energy
SERI = Solar Energy Research Institute Report
SLR = Solar Law Reporter
SUN II = Proceedings of the International Solar Energy Society

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