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Electric-Utility Value Determination for Wind Energy

Volume I: A Methodology

David Percival
James Harper

SERI

Solar Energy Research Institute
A Division of Midwest Research Institute

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Golden, Colorado 80401

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PREFACE

This report, the first of two volumes and prepared within the Utility Applications and Policy Branch of SERI for the Department of Energy's Wind Energy Systems Division under Subtask 3532.15, contains a methodology to determine the value of wind energy conversion systems to electric utilities. A complete description of the associated computer programs developed by and available from SERI is also included. Volume II is a user's guide for the computer programs.

The authors wish to recognize George Fegan for his contributions to the formulation of the methods described in this report. We also wish to acknowledge Theresa Flaim, Dean Nordman, and Roger Taylor of SERI for their assistance during the project and the review of this report.

We would also like to thank the following people for their constructive review: John H. Bannick, New England Regional Commission; Jill S. Baylor, Duke Power Co.; John T. Day, Westinghouse Electric Corp.; Oliver D. Gildersleeve, Electric Power Research Institute; Robert L. Sullivan, University of Florida; and George Tennyson, DOE Wind Energy Systems Division. They are, of course, not responsible for any errors that may remain in the final document.

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SUMMARY

Objective:

The objective of this report is to describe a method developed by the Solar Energy Research Institute (SERI) for determining the value of Wind Energy Conversion Systems (WECS) to electric utilities. The method is performed by a package of computer models available from SERI. These models vary in sophistication and may be used with most utility planning models. Only minimal effort should be required to make the programs operational on hardware other than the CDC hardware on which the programs were developed and used.

Discussion:

This report consists of two volumes. The first volume describes the value determination method and gives detailed discussion on each computer program available from SERI. The second volume is a user's guide for these computer programs.

The value determination process begins with the processing of weather data by computer programs WTP or WEIBUL to produce hourly wind speed data or wind probability distributions, respectively. These data are then provided as input to the program ROSEW, which estimates wind-derived electricity production.

The results from ROSEW, which can give the probabilities of certain WECS power levels being produced, are next provided as input to the program ULMOD so that the utility load forecast may be modified to incorporate the WECS generation. These results, which are for as many years as desired, are provided to the utility planning models. The expansion planning model develops an optimal scenario of conventional generating unit additions. This amount of conventional units is given to a production cost model to develop a more accurate estimate of the variable operating costs needed for the conventional generating system. This cost information and the conventional capacity information from the expansion model for the base case (zero WECS) and for all the change cases (varying WECS capacity) are provided to FINAM. This final routine determines the break-even cost of each WECS penetration ($/rated kW) and the WECS marginal value ($/rated kW), where value is the utility's present worth savings of reduced operating costs and modified capital additions. These values may be combined with total WECS cost to determine the maximum amount of WECS capacity that can be economically justified for addition to the utility system.

If the WECS value obtained exceeds the amount for which WECS may be purchased, the utility planner might next perform a financial analysis by the utility's corporate model to determine the effects on cash flow, debt requirements, etc.

While the analysis was primarily developed for utility-owned and controlled WECS, the analysis could easily be applied to nonutility-owned WECS with proper treatment of WECS availability.

Conclusions and Recommendations:

A planning group interested in this wind value determination method should obtain copies of the SERI-developed computer programs (WTP, WEIBUL, ROSEW, ULMOD, and FINAM) together with Volumes I and II of this report. The utility expansion planning and production cost models are currently used by many utilities and are not available through SERI. The utility may also prefer to use its own financial model instead of FINAM in the last step of the method.

This group of programs and associated materials are identified by the name WECS. The SERI codes are available through two sources. Qualifying organizations may use the SERI Solar Energy Information Data Bank (SEIDB) network, which houses these computer models. To determine qualification status, contact: Rafael Ubico, SEIDB Coordinator, SERI, 1617 Cole Blvd., Golden, CO 80401; 303-231-1032 (FTS-327-1032). These models are also available through National Energy Software Center, Argonne National Lab, 9700 S. Cass Ave., Argonne, IL 60439.

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SECTION 1.0

INTRODUCTION

During the past several years there have been a number of studies on the value of Wind Energy Conversion Systems (WECS) to electric utilities [1-6]. Because the approaches taken varied from study to study and different degrees of sophistication were used, the Solar Energy Research Institute (SERI), sponsored by the Wind Energy Systems Division of the U.S. Department of Energy (DOE), began to develop a package of computerized tools to determine the value of WECS to electric utilities. These tools were to be capable of varying sophistication and were not to require the modification of the electric utility planning models that must be used in concert with the models developed here. The programs were not to be built around any specific versions of the utility planning models. All computer models developed by SERI and described in detail here are available from SERI. Although the programs were developed and used on CDC hardware, the effort required to make them operational on other hardware should be minimal.

This report consists of two volumes. The first volume begins with an overview of the method of WECS value determination and a brief description of the process. Then follows a detailed discussion of how each computer program available from SERI can be used in the value determination process, as well as the execution options available and calculations performed. The second volume is a user's guide for these computer programs and includes the inputs required, outputs available, the important internal variables used, and a description of external data files employed. Also included in Volume II is a sample runstream necessary to execute the program and a description of possible modifications necessary to utilize the program on another computer facility.

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SECTION 2.0

OVERVIEW

This report contains a method for determining the value of WECS to an electric utility. The necessary procedures are incorporated in five computer programs available from SERI: WTP, WEIBUL, ROSEW, ULMOD, and FINAM. Also needed are two traditional utility planning models: an expansion planning model and a detailed electric utility production cost model. The relationship of all the computer programs is shown in Fig. 2-1.

As the figure shows, the value determination procedure begins with the processing of weather data by computer programs WTP or WEIBUL to produce hourly wind speed data or wind probability distributions, respectively. These data are then provided as input to ROSEW, which estimates wind-derived electricity production. The amount of electricity produced depends on the amount of WECS installed capacity. The results of ROSEW are next provided to ULMOD so that the utility load forecast may be modified to incorporate the WECS generation. These results, which may be produced for as many years as desired, are provided to the utility planning models. The expansion planning model develops an "optimal" scenario of conventional generating unit additions. This schedule of additions of conventional units is given to the production cost model to develop a more accurate estimate of the variable operating costs needed for the conventional generating system. This cost information and the conventional capacity information from the expansion model for the base case (zero WECS) and for all the change cases (varying WECS capacity) are provided to FINAM. This final routine determines the break-even cost of each WECS penetration (\$/rated kW). Also determined is the WECS marginal value (\$/rated kW), which may be used to determine the maximum amount of WECS capacity that can be economically justified for addition to the utility system. An electric utility trying to determine the value of WECS penetrations may prefer to use their corporate financial model instead of FINAM.

The remainder of this section provides additional information about each computer program depicted in Fig. 2-1. Later sections contain detailed discussions of the performance of each computer routine available from SERI.

2.1 WEATHER TAPE PREPROCESSOR—WTP

The function of WTP is to convert a single year of standard weather data into a format acceptable to the program ROSEW. (WTP was developed by the Stone & Webster Corporation and later adapted to SERI's use.) There are four types of weather data acceptable to WTP: SOLMET, TMY, TDF, and Aerospace. SOLMET, TMY, and TDF data are available on computer tapes from the National Weather Service. SOLMET data are available for 26 cities around the United States, with some of these data going back to the early 1960s. Developed from the SOLMET data, TMY data represent an attempt to produce a typical meteorological year for each of those 26 cities. The TDF data are available for many cities, but the quality and quantity of data are significantly lower. Aerospace data are available only from Aerospace Corporation and were developed for just a few Southwestern cities. If the user has weather data that are not in one of

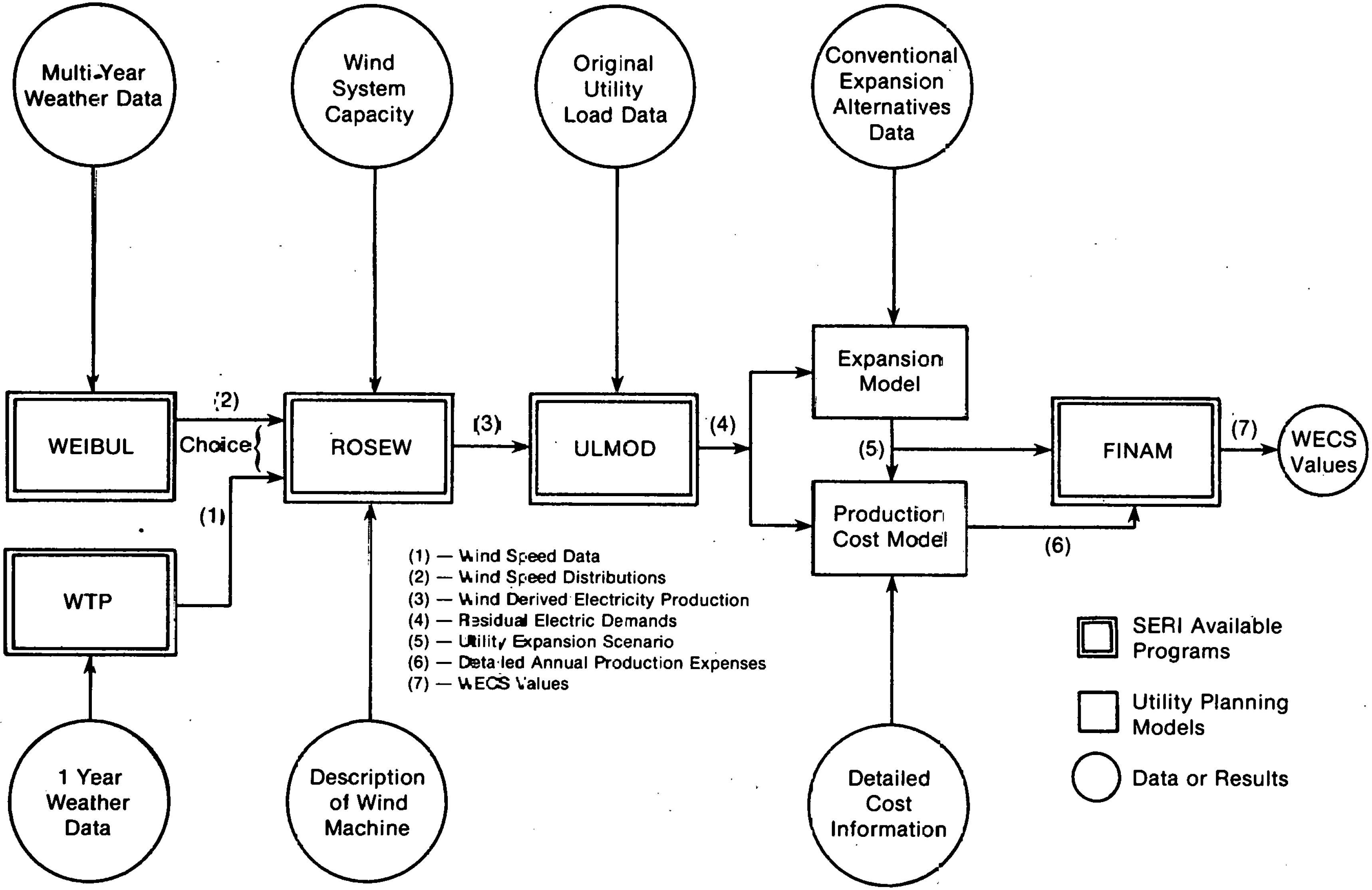

Figure 2-1. Value Model Overview

these formats, then transforming the new data into one of these four formats is recommended.

Whichever of the four weather data formats is employed, WTP ignores the extraneous data, converts the needed data to metric units, and produces a computer data file of the results. If not all data are available from the original weather tape, WTP performs interpolation to fill in the missing data points. This resulting weather data file [indicated by (1) on Fig. 2-1] consists of a single value per hour of the year for wind speed, dry-bulb temperature, relative humidity, barometric pressure, opaque sky cover, and, if available, direct and total insolation. Refer to Sec. 3.0 for additional WTP details.

Since the amount of power in the wind is proportional to the cube of the wind speed, accurate representation of the wind resource is of utmost importance in the WECS value determination process. With this in mind, several problems that arise with the use of this hourly data must be presented. First, the hourly value is not an average value over the hour but merely a single observation sometime during that hour. Use of this type of wind data assumes that the wind velocity has this constant value over the entire hour, when in reality the wind velocity can fluctuate widely and rapidly during the hour. Secondly, since only one year of these hourly values are used, the long-term nature of the weather at this site has certainly not been represented.

There are several possibilities that may alleviate these difficulties. If it is possible to acquire or develop an average or typical year of data to use, then the long-term weather averages could possibly be represented. But the difficulty of which definition of average to use is always present, and the important weather variability is still not represented. Another option is to go through the entire value methodology for several years of weather data. Given enough years of data, the results would be useful, but the significant increases in computer costs would discourage this practice. The best way to capture long-term weather variability is to develop a statistical representation from as many years of weather data as possible; the program WEIBUL is based on this concept. The authors recommend the program WEIBUL be used to process the weather data instead of WTP if two or more years of weather data are available.

2.2 WEIBULL DISTRIBUTION DEVELOPMENT—WEIBUL

WEIBUL is preferable to WTP if two or more years of weather data are available because WEIBUL's probabilistic representation of hourly wind speeds is more likely to closely approximate the long-term wind speeds than WTP's hourly average wind speeds. This additional accuracy could be extremely important in the calculation of total capturable energy. Also, the unpredictability of wind velocity should be reflected in electric utility studies. These points are discussed more fully in the conference paper included as Appendix A.

The function of WEIBUL is to convert one or more years of weather data into a statistical format acceptable to the program ROSEW. Because WEIBUL was developed by modifying WTP, it can use the same four types of input weather data to obtain as large a statistical sample as possible. Unlike WTP, WEIBUL should be used with more than one year of data. The results of WEIBUL execution are, for each hour of a typical day for each month, a probabilistic representation of wind speed and averages of dry-bulb temperature, barometric pressure, relative humidity, and wind speed. The probabilistic wind speed results are the C and K parameters of the Weibull distribution curve. Several sources have pointed out the appropriateness of this distribution [7-10], and sample cases to date have confirmed this. Refer to Sec. 4.0 for an expanded discussion of WEIBUL.

2.3 WECS ELECTRIC POWER CALCULATION—ROSEW

ROSEW (Representation of Solar Electrics-Wind) estimates the amount of wind-derived electricity that may be delivered from a specific WECS design and requires the weather data results of either WTP or WEIBUL, as well as the number of WECS for which operational descriptive data are provided. The calculation of recoverable electric energy may be performed in one of two ways. The first method determines the amount of wind energy (cubic law at the hub) over the WECS rotor area. Then the successive application of the WECS coefficient of performance, mechanical efficiencies, and the efficiency of the generator reduces this amount. The second method applies a user-supplied curve of electrical generation versus wind speed. Refer to Sec. 5.0 for a more complete discussion of ROSEW calculations.

The specific calculations used and, consequently, the output available from ROSEW, depend on whether WTP or WEIBUL is employed to produce the weather data inputs to ROSEW. If the preferred model WEIBUL is used, then the ROSEW-produced results are a stepwise-approximated probabilistic distribution of WECS-derived energy for each hour of a typical day for each month. This distribution gives the probability of zero and maximum power capability of the WECS, the maximum (rated) power capability under average air density conditions, and a number of intermediate WECS power levels and associated probabilities.

Results may be provided in several forms if WTP is used. The most obvious result available from ROSEW is the WECS electric output for each hour for which weather data are provided. These calculations assume that the reported wind speed is constant over that hour. In addition, all these values (31 days times 24 hours for a "January") can be summarized into either one, two, or three typical days of WECS-derived electricity. Section 5.0 discusses these output possibilities in more detail.

2.4 UTILITY LOAD MODIFICATIONS—ULMOD

ULMOD can reflect the electricity production of intermittent generation sources such as WECS in utility planning models by reducing the forecasted utility loads by the amount of intermittent generation. The resulting values are called residual loads. Since both the utility loads and solar resources are diurnal, the load reduction must be done hourly (see Appendix A). The simple reduction of hourly loads is an acceptable modeling procedure because of the low variable cost of electricity production from intermittent generation sources. Since the variable production cost is so low, all energy available would be accepted by the utility, except possibly of a predominantly hydro utility. In this case, significant intermittent capacity could encroach into hydroelectric production. If enough storage is available behind the dams, and other constraints such as irrigation and navigation rights do not interfere, the water could be saved for later. Another possible exception to the rule of always accepting alternatively produced energy might arise if intermittent generation forces the residual load below the total of minimum allowable loads on the base load (such as nuclear or large coal) units. This situation might require either the dumping of excess intermittent generation or the creation of agreements with neighboring utilities to accept this excess energy and to repay it later.

ULMOD can use any of the ROSEW results depicting WECS energy production. Utility-forecasted hourly loads may be for all days of each month or for a typical week each month. Depending on the data input, various results of ULMOD execution are available both on a computer data file and in printed form. The results could be used with almost all existing utility planning models and not just those at SERI. ULMOD is unique because it accounts for certain variability or uncertainty in electric utility load forecasting by using megawatt modifiers to the load levels around the minimum and maximum forecasted loads. These modifiers are associated with probabilities that the modifiers will be applied. The background for this feature is included in Appendix B. Section 6.0 describes all calculations and results available in ULMOD.

2.5 UTILITY EXPANSION MODEL

The Utility Expansion Model, a common utility planning model not available directly from SERI, is an automated technique for optimally developing a schedule of conventional generating unit additions. An expansion scenario is usually considered optimal if there is no other scenario with a lower cumulative present worth of utility revenue requirements during the planning horizon. The methods used in expansion models vary greatly, but common optimization techniques are linear programming, dynamic programming, and year-to-year minimization. Typical inputs to such a computer program are (1) a brief description of the operating costs and characteristics of all existing capacity and potential expansion unit types, (2) escalation rates for each cost given, (3) certain utility financial parameters such as fixed charge rates, (4) a description of the utility load shapes together with future energy and peak demand requirements, and (5) the minimum amount of total capacity in excess of the expected peak demand that is required. The result of an expansion planning model includes a year-by-year schedule of conventional unit additions and may also include estimates of the operation of the available generation capacity together with associated costs and fuel usage. Owing to the approximations usually required to keep the expansion problem within reasonable computer size and time limits, the operation estimates produced are usually less precise than those available from a detailed production cost model. Production cost models are discussed briefly in Sec. 2.6.

In relation to how much a particular alternative generation source (such as WECS) is worth to an electric utility, the primary function of an expansion model is to determine the desirable changes in the capacity additions of each conventional generation type resulting from the installation of intermittent generation. This value determination process requires the execution of a base case with zero intermittent generation, followed by a change case for each alternative generation penetration desired. (SERI is currently unaware of any expansion models that can select intermittent generation sources.) The residual utility loads are derived for each penetration from the routine ULMOD. The conventional capacity addition results of the expansion model for the base and change cases are then included in FINAM, the model performing the financial analysis. Also to be input to FINAM are the conventional system's operating costs, calculated from either the expansion model or the production cost model. If it is felt that the year-to-year production cost estimates of the expansion model are sufficiently accurate, these results can be given to FINAM, and the use of a detailed production cost model may be avoided. Whether this is possible depends on the expansion model used, the desired precision of the results, and the complexity of the conventional generating system. Several test comparisons of the expansion model production cost estimates with those of a detailed production cost model are advisable. A detailed production cost model may be required to investigate the effects of the following elements on a conventional system: (1) the spinning reserve requirements [11], (2) system storage, (3) the infringement on the minimum load areas of base load generation, or (4) the inadequacy of an expansion model to reflect important constraints such as fuel contracts or electricity purchases and sales.

Difficulty may arise in using the expansion planning models to compare the change case capacity additions with those of the base case because the change case reliabilities may not be the same as those of the base case. Most expansion models add enough capacity to exceed a given percentage of reserve constraint, allowing the reserve results to vary from case to case. Even if the reserve results were identical, this would not guarantee that the more popular reliability indices--loss of load probability (LOLP) or expected unserved energy--would be equal. Hence, we recommend that the amount of new capacity (peaking capacity if it is being added) be adjusted to equalize change case reliability with that of the base case by either a LOLP routine or a probabilistic production cost model for expected unserved energy equalization.

2.6 DETAILED UTILITY PRODUCTION COST MODELS

Utility production cost models (PCM) are usually used to estimate operating expenses incurred by supplying the electricity demands of a utility network. The type of PCM to be used for this report analyzes periods of one or more years, and gives results such as the cost of fuels and the operating and maintenance costs for each generating unit in the system for each month of the period being studied. This information can then be summarized in a variety of ways. To produce these results, the following data (in the detail required by the PCM being used) is required: descriptions of each generating unit, fuel costs for the future, a description of the loads to be served, and descriptions of any existing electricity purchases or sales. PCMs usually consider the system's required operating or spinning reserve and approximate the scheduling of a generating unit's planned maintenance. Both of these features require appropriate data. Potential equipment failures or forced outages are usually accounted for by either appropriate capacity deration or probabilistic techniques. The latter method is usually preferred. The probabilistic PCMs also give two reliability measures that are gaining popularity: the amount of expected unserved energy and the expected number of hours of capacity deficiencies; both measures are related to the traditional loss of load probability results. The simulation interval used depends on the specific PCM being used. The interval can be hourly or based on load duration curves covering periods from one week to a season. Because this is a standard utility planning model and most are proprietary, SERI is not in a position to distribute a PCM.

To determine the value of intermittent generation sources, a PCM is used to develop the detailed operating cost estimates for the financial analysis model FINAM. The corresponding results from the expansion planning model may be adequate for the particular evaluation being performed, especially if it is to give only an initial estimate of value. It is felt, however, that several tests using a PCM should be performed before a decision is made to use the expansion model operating cost estimates in the value determination.

2.7 FINANCIAL ANALYSIS MODEL—FINAM

The last step in the WECS value determination, FINAM performs the economic comparison between the base case (no alternative generation) and each of the change cases. Electric utilities studying the value of WECS to their system may prefer to use their corporate model to provide the necessary data. All calculations by FINAM are based on present-worth economics. A maximum of 10 change cases can be analyzed simultaneously. Each case requires information about the conventional capacity being added to the system and operating costs for each generation type and for each planning year desired. The capacity additions for future years would be provided by an expansion planning model. The operating costs should be developed by a detailed utility production cost model. The results of FINAM are the break-even cost and marginal present-worth value in $/rated kW for the intermittent generation capacity of each change case.

The value of the WECS is the utility's present worth savings of reduced operating costs and modified capital additions. Operating costs include fixed and variable operation and maintenance, fuel, and unserved energy. Modified capital additions includes the early retirement of an existing generating unit or deferring or cancelling a planned unit addition.

FINAM can also perform a wide variety of sensitivity studies. However, one should use the sensitivity feature cautiously. It is assumed in the sensitivity calculations that the amount of each conventional capacity type installed and the amount of generation produced does not change. This is obviously incorrect for wide changes in assumed inputs, especially fuel costs. But the sensitivity feature can be useful if used with this knowledge. Refer to Sec. 7.0 for a more detailed discussion of FINAM.

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SECTION 3.0

WTP—WEATHER TAPE PREPROCESSOR

Figure 2-1 indicates that WTP is an intermediate processor between yearly weather data and ROSEW if the Weibull option is not chosen. WTP was created for DOE by the Stone & Webster Corporation and adapted slightly for SERI's use.

WTP accepts any one of four types of weather data and then produces an output weather file in a single format suitable for use by ROSEW. The four types of weather data are:

- TDF-14 (Tape Data Family-14): This format represents hundreds of sites across the country and is controlled by the National Climatic Center (NCC) in Asheville, N.C.
- Aerospace: These sets of primarily Southwestern weather data are collected and controlled by the Aerospace Corporation. Limited sites, limited years of collection, and poor accessibility make this a little-used format.
- SOLMET: This format is used for 26 U.S. sites and is widely known for its total and direct insolation data. It is also available through NCC.
- TMY (Typical Meteorological Year): This set is one typical year of data made up from twelve typical months of SOLMET data. TMY data sets represent all 26 SOLMET sites and are also available from NCC.

If wind data are available in a format that is not one of these four types, then transforming this new data into one of these four standard formats is recommended. If this is not possible, custom modification of WTP or WEIBUL to accommodate the data would not be difficult.

A simplified flowchart in Fig. 3-1 shows the the program's operation. First, WTP takes any one of the four types of data and reads only the weather data applicable to our present and projected needs. It then converts the data to the appropriate metric units. Table 3-1 gives the weather parameters and units handled by WTP for each weather file type.

WTP then replaces invalid or missing values with those obtained by linear interpolation from surrounding hours. If there are several consecutive hours of missing data, the last good values before and after the bad sequence are interpolated. Two days of data are always available for interpolation, and if no good values are found in this set, then the last good value known replaces all bad values. If there is bad data for the first or last values of the year, then an adjacent good value replaces this bad data. If there are no good values for the first two days of the year, then a default value is used to replace this void. The default values are listed in Table 3-2.

With the weather data complete and in the proper units, WTP outputs the results on a file to be used by ROSEW. For visual inspection, a file is also

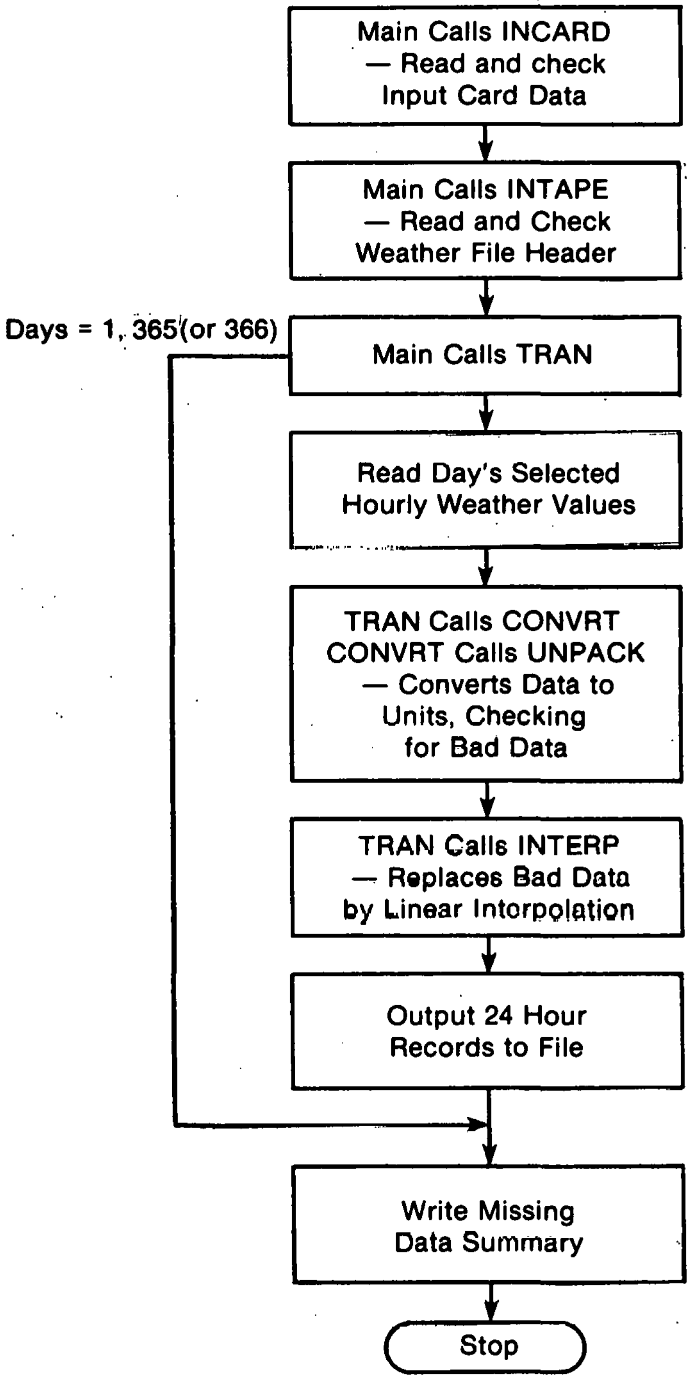

Figure 3-1. WTP

created that echoes the input card data and reports the number of hours of each type of weather data that are missing or not within an acceptable range. This file is thoroughly described and illustrated in Sec. 2.0 of the User's Guide.

Table 3-1. WEATHER PARAMETERS

Parameter	TDF-14	Aerospace	SOLMET or TMY	WTP
Dry-bulb temperature	°F	°C	°C	°C
Barometric pressure	in. Hg	millibars	kPa	bars
Relative humidity	%	not on tape	not on tape	(fraction)
Wind speed	knots	m/s	m/s	m/s
Opaque skycover	(fraction)	(fraction)	(fraction)	(fraction)
Insolation, direct	not on tape	kW/m^2	kJ/m^2	kW/m^2
Insolation, total	not on tape	kW/m^2	kJ/m^3	kW/m^2

Table 3-2. DEFAULT WEATHER PARAMETERS

Parameter	Default Value
Dry-bulb temperature	10°C
Barometric pressure	1.0132 bars
Relative humidity	0%
Wind speed	0 m/s
Opaque sky cover	0%
Direct insolation	0 kW/m^2
Total insolation	0 kW/m^2

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SECTION 4.0

WEIBUL—WEIBULL PROBABILITY PROCESSOR

As previously discussed in Sec. 2.0, the wind's variability can be accounted for by developing a Weibull probability distribution for the wind resource. Created from ordinary weather data in the computer code WEIBUL, this Weibull curve, shown in Fig. 4-1, describes the probability of the wind being in certain wind speed intervals. Figure 2-1 indicates that if the user chooses the Weibull option, then these wind probability curves are sent to ROSEW. Once again, if WEIBUL is chosen, then WTP is not needed.

A simplified flowchart of WEIBUL, Fig. 4-2, gives a glimpse of the program's structure. Since WEIBUL was developed by modifying WTP, the two programs have many similarities:

- both accept TDF-14, Aerospace, SOLMET, and TMY weather tapes (see Sec. 3.0);
- both accept only needed weather data;
- both convert data to consistent metric units; and
- both replace missing or invalid data by interpolation from surrounding values.

After WEIBUL performs these tasks, it then creates Weibull probability distribution curves for each hour of a typical day for each month (24 × 12 curves). To build these curves, data from more than one consecutive year are strongly encouraged because the more data that are available to create the distribution, the closer the distribution approximates reality. Of course, this additional accuracy must be weighed against the additional computer time necessary to process this extra data.

These 288 curves are each described by a shape factor K and a scale factor C. K is dimensionless and varies from about 1.0 to 4.0 for typical wind distribution, and C has dimensions of wind speed and is approximately 1.1 times the average wind speed. References 8, 9, and 10 describe these Weibull distribution characteristics in much more detail.

The wind distribution below a wind machine's cut-in wind speed is unimportant to the wind machine's performance, but the percentage of time the wind is in this region is useful. Because of this concept, WEIBUL curves are developed only in the wind velocity region above a user input cut-in wind speed. As a result, a good WEIBUL curve fit is obtained in this region. The region below this cut-in wind speed is represented only by the probability of the wind being in this area. A cut-in value of zero will create a WEIBUL curve for the entire range of wind speeds, with the curve fit not being as accurate in the area above cut-in as in the case where a positive cut-in value is specified.

This cut-in wind speed that is input to WEIBUL will need to reflect the difference in wind speeds between the height of the wind measurement tower and the wind machine hub height. A hand calculation as follows will indicate which value of the cut-in wind speed is input to WEIBUL:

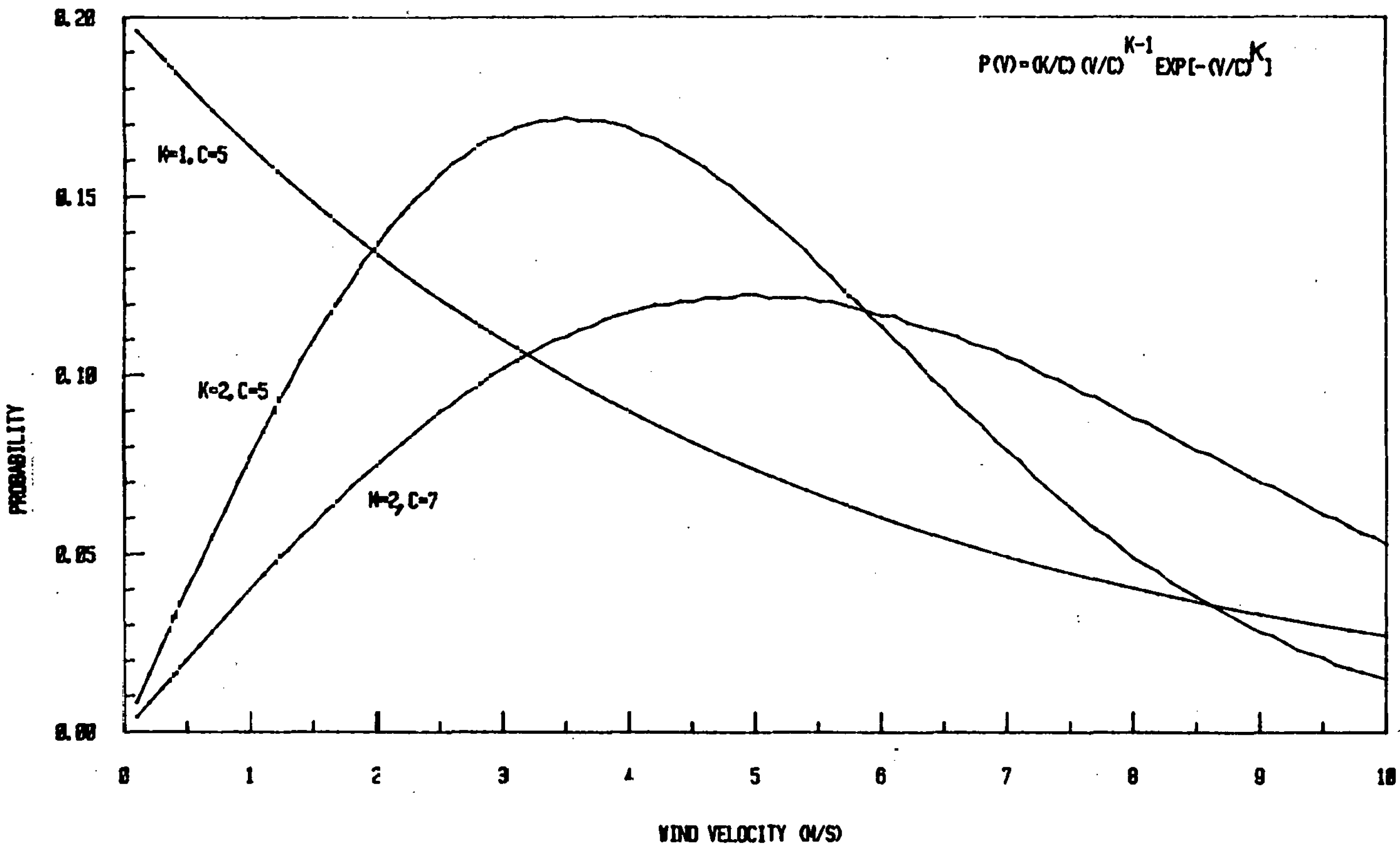


Figure 4-1. WEIBULL Wind Distribution (Examples of Different C and K Values)

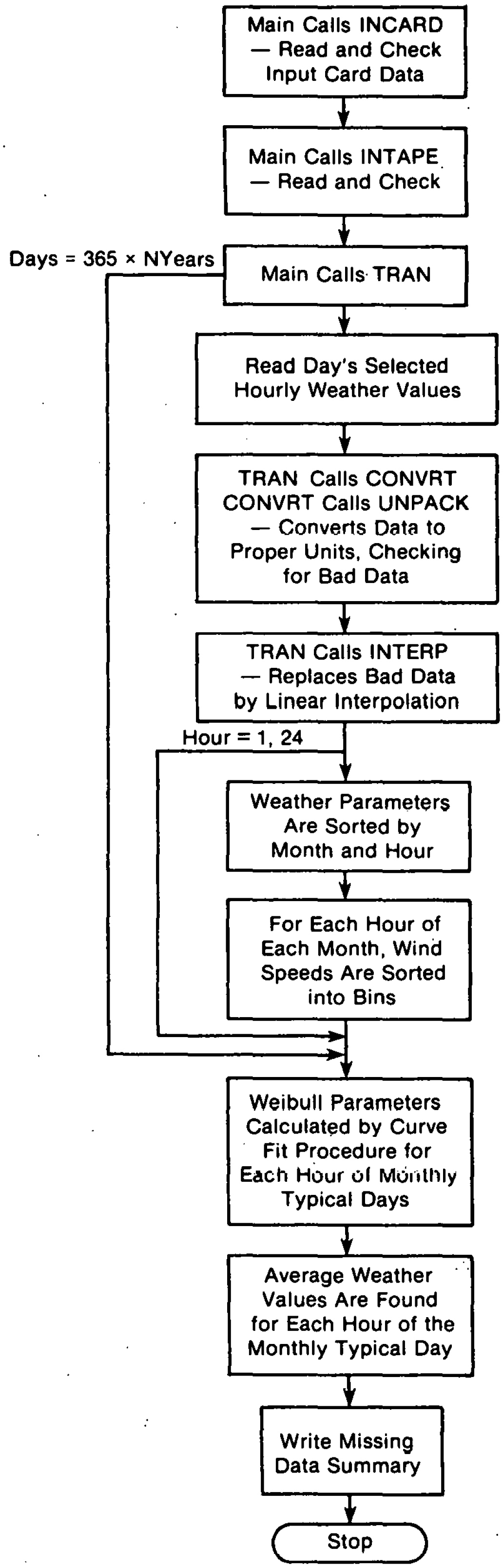


Figure 4-2. WEIBUL

$$V_{ciw} = V_{cihub} (H_w/H_{hub})^{\alpha} ,$$

where

Y_{ciw} = cut-in velocity to be input to WEIBUL,

V_{cihub} = wind machine cut-in velocity at hub height,

H_w = height of wind measurement tower,

H_{hub} = wind machine hub height, and

α = terrain factor to be input to ROSEW.

This calculation should be made for all wind machines to be analyzed, with the minimum value of Y_{ciw} input to WEIBUL.

WEIBUL can use either of two methods to determine the shape and scale factors, with the user selecting one. The first method is a least-squares fit of cumulative probabilities [10]. For this approach, all the observed wind speeds for one hour of a month are divided into n velocity intervals: $V_{cut-in}-V_1$, V_1-V_2, . . ., $V_{n-1}-V_n$. Each interval has a frequency of occurrence f_1, f_2, . . ., f_n, as well as cumulative probabilities $P_1 = f_1$, $P_2 = P_1 + f_2$, . . ., $P_n = P_{n-1} + f_n$.

The Weibull cumulative probability distribution function is given by:

$$P(V \leq V_X) = 1 - \exp\left[-(V_X/C)^K\right] . \tag{4-1}$$

To estimate parameters C and K, we wish to transform the data so that it will satisfy a linear relationship. Hence, we take Eq. 4-1 for any interval j:

$$P_j = 1 - \exp\left[-(V_j/C)^K\right] ;$$

and if we regroup, we obtain

$$-\ln\left(1 - P_j\right) = \left(V_j/C\right)^K ,$$

or

$$\ln\left[-\ln\left(1 - P_j\right)\right] = K \ln V_j - K \ln C . \tag{4-2}$$

Now, we let

$$X_j = \ln V_j$$

and

$$Y_j = \ln \left[-\ln \left(1 - P_j\right)\right] .$$

Then we see that Eq. 4-2 is of the linear form

$$Y = a + bx \quad ,$$

where

$$a = -K \ln C$$

and

$$b = K \quad .$$

In conclusion, we find that

$$C = \exp \left(- \frac{a}{b}\right)$$

and

$$K = b \quad .$$

Coefficients a and b can now be determined by a standard least-squares fit routine, such as the unweighted solution

$$a = \left(\sum Y_j \sum X_j^2 - \sum X_j \sum X_jY_j\right)/D$$

and

$$b = \left(n \sum X_jY_j - \sum X_j \sum Y_j\right)/D \quad ,$$

where

$$D = n \sum X_j^2 - \left(\sum X_j\right)^2 \quad .$$

Care must be taken in the calculation to avoid including the very last contribution of cumulative probability ($p_n = 1$) because of the resulting undefined Y_n. Any zero cumulative probabilities must also be ignored in the calculation for the same reason.

Because this is a curve fit, as many velocity intervals as possible should be used for accuracy. WEIBUL allows up to 100 intervals if extreme accuracy is desired, and only slightly extra computer time is required.

The second method to calculate the Weibull parameters is the maximum likelihood technique, believed to be more accurate than the least-squares method [9,10]. An iterative solution is required for the equations

$$c = \left(\frac{1}{N} \sum_{i=1}^{N} A_i X_i \right)^{1/K}$$

and

$$K = \left[\left(\sum_{i=1}^{N} A_i X_i^K \ln X_i \right) \left(\sum_{i=1}^{N} A_i X_i^K \right) - \frac{1}{N} \sum_{i=1}^{N} A_i \ln X_i \right]^{-1} ,$$

where

N = total number of nonzero wind speed observations, and
A_i = number of observations of wind speed X_i.

Both methods can be tried by the user before final selection. Experience has indicated that results from both methods are very similar.

For both methods WEIBUL also calculates average temperature, pressure, relative humidity, and wind speed for each hour of the monthly typical day. These values are simple averages of all the individual values.

Now WEIBUL has calculated C and K parameters, the probability of the wind speed being less than a cut-in value, and averages of temperature, pressure, relative humidity, and wind speed for each hour of the monthly typical day for 12 months. These values are output to a file that is to be used as input to ROSEW for wind power calculations. The User's Guide, Sec. 3.0, gives much more detail on WEIBUL's inputs, outputs, and program structure.

SECTION 5.0

ROSEW—WECS ELECTRIC POWER CALCULATION

The computer code ROSEW (Representation of Solar Electrics-Wind) calculates the electrical energy available from wind machines. As Fig. 2-1 shows, ROSEW accepts either processed weather data from WTP or Weibull wind distributions from WEIBUL. These data are combined with wind machine design information to determine the wind-derived electrical energy. These results proceed to ULMOD, where the utility load forecasts are modified to account for this wind energy. ROSEW is a strongly modified version of ROSPAM, which was developed for DOE by the Stone and Webster Corporation.

5.1 OPTIONS

ROSEW has three different execution options: Weibull Option, Hourly Power Option, or Typical Day Option. The Weibull Option is the recommended execution strategy for ROSEW because it can capture the long-term wind speed expectation and randomness of the wind resource. With this option, the Weibull wind distributions for each hour of a monthly typical day created from WEIBUL are used as input data. ROSEW uses these Weibull distributions to determine a distribution of expected wind-derived electrical energy. These results appear as a number of power-probability pairs, each expressing the probability of a certain amount of power being supplied to the grid.

The Hourly Power Option produces single-hour wind powers based on the hourly weather data produced from WTP. This option assumes incorrectly that the reported wind speed is constant over the entire hour; it does not represent the variability of the wind resource.

The Typical Day Option also uses WTP data to calculate hourly energies and thus is similar to the hourly option in its failure to accurately represent wind power. These hourly energies are used for the creation of one, two, or three average typical days for any given month. A single typical day in any month would contain 24 hourly values made up of hourly averages. For example, all 2 a.m. to 3 a.m. values of wind energy in January (31 values) are averaged to obtain that hourly average for January's typical day.

Two typical days for a month consist of a typically high-wind power day and a typically low-wind power day. The user inputs how to divide the month's days among the low and high values. For example, of the 31 days in January, the 16 highest values for a certain hour may be chosen to determine the high day's average for the hour. Therefore the low day's average for that hour consists of an average of the 15 lowest wind energy values. Three typical days per month are handled similarly, with the user inputting the number of values to be used to determine the averages for the low, medium, and high days.

A simplified flowchart of ROSEW in Fig. 5-1 gives an overview of the program's operation. Other detailed discussion of the program's contents follows.

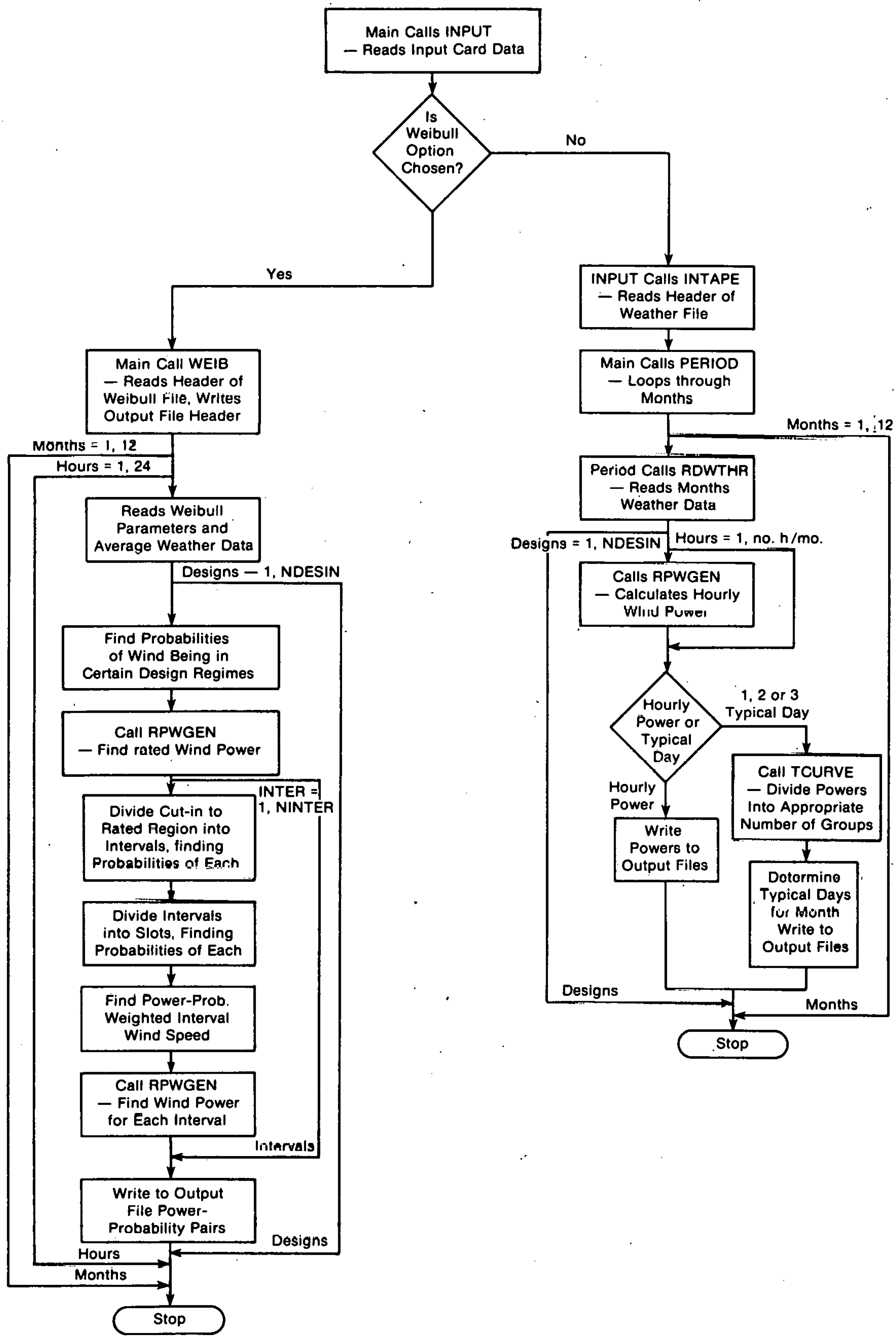


Figure 5-1. ROSEW

5.2 CALCULATIONS

First, the program reads in the wind machine design and capacity data. Data for up to nine wind machine designs can be input with up to 999 of each type of design acceptable. The number of each type of wind machine can be changed each month, a feature that can simulate planned maintenance.

5.2.1 Weibull Execution

Since the Weibull Option is the most desirable and most often used, it is important to understand some of the concepts of this type of ROSEW execution.

5.2.1.1 Hub-Height Wind Speed

After reading input data, the Weibull output file produced by WEIBUL is connected and the first Weibull distribution C and K parameters are read (for the first hour of January's typical day). As previously discussed in Sec. 4.0, these two parameters completely describe a wind probability distribution for this monthly typical hour. These Weibull C and K parameters were determined for the height of the anemometer tower at which the data was collected and will be different for the wind turbine hub height. Thus, assuming that the wind regime is approximately the same at the weather station and the wind turbine site, the Weibull C and K values can be projected up to the hub height by many means given in the literature [10,12,13]. Based upon knowledge of the terrain factor alpha (power exponent), the power law is chosen as the most appropriate method.

If alpha is known for the specified site from measurements on a representative day, it can be input by the user (see "STTERR" in "ROSEW Inputs" in Sec. 4.0 of Volume II). However, this terrain factor is generally not measured, and some advocate the blanket use of $\alpha = 1/7$ as a conservative estimate for flat terrain [13]. If the user does not want to input the terrain factor, it is calculated by the following method from Justus [10]:

$$\alpha = \left(0.37 - 0.088K \ln C\right)/\left[1 - 0.088 \ln \left(Z/10\right)\right] ,$$

where

C = Weibull scale factor (m/s),
K = Weibull shape factor, and
Z = anemometer height (m).

Whether alpha is input or calculated, Weibull parameters C and K are projected up to hub height by the following method, also from Justus [10]:

$$C_h = C_a \left[\frac{H_h}{H_a}\right]^{\alpha}$$

and

$$K_h = K_a[1 - 0.088 \ln (H_a/10)]/[1 - 0.088 \ln (H_h/10)] ,$$

where

C_h = C at hub height,
C_a = C at anemometer height,
K_h = K at hub height,
K_a = K at anemometer height,
H_h = hub height, and
H_a = anemometer height.

5.2.1.2 Wind Speed Probabilities

Now that the wind speed probability distribution at the turbine hub has been estimated for this typical hour, the wind turbine's behavior in these winds is to be calculated. Figure 5-2 shows a typical power curve for a wind turbine.

As Fig. 5-2 indicates, no power is produced until the wind reaches the machine's cut-in velocity. After that, power increases by roughly a cubic relationship until the machine's rated velocity is reached. As wind speed exceeds rated velocity, power output is held constant by blade feathering. Once cut-out velocity is reached, the blades feather completely to protect the turbine, and power output drops to zero.

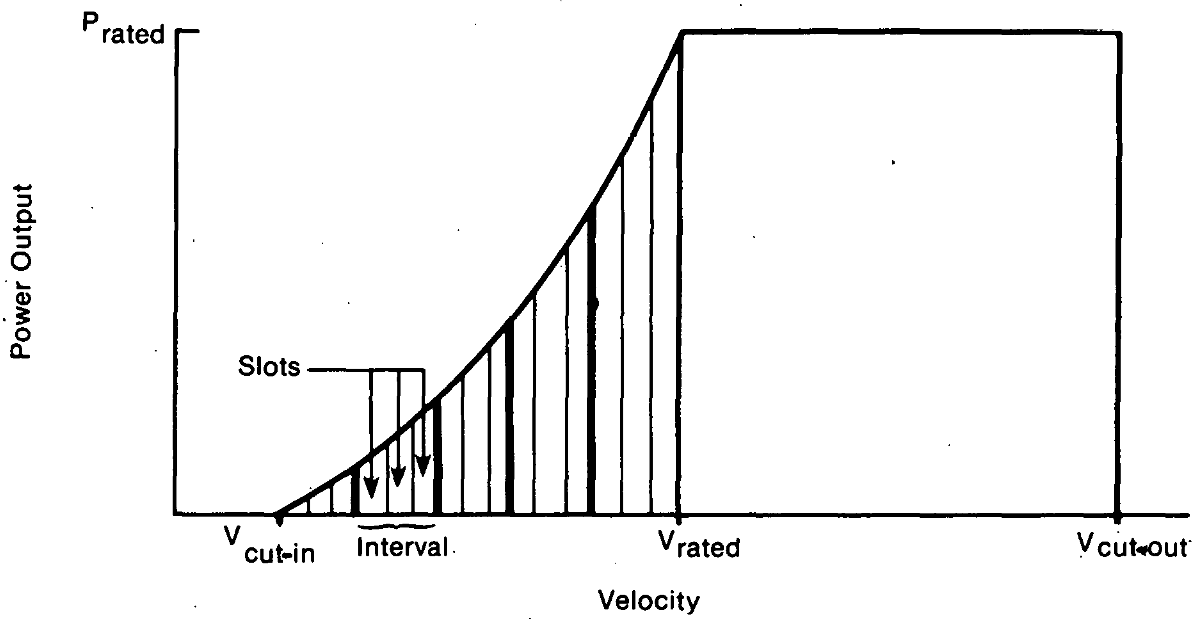
As stated in Sec. 4.0, the Weibull distribution is created only for velocities greater than or equal to a cut-in velocity that is input to WEIBUL (W). This cut-in velocity represents a value at the wind anemometer height. Therefore, this velocity is extrapolated to the hub height by using:

$$W_{ci} = W(H_h/H_a)^{\alpha} ,$$

where W_{ci} = cut-in wind speed at machine hub (the other variables have been defined previously). Together with the Weibull parameters, the probability of the wind occurring below this wind speed $[P(V < W_{ci})]$ is given to ROSEW.

The cut-in velocity for the specific wind machine being analyzed in ROSEW (U_{ci}) must be greater than or equal to W_{ci}. Note that the Weibull distribution input to ROSEW was created with W_{ci} as the effective "zero point." Therefore, the machine velocities for cut-in (U_{ci}), rated (U_r), and cut-out (U_{co}) must be shifted by the amount W_{ci} before the Weibull distribution can be used for finding wind probabilities. Thus, for the probability calculations only:

$$V_{ci} = U_{ci} - W_{ci},$$
$$V_r = U_r - W_{ci}, \text{ and}$$
$$V_{co} = U_{co} - W_{ci} .$$



Note: Cut-in to rated region shown with five intervals, 3 slots each.

Figure 5-2. Wind Turbine Power Curve

For the power calculations in the following section, these velocities are not shifted by W_{ci}.

Also, any probabilities found from the Weibull distribution must be multiplied by $[1 - P(V < W_{ci})]$; since the actual area under the curve (total probability) created in WEIBUL is $[1 - P(V < W_{ci})]$, and the area under the curve as viewed by ROSEW is 1.

By using the probability curve, one can determine the amount of time that the wind velocity is between these wind machine control velocities. Since the Weibull probability density function is

$$P(V) = (K/C)(V/C)^{K-1} \exp\left[-(V/C)^K\right] ,$$

it can be easily shown that the probability of the wind being below cut-in velocity (no power production) is

$$P(V \le V_{ci}) = P(V < W_{ci}) + (1 - \exp[-(V_{ci}/C)^K])*[1 - P(V < W_{ci})] .$$

The probability of the wind being greater than cut-in velocity but less than rated velocity is

$$P(V_{ci} \le V \le V_r) = \exp\left[-(V_{ci}/C)^K\right] - \exp\left[-(V_r/C)^K\right]*.\ [1 - P(V < W_{ci})] . \tag{5-1}$$

Likewise, the probability of the wind being between rated and cut-out (producing rated power) is

$$P(V_r \le V \le V_{co}) = \exp\left[-(V_r/C)^K\right] - \exp\left[-(V_{co}/C)^K\right]*.[1 - P(V < W_{ci})] .$$

Finally, the probability of the wind exceeding cut-out velocity (also no power production) is

$$P(V \ge V_{co}) = \exp\left[-(V_{co}/C)^K\right]*.(1 - P(V < W_{ci})] .$$

Thus, we have the probabilities for this hour of zero power output, maximum (rated) power output, and variable power output, when the machine is between cut-in and rated velocities.

This cut-in to rated region is handled by dividing it into equally spaced intervals so that each interval will possess a single power-probability pair. The number of intervals is input by the user. The probability of the wind speed being in these intervals is easily found by Eq. 5-1. Finding a representative wind speed (and thus, power) is somewhat more involved because wind power is proportional to the wind speed cubed. To account for this, each interval is divided into a user-directed number of "slots," as Fig. 5-2 shows. The probability of the wind being in each slot is calculated, and an average wind speed for each slot is found by the following calculus-based method:

$$\bar{V}_{SLOT} = \left(V_2^4/4 - V_1^4/4\right)\left(1/(V_2 - V_1)\right)^{1/3} ,$$

where V_1 and V_2 are velocities on the edges of the slot.

From all of the slot data, an interval "power-probability weighted wind speed" V_{int} is then found:

$$V_{int} = \left[\sum_{slots=1}^{N}\left(\bar{V}^{3}_{slot} \cdot \frac{P_{slot}}{P_{int}}\right)\right]^{1/3} ,$$

where

V_{int} = power-probability weighted interval wind speed,

P_{slot} = probability of wind speed being in slot, and

P_{int} = probability of wind speed being in interval.

The use of this wind speed to calculate power for this interval will yield accurate results.

5.2.1.3 Output Power

Now that we have the rated velocity and all representative velocities for the intervals between cut-in and rated, the wind turbine's power output for each of these velocities must be found. These velocities are the actual input values and are not shifted as in the probability calculations. First, we find the wind power that passes through the swept rotor area for the specific wind velocity being considered:

$$P_{swept} = 0.5\rho AV^3 ,$$

where

P_{swept} = wind power through swept area (W),
ρ = air density (kg/m^3),
A = swept rotor area (m^2), and
V = wind velocity (m/s).

Since $A = \pi R^2 = \pi D^2/4$, we find $P_{swept} = (\pi/8)\rho D^2 V^3$, where D = rotor diameter (m).

Of course, not all of this wind power is captured by the turbine, and aerodynamic losses are inevitable. Thus, the power coefficient C_P of the turbine is introduced, representing the ratio of wind power captured by the blades to the total wind power available through the swept area. C_P is generally dependent on wind speed and has a theoretical maximum limit of 0.593.

Losses also occur in the wind machine's gearbox, generator, and transformer before the power actually reaches the utility grid. The change of these efficiencies with the wind machine's power level must also be accounted for.

A general expression for the power output from the wind turbine is

$$P_{out} = (\pi/8) C_P \eta_{gear} \eta_{gen} \eta_{tran} \rho D^2 V^3 \quad ,$$

where

C_P = power coefficient (range: 0-0.593),
η_{gear} = gearbox efficiency (range: 0-1.0),
η_{gen} = generator efficiency (range: 0-1.0), and
η_{tran} = transformer efficiency (range: 0-1.0).

Values of the power coefficient and efficiencies are input by the user as tables. The power coefficient must be known as a function of the wind machine's tip speed ratio (ratio of the blade's tip speed to hub height wind speed), and the efficiencies vary with the machine's power level. See Volume II, Sec. 4.0 for input details.

The air density is found for each hourly set of calculations by the ideal gas law:

$$\rho = P/RT \quad ,$$

where

ρ = air density (kg/m^3),
P = average barometric pressure (bars),
T = average dry-bulb temperature (K), and
R = ideal gas constant [bar m^3/(kg K)].

R is calculated by

$$R = R_{air}(P - P_{H_2O})/P + R_{H_2O}(P_{H_2O}/P) \quad ,$$

where

R_{air} = ideal gas constant for dry air [0.00287 bar m^3/(kg K)],
R_{H_2O} = ideal gas constant for water vapor [0.0046 bar m^3/(kg K)], and
P_{H_2O} = partial pressure of water vapor (bars).

P_{H_2O} is calculated using an approximate saturation pressure of water as a function of temperature:

$$P_{H_2O} = P_{sat}\phi \quad ,$$

where

ϕ = average fractional relative humidity,
P_{sat} = 218.17(10^X),
X = $-(\beta/T)(3.24 + 0.0059\beta + 1.17 \times 10^{-8}\beta^3)/(1 + 0.0022\beta)$, and
β = 647.27 − T.

Remember that average temperature, pressure, and relative humidity are passed over to ROSEW from WEIBUL. Relative humidity is included in the calculation but is supplied only if the original data were from the TDF-14 format.

The final step in the power calculation accounts for forced outages of the wind turbines and can be approached in two ways. The first method derates the power output by multiplying the power by the availability (1 - forced outage rate):

$$P_{final} = P_{out}N(1 - F) \quad ,$$

where

P_{out} = single machine power previously calculated,
N = number of wind machines of this design for this month, and
F = forced outage rate (1 - availability).

The second method, which is recommended for the Weibull option, adjusts the probabilities of certain power outputs. The probabilities of all power outputs, except zero power output, are multiplied by the availability. These adjusted probabilities are added, and the sum is subtracted from one. This remaining value is now the adjusted probability of zero power output. These adjusted probabilities can now be matched with the corresponding power outputs (NP_{out}) for output to ULMOD.

The user chooses which method he or she will use for all machine designs.

5.2.1.4 Enhancements

Some enhancements are possible throughout the previously discussed calculations to improve the accuracy of the wind power results. The first of these involves the inaccuracy of the wind data itself. Justus corrects the measurement errors in the anemometers that measure wind speed [10]:

$$\frac{V_{true}}{V_{obs}} = [1 - 0.5(\sigma_u/V_{obs})^2]\ [1 - 0.5(\sigma_w/V_{obs})^2]\ [1 - 0.5(\sigma_y/V_{obs})^2] \ ,$$

where

V_{true} = true wind speed,
V_{obs} = observed wind speed,
σ_u = longitudinal rms gust magnitude,
σ_ω = vertical rms gust magnitude, and
σ_y = horizontal rms gust magnitude.

Generally, σ_u, σ_ω, and σ_y are hard to determine, but a conservative average value for σ_u/V_{obs}, σ_ω/V_{obs}, and σ_y/V_{obs} is 0.2. If this value is input, as recommended, the previous equation reduces to $V_{true} = 0.94\ V_{obs}$. This correction is made to the wind speed before the power calculation.

A correction procedure for wind gusts is also included in the program, since turbines usually respond to gusts of a few seconds duration which are not represented by the initial data. This correction (also from Justus) is incorporated after the initial swept power has been calculated:

$$\frac{P_{true}}{P_{swept}} = 1 + 3(\sigma_u/\bar{V})^2 \ ,$$

where

P_{true} = gust-corrected swept power,
P_{swept} = uncorrected swept power,
σ_u = longitudinal rms gust magnitude, and
$\bar{V}$ = mean wind velocity.

Once again, if $\sigma_u/\bar{V}$ is a conservative 0.2, then P_{true} equals $1.12P_{swept}$ $\left(\text{or } V_{true} = 1.038V_{obs}\right)$. The anemometer error and gust corrections tend to cancel each other, although not exactly.

The last correction deals with the boundary layer (wind shear) effect. The problem of wind velocity varying with height above ground has previously been discussed in regard to obtaining the value of the scale factor C at the hub height. This vertically nonuniform wind velocity profile across the swept rotor area presents a problem, since wind machine power is calculated assuming uniform hub-height wind speed across the entire swept area. Justus gives a numerical approximation of the wind power corrected for this phenomena [10]:

$$\frac{P_{corr}}{P_{swept}} = a + b\alpha + c\alpha^2 \quad ,$$

where

P_{corr} = shear corrected swept power,

$a = 0.9949 + 0.194(R/Z) - 0.02(R/Z)^2$,

$b = 0.035 - 0.1267(R/Z) - 0.255(R/Z)^2$,

$c = -0.0441 + 0.1574(R/Z) + 0.98(R/Z)^2$,

R = rotor radius (m),

Z = hub height (m), and

α = terrain factor.

This terrain factor can either be input by the user or calculated by a method similar to the one used when projecting the scale factor C up to the hub height:

$$\alpha = \left[0.37 - 0.088 \ln \bar{V}\right]/\left[1 - 0.088 \ln (H/10)\right] \quad ,$$

where

$\bar{V}$ = mean wind velocity (m/s), and
H = height of weather station anemometer (m).

After these final power corrections are made, ROSEW has successfully calculated a number of power-probability pairs for this first hour of a typical day in January. There are pairs now for zero power output, rated power output, and a known number of power outputs between zero and rated. ROSEW then loops to the second hour of January's typical day, and the process is repeated until every hour of the twelve months' typical days are completed. These results, shown in Volume II, Sec. 4.0, are then available to ULMOD for processing.

5.2.1.5 Input Power Table

The previously discussed computation of machine power output may not apply to certain vertical-axis or innovative wind turbines. To account for these machines, an option exists to input a set of matched wind velocity-turbine power output values. One can think of these pairs representing points on a curve of wind speed versus machine power output. Given a wind speed that falls between these points, the program uses linear interpolation between the known points to find a representative power output.

Since these wind speed-power output pairs are probably obtained from empirical data of velocities and wind machine power outputs, no enhancement or efficiency calculations can be made. The variation of air density that is not treated here must also be remembered when considering the accuracy of the results.

This option for one or more wind machine designs can be used smoothly in conjunction with other machines that require the power calculations. Section 4.0 of Volume II indicates the input changes required. Care has been taken in the program to project the wind speed data from the recorded height to the height used for velocity in the velocity-power pairs input.

5.2.2 Hourly Power Option

The Hourly Power Option is handled with much greater ease than the previously described Weibull Option. First, the wind machine data and hourly weather data from WTP are read in. Then for each hour, weather data are converted into hourly wind machine power outputs by much the same techniques as previously discussed. The air density calculation is identical to the calculation in the previous Weibull section, since WTP and WEIBUL pass the same weather parameters to ROSEW. The wind speed is projected up to hub height by the simple power law, with the terrain factor either input or calculated as before. The previously discussed input power table can be used, and all of the enhancements except the improved forced outage adjustment are available. The forced outage rate adjustment cannot be made to the probabilities, since the probabilities are not calculated with this option. The hourly output values, shown in Volume II, Sec. 4.0, are also available to ULMOD for utility load modification.

5.2.3 Typical Day Option

The performance of this option is identical to the hourly power option, except that all calculated hourly powers are averaged together to create either one, two, or three monthly typical days.

As mentioned earlier, a single typical day in any month consists of mean hourly power values created by averaging all powers of that hour for that month. For example, the 31 hourly wind power values for 1 p.m. to 2 p.m. in July (31 days) are averaged together to come up with the average power for 1 p.m. to 2 p.m. for the typical day.

With two typical days per month, one typical day represents a low wind power day and the other, a high wind power day. The user can input the number of the lowest hourly values used to find the average for the low typical day, and the number of the highest values that make up the high day's average. For example, suppose April's 30 power values (30 days) for midnight to 1 a.m. consist of: 6 hours of 100 MW, 6 hours of 150 MW, 6 hours of 200 MW, and 12 hours of 300 MW. Also assume that the user wants the low day to be made up from the average of 13 values and the high day to use 17 values (the sum of the low and high values must equal the days of the month). Then the low typical day's average power from midnight to 1 a.m. is 130.8 MW [(6 × 100 + 6 × 150 + 1 × 200)/13]. Similarly, the high day's power from midnight to 1 a.m. in April is 270.6 MW [(5 × 200 + 12 × 300)/17]. Obviously, each of the two typical days for each month has 24 hourly values.

Three typical days represent low, medium, and high wind power days for each month. As in the case of two typical days, the user decides how to divide the month's values for the averaging calculation for each of the three typical days. Example: In June (30 values for each hour), each day may receive 10 values that constitute the hourly averages. Alternatively, the low day can have 5 values for its averaging, the medium day 15, and the high wind power day 10. Again, the sum of all three averaging assignments must equal the days of the month.

Example output from this option is shown in the User's Guide, Sec. 4.0. Not surprisingly, these results are also available to ULMOD.

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SECTION 6.0

ULMOD—UTILITY LOAD MODIFICATION

The location of ULMOD in the overall value determination process is displayed in Fig. 2-1 and is discussed in Sec. 2.4. The function of ULMOD is to incorporate the estimated intermittent generation into the utility load forecast so that the results can be easily provided as inputs to electric utility planning models. This section describes how this model performs. Refer to Sec. 5.0 of the User's Guide for a description of the required inputs and available results as well as definitions of important variables and required computer data files.

6.1 OPTIONS

There are three input options available for the WECS power data provided from ROSEW. The preferred is the power-probability option for which the intermittent generation data are provided in sets of power and probability pairs for each hour of a typical day for each month. These pairs were created in ROSEW by processing the appropriate Weibull wind distributions. Each set of power and probability pairs consists of a group of estimated intermittent generations ranging from zero to maximum possible generation. Associated with each of these powers is the probability of its occurrence. The second option is a single power estimate made from each hour of weather data in the year. The third option entails the calculation of one to three typical days of single hour values per month. The calculations for these ULMOD intermittent generation input options are provided in Sec. 5.0. Also, a discussion of the advantages and disadvantages of each option is contained in Sec. 2.0.

Since ROSEW output may include more than one wind machine design, ULMOD will select the design indicated by the user. From this point, the entire value method must continue with only this one design being considered. ULMOD and the following programs must be executed again to consider other machine designs. For completeness, the user may also execute ULMOD with no intermittent generation inputs and thus provide base case load data to the utility planning models.

There are only two utility load input data options. These are to provide (1) a typical week of hourly load data per month or (2) a full year's worth of hourly load data. The calculated results of ULMOD can be output to paper and/or a computer data file at the user's option and control. Note that the load data provided to ULMOD should be in local standard time and should not be shifted according to daylight saving time.

Uniquely, ULMOD can simulate the uncertainty or variability of utility load forecasting. This is a requestable option requiring information about the portions of the utility loads that are subject to variation, the amount and direction that the load forecast might vary in these regions, and the probabilities that these variations from the forecast will occur. An additional option within variability is whether the potential amount of forecast variance will (1) be applied to all points of the desired load portions equally or (2) taper from the maximum value (as input) down to near zero (for explanation, see the calculations in Sec. 6.2.5).

6.2 CALCULATIONS

The mathematical functions performed in ULMOD are relatively simple and straightforward, but the organization of all the data and results is complicated. The flow of operations performed by ULMOD are depicted in Fig. 6-1. The center path represents the flow of calculations when the WECS power data being used is either the power-probability (using Weibull curve results) option or the two or three typical days of WECS power per month. Since this is the most difficult calculation path, it is discussed first, in Sec. 6.2.1. When the WECS power data being used are made up of either a full month of hourly values or a single typical day of values per month, the calculation process is greatly simplified by the absence of probability data. The calculations performed for this situation are given in Sec. 6.2.2. For completeness, it is also possible to have no intermittent generation and to perform various operations to the unmodified input utility loads (see Sec. 6.2.3). So that the results of ULMOD may be used by utility planning models requiring segmented or stepwise-approximated load duration curves as load data inputs, the ability to create these is included and is discussed in Sec. 6.2.4. Finally, in the process of forecasting loads, many utilities also develop a measure of the uncertainty of the mean demand forecast. As described in Sec. 6.2.5, ULMOD can handle this uncertainty. Each calculation box of Fig. 6-1 is numbered to assist the reader.

6.2.1 Power-Probability, or Two or Three Typical Days

All these possibilities have probabilities associated with each intermittent generation point developed. The power-probability data can have up to 12 data pairs per hour of each month's typical day, and this information can be developed from a number of years of weather data. The two or three typical days data are made from only one year of weather data and only have what can be interpreted as two or three power-probability pairs, respectively. The calculations are the same for these intermittent generation options, although the quantity of data to be processed can be much larger for the power-probability data. Similarly, calculations are the same for both utility load options, but the number of calculations are increased by at least a factor of four if all hours in the year are input instead of a typical week per month. To help the reader understand ULMOD's operations, a hypothetical numerical example is provided, consisting of the single day of utility load data shown in Table 6-1 and the typical day of power-probability data shown in Table 6-2.

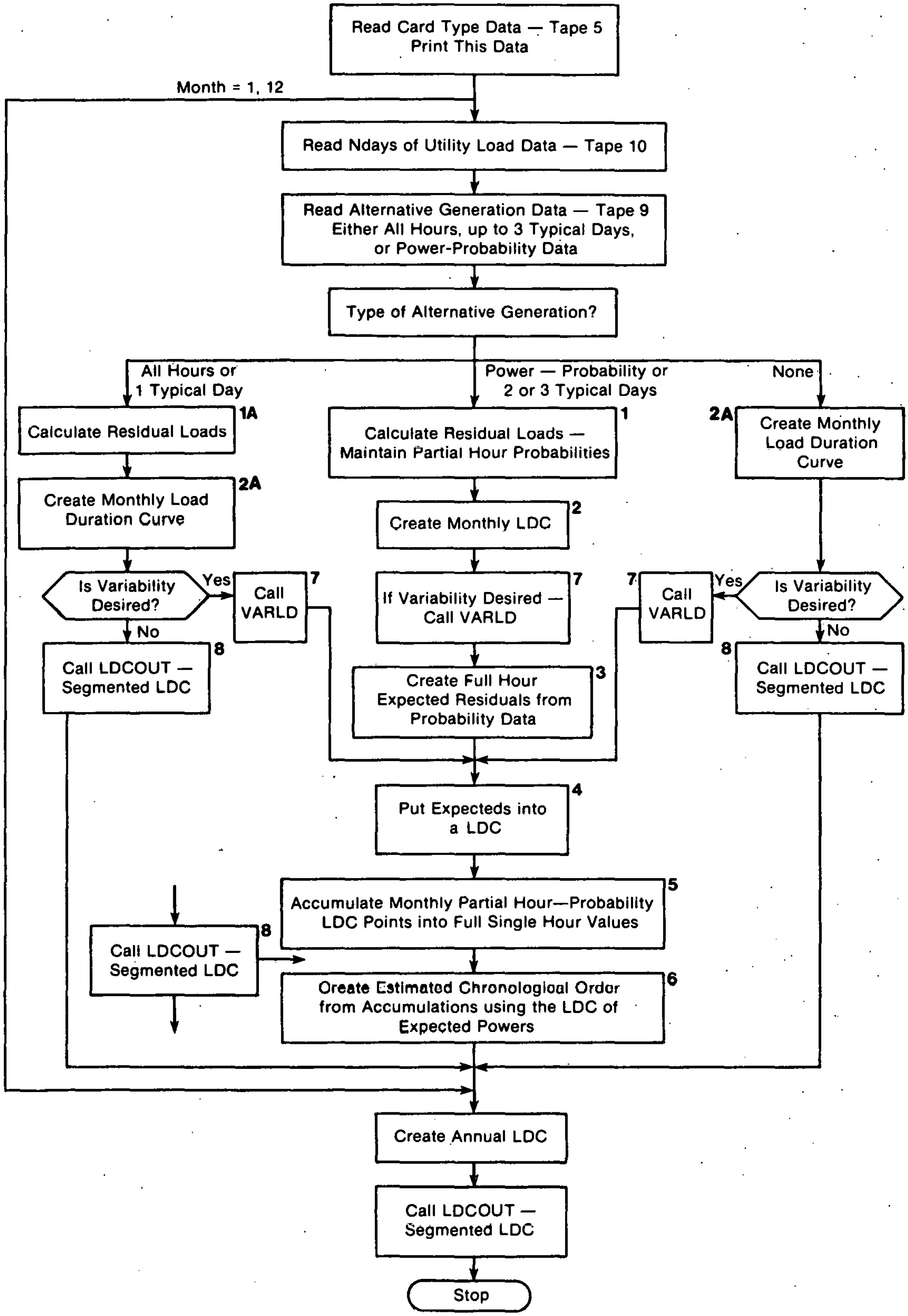

Figure 6-1. ULMOD

Table 6-1. SAMPLE UTILITY LOADS
Local Standard Time
(Only Day 1 Presented)

Hour	Utility Load (MW)	Hour	Utility Load (MW)
1	600	13	850
2	550	14	900
3	500	15	1000
4	450	16	950
5	400	17	900
6	500	18	850
7	550	19	800
8	600	20	750
9	650	21	700
10	700	22	650
11	750	23	600
12	800	24	600

The day of utility data represents Day 1 of a month and would normally be accompanied by 6 (for typical week option) to 30 (for a 31-day month) additional days of data. The example of intermittent generation data represents all the power-probability data needed for the month if only three data pairs are given per hour. This is similar to the maximum data available for the three typical days option and is more than what is available for the two typical days option. The calculations performed in the boxes of Fig. 6-1 are explained in the order of the boxes, except that Variability (Box 7) and Segmented LDC (Box 8) are discussed later (Secs. 6.2.5 and 6.2.4, respectively) to maintain continuity.

Box 1: Calculate Residual Loads--This function is a simple subtraction of intermittent generation from the appropriate utility loads to create what are called residual loads. This process is complicated more than one intermittent generation and the associated probability of occurrence. Each of the power points of intermittent generation (three in the example) are subtracted from the proper hour of all days of utility load data, and the associated intermittent generation probabilities are transferred to the residual load results. Table 6-3 presents the result for the example.

Box 2: Create Monthly Load Duration Curve (LDC)--This function orders all Table 6-3 residual loads into descending order, while keeping the associated probabilities. This step for the example is shown in Table 6-4. Within ULMOD, the sorting is performed by the CDC Sort/Merge package. Any similar package could be used for this purpose. The possible number of residual loads per month is 8928 (31 days × 24 hours × 12 maximum powers), and each of these has an associated probability.

Table 6-2. INTERMITTENT GENERATION POWERS AND PROBABILITIES
(One Typical Day per Month)

Hour	Power (MW)	Probability (%)	Power (MW)	Probability (%)	Power (MW)	Probability (%)
1	0	25	40	60	100	15
2	0	15	50	75	100	10
3	0	15	40	70	100	15
4	0	20	30	60	100	20
5	0	40	50	35	100	25
6	0	35	30	60	100	5
7	0	25	20	45	100	20
8	0	20	40	70	100	10
9	0	30	20	55	100	15
10	0	35	30	55	100	10
11	0	40	40	30	100	30
12	0	30	50	40	100	10
13	0	35	50	45	100	20
14	0	30	40	60	100	10
15	0	20	30	75	100	5
16	0	25	40	60	100	15
17	0	20	20	30	100	10
18	0	30	30	55	100	15
19	0	25	40	55	100	20
20	0	20	50	55	100	25
21	0	15	30	65	100	20
22	0	20	20	65	100	15
23	0	30	30	60	100	10
24	0	35	40	50	100	15

Table 6-3. RESIDUAL LOADS AND HOURLY EXPECTEDS

Day	Hour	Residual (MW)	Probability (%)	Residual (MW)	Probability (%)	Residual (MW)	Probability (%)	Expected Residual (MW)
1	1	600	25	560	60	500	15	561.0
1	2	550	15	500	75	450	10	502.5
1	3	500	15	460	70	400	15	457.0
1	4	450	20	420	60	350	20	412.0
1	5	400	40	350	35	300	25	357.5
1	6	500	35	470	60	400	5	477.0
1	7	550	25	530	55	450	20	519.0
1	8	600	20	560	70	500	10	562.0
1	9	650	30	630	55	550	15	624.0
1	10	700	35	670	55	600	10	673.5
1	11	750	40	710	30	650	30	708.0
1	12	800	30	750	60	700	10	760.0
1	13	850	35	800	45	750	20	807.5
1	14	900	30	860	60	800	10	866.0
1	15	1000	20	970	75	900	5	972.5
1	16	950	25	910	60	850	15	911.0
1	17	900	20	880	70	800	10	876.0
1	18	850	30	820	55	750	15	818.5
1	19	800	25	760	55	700	20	758.0
1	20	750	20	700	55	650	25	697.5
1	21	700	15	670	65	600	20	660.5
1	22	650	20	630	65	550	15	622.0
1	23	600	30	570	60	500	10	572.0
1	24	600	35	560	50	500	15	565.0

Table 6-4. **RESIDUAL LOADS IN DESCENDING ORDER**
(Load Duration Curve)

Residual (MW)	Probability (%)	Residual (MW)	Probability (%)	Residual (MW)	Probability (%)
1000	20	710	30	550	15
970	75	700	35	550	25
950	25	700	10	550	15
910	60	700	20	550	15
900	30	700	55	530	55
900	5	700	15	500	75
900	20	670	55	500	35
880	70	670	65	500	15
860	60	650	30	500	10
850	15	650	30	500	15
850	30	650	25	500	10
850	35	650	20	500	15
820	55	630	55	470	60
800	25	630	65	460	70
800	30	600	20	450	20
800	45	600	10	450	10
800	10	600	20	450	20
800	10	600	30	420	60
760	55	600	25	400	40
750	40	600	35	400	15
750	60	570	60	400	5
750	20	560	50	350	35
750	15	560	70	350	20
750	20	560	60	300	25

Table 6-5. **EXPECTED RESIDUAL LOADS IN DESCENDING ORDER**
(Load Duration Curve)

Actual Day	Actual Hour	Expected Residual (MW)
1	15	972.5
1	16	911.0
1	17	876.0
1	14	866.0
1	18	818.5
1	13	807.5
1	12	760.0
1	19	758.0
1	11	708.0
1	20	697.5
1	10	673.5
1	21	660.5
1	9	624.0
1	22	622.0
1	23	572.0
1	24	565.0
1	8	652.0
1	1	561.0
1	7	519.0
1	2	502.5
1	6	477.0
1	3	457.0
1	4	412.0
1	5	357.5
	TOTAL	15,740.0

Box 7: Variability--See Sec. 6.2.5.

Box 3: Full Hour Expected Residuals--The term "expected" here means the residual load that is most likely to occur. This is determined by calculating the probability-weighted average of the original residual loads (see Table 6-3). These original residuals are still in chronological order. The day and hour together with each expected residual load are stored on a computer data file (TAPE20) for later use in Box 4.

Box 4: Expected Residuals LDC--Like that of Box 2, this operation is to create a list of residuals in descending order. The expected residuals of Table 6-3 are ordered, and the associated day and hour are carried along in the sort process. The example is presented in Table 6-5. There are no probabilities, since they have all been eliminated in the averaging calculation of the expected residuals. The Day column of Table 6-5 contains only one value, whereas in an actual case this column would contain a variety of values ranging from 1 to the given maximum number of utility load days for the month. If there were 31 days of utility loads input, then the actual table corresponding to Table 6-5 would contain 744 (31 × 24) rows of information.

Box 5: Accumulate Residuals LDC--The results of Box 4 are useful but would not take full advantage of the power-probability data available, since this is equivalent to subtracting the single expected alternative generation from the forecasted utility loads. To take full advantage, the results of Box 2 (Table 6-4) will be processed for ready use by utility planning models because few utility models are designed to handle anything more detailed than one load per hour. To reduce data, a process similar to that of Box 3 is performed. This operation calculates the probability-weighted average residuals by proceeding down the results of Box 2 by increments of 100% probability. Where necessary, a given residual's probability of occurence is split; the part not needed to total 100% is saved for the next calculation sequence. In this way, all of the original residuals (all with probabilities less than 100%) are accumulated into new residuals with a likelihood of 100%. Table 6-6 gives the result for our example. Like the result of Box 4, the actual result of this box would contain up to 744 rows of information.

Box 8: Segmented LDC--See Sec. 6.2.4.

Box 6: Estimated Chronological--Many utility production cost models require their input loads to be chronological. Therefore, to estimate this order from Box 5 results, the Box 4 results (Table 6-5) will be used. Since the Box 4 and Box 5 results are both in descending order, consist of only 100% probability (whole hour) values, and contain the same number of rows, it is assumed that the chronological order of the expected residuals (Box 4) will be a suitable estimate for the accumulated values. To estimate the day and hour values given in Table 6-6, the values of Table 6-5 are taken in order. It is important to note that the total residual energy to be served by the utility is the same for both the Box 4 and Box 6 results (as shown in Tables 6-5 and 6-6).

Table 6-6. WHOLE-HOUR ACCUMULATED RESIDUAL LOADS IN DESCENDING ORDER AND ESTIMATED CHRONOLOGICAL LOCATION

Accumulated Residuals (MW)	Estimated Day	Estimated Hour
975.0	1	15
916.0	1	16
887.0	1	17
857.5	1	14
833.5	1	18
800.0	1	13
765.5	1	12
750.0	1	19
718.0	1	11
698.5	1	20
670.0	1	10
653.0	1	21
634.0	1	9
612.0	1	22
594.0	1	23
564.0	1	24
560.0	1	8
550.0	1	1
513.5	1	7
500.0	1	2
474.0	1	6
455.0	1	3
412.0	1	4
347.5	1	5
TOTAL 15,740.0		

The rationale for executing the extra complications of Boxes 2, 5, and 6 instead of using the results of Box 4 is to better represent the fluctuations in the residual loads when intermittent generation sources are on the system. This effect is captured by the residuals of Box 6 (Table 6-6) being larger than those of Box 4 (Table 6-5) near the peak residual and smaller than those of Box 4 near the minimum residual (see Fig. 6-2 for the peak portion of our example). For an actual case and with more power-probability points per hour, the graphic results would be smoother and even better illustrative of this result. Whether the differences are significant will depend on several points including the particular utility's load profile, generation mix, the penetration of the intermittent generation source into the utility system, and the correlation of the intermittent generation with the utility's load profile.

6.2.2 All Hours or One Typical Day

The calculations are much more straightforward when the WECS power estimate is given for either all hours in the year or only a single typical day each month because of the lack of any probability information. The lack of probability information that is more reflective of long-term expectations is also this option's shortcoming. No numerical example is needed for this explanation. In Fig. 6-1 the flow of calculations is down the left side.

The residual load calculation (Box 1A) is a subtraction of the hourly intermittent generation from the utility hourly load forecast. If only a single typical day of intermittent generation is given, each hour's generation is subtracted from the corresponding hour of each day's worth of utility loads provided. If a full month of both utility loads and intermittent generation are provided, then the residuals are calculated in a straight hour-by-hour process. A full month of intermittent generations is not allowed if only a typical week of utility loads is provided. These residuals are next put into descending order (Box 2A) to form a load duration curve (LDC). Discussion of variability and segmented LDCs is deferred since their treatment is the same for each intermittent generation option.

6.2.3 No Alternative Generation

To create data for a base case, this option is also available and is shown as the right side of Fig. 6-1. Since there is no intermittent generation, residuals need not be calculated, and the first step is to sort these utility-forecasted loads into a LDC. Discussion on variability and segmented LDCs follows.

6.2.4 Box 8: Segmented Load Duration Curve (LDC)

Since many utility models, especially expansion planning models, require segmented or stepwise-approximated LDCs as the input for utility loads, a means of creating such curves is desirable. There is no optimization involved in this segmentation process. Rather, the actual hour-by-hour LDC is broken up by the user who must tell ULMOD how many segments or time periods are desired

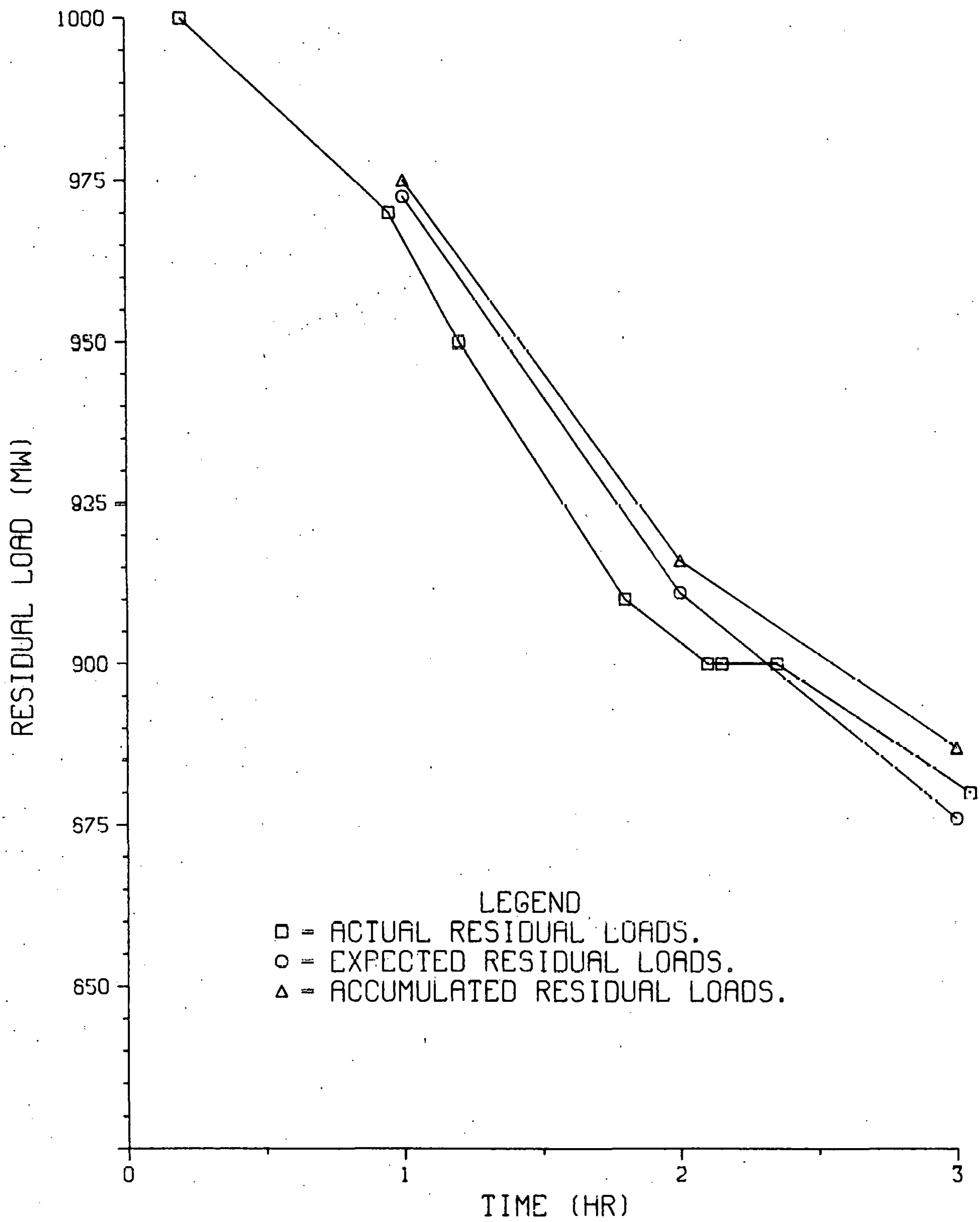

Figure 6-2. Residuals Comparison

and what percentage of time during the month (or year) each segment is to cover. Each of these segments can also be further divided into a number of smaller, equally spaced pieces.

The point at which segmentation in ULMOD is required depends on the intermittent generation option being used. These locations are shown on Fig. 6-1.

Enough residual load points (a full hour each) are identified to equal the desired time percentage of each LDC segment by adding the probabilities associated with the residuals until the desired amount of time is equaled or just exceeded. If the total exceeds the time desired, the last probability point is split to equal this time period, and the unused portion is used to begin the next segment. If a typical week of utility loads is provided, it is assumed that each hour point occurs during the month a number of times; this number equals seven divided into the number of days in the month. After the members of the LDC segment are identified, these may be divided into any desired number of smaller pieces. All points belonging to a common piece are then averaged, with these averages being the final result. There is wide flexibility in the number of these small, equally spaced pieces per segment, but there can only be up to 15 segments produced.

6.2.5 Box 7: Load Forecast Uncertainty or Variability

Appendix B discusses the role of utility load forecasting uncertainty or variability in relation to intermittent generation variability. ULMOD attempts to accommodate utility load forecasting variability into value determinations. This is done with five input amounts by which the peak demand might vary from the forecasted mean and a probability that this variation will manifest itself. Each of these five points represents an area or interval of MW loads (such as segments of a Gaussian distribution), each interval having a probability of occurence. Usually one of these intervals will be centered about the forecasted mean (zero MW variance). (All discussion will refer to the peak portion of the LDC, but there is the same capability for the minimum load portions of the LDC.) This variability in demand (expressed in MW) can be applied in one of two ways referred to as the "full" and "taper" methods. Each of these methods will be illustrated by elaborating on the previous numerical example that followed the middle column of Fig. 6-1. If variability is desired for either of the outside paths of Fig. 6-1, probability values are created, requiring a jump into the center path of the figure, as shown. Since there were no probability data before the variability step, a substitute for the result of Box 3 is needed to estimate chronological order (Box 6). The substitute is either the result of Box 1A or the original utility loads, depending on the original direction down Fig. 6-1.

6.2.5.1 Full Method Uncertainty

Figure 6-1 shows that if consideration of load forecast uncertainty is desired for the power-probability option, it is performed immediately after the complete set of residual load points are put into descending order, corresponding to Table 6-4 of our example. To illustrate, let us assume that it is desirable to perform variability calculations on 10% of the time this month, starting with the peak residual load, and the maximum amount of variability is 75 MW. Let us further assume that 75-MW variability has a 15% probability of being applied positively and 10% probability of being applied negatively. (This example uses only three of the possible five points of uncertainty modification.) Our example consisted of only a single day of utility loads instead of 7 days or up to 31 days. For this example, we will assume that 31 days of utility data are provided, but we will apply the variability to the top 2.4 accumulated hours instead of the actual 74.4 (31 × 24 × 0.10). For this case, the accumulation to total 2.4 proceeds from the 1000 MW and 20% point through the 900 MW and 20% point and also needs 5% of the 880 MW and 70% point. (If there were only a typical week of utility load data provided, to accumulate the desired amount of time would require a ratio to be multiplied by each probability, the ratio being a value such as 31/7 for a 31-day month, before the accumulation was actually done.) Under the full variability method, the assumed 75 MW will be applied to all points indicated previously, and the associated probabilities will be modified by the variability probabilities (see Table 6-7). The uncertain residual load probability is equal to the product of the probability of the original residual load and the probability of the proper MW variability.

Before considering again the flow of Fig. 6-1, the results of variability (both top and bottom of LDC) must be merged with the unchanged center area of the LDC and all residuals put into descending order (similar to the result of Box 2). If a whole month of utility load data is provided and the maximum of 12 power-probability pairs are used, the total number of residuals is equal to 8928. If variability is also desired, the total number could be as much as 5 × 8928. If all days of utility loads are provided and the power-probability option is desired, a check is performed to see if a reduction of data points is needed to prevent expansion above 8928. The total number of points created in the variability process (five times the number needed to total the desired time period) is known. In the reordered result created, this total number of points is probability weighted in groups of fives, allowing the total number of residuals to be kept to no more than 8930. The difference between 8928 and 8930 is due to the fact that an extra point on the top and bottom may be created by splitting residual-probability points to equal the desired time period. As far as the rest of ULMOD knows, calculations are the same as before except that the total number of power-probability pairs has probably been increased. Similar to the effect of power-probability data, the taking of load variability into account tends to increase the residuals near the peak and decrease those near the minimum.

6.2.5.2 Taper Method Uncertainty

The only difference between the taper and full methods is the amount of the input MW of variance that is applied to each starting residual load. The full method applies the input MW variance to all points equally. By the use of a multiplier to the MW variance, the taper method varies this variance amount from the input maximum at the peak residual point to near zero at the last desired variance point. The rationale for the taper method is that the ability to forecast in the area of the peak is less reliable than in the center area. The MW variance multiplier is determined by a fraction, where the denominator is equal to the total number of points in the upper residuals section to which variability will be applied, and the numerator is equal to the denominator minus the number of residual points that the current calculation point is away from the peak. For our example, the denominator equals 8, and the numerator varies from 8 at the peak to 1 at the 880 MW, 5% point. The use of this taper fraction is the only difference between the full and taper methods. Table 6-8 shows the results of our example using taper variability.

Table 6-7. UNCERTAINTY DEMONSTRATION—FULL METHOD
(75 MW, 15% Positive, 10% Negative, 75% Unchanged)

Original		Positive		Unchanged		Negative	
Residual (MW)	Prob. (%)	Residual (MW)	Prob. (%)	Residual (MW)	Prob. (%)	Residual (MW)	Prob. (%)
1000	20• R[a]	1075	3	1000	15	925	2
970	75• R	1045	11.25	970	56.25	895	7.5
950	25• R	1025	3.75	950	18.75	875	2.5
910	60• R	985	9	910	45	835	6
900	30• R	975	4.5	900	22.5	825	3
900	5• R	975	0.75	900	3.75	825	0.5
900	20• R	975	3	900	15	825	2
880	5• R	955	0.75	880	3.75	805	0.5
880	65	Unchanged portion remaining					

[a]R = Ratio of number of days in the month to the number of days of load data provided; R = 1.0 if all utility loads during month are given; R = 31/7 for a month with 31 days and if only a typical week of utility loads is given.

Table 6-8. UNCERTAINTY DEMONSTRATION—TAPER METHOD
(75 MW, 15% Positive, 10% Negative, 75% Unchanged)

Original			Positive		Unchanged		Negative	
Residual (MW)	Prob. (%)	Taper Fraction	Residual (MW)	Prob. (%)	Residual (MW)	Prob. (%)	Residual (MW)	Prob. (%)
1000	20• R[a]	8/8	1075	3	1000	15	925	2
970	75• R	7/8	1035.63	11.25	970	56.25	904.38	7.5
950	25• R	6/8	1006.25	3.75	950	18.75	893.75	2.5
910	60• R	5/8	956.88	9	910	45	863.13	6
900	30• R	4/8	937.50	4.5	900	22.5	862.5	3
900	5• R	3/8	928.13	0.75	900	3.75	871.88	0.5
900	20• R	2/8	918.75	3	900	15	881.25	2
880	5• R	1/8	889.34	0.75	880	3.75	870.63	0.5
880	65	Unchanged portion remaining						

[a]R = Ratio of number of days in the month to the number of days of load data provided; R = 1.0 if all utility loads during month are given; R = 31/7 for a month with 31 days and if only a typical week of utility loads are given.

SECTION 7.0

FINAM—FINANCIAL ANALYSIS MODEL

As can be seen in Fig. 2-1, FINAM is the final program needed in the value determination process. Note that ULMOD has been executed for each of the change cases (different WECS penetrations), creating modified load shapes for each case. The utility planning models have been executed for each of these modified load shapes, as well as for the base case with no WECS generation (unmodified load shape). Now FINAM compares the planning model results of each of the change cases to the results for the base case. These comparisons yield the break-even cost of WECS for each of these WECS penetrations. This value is the utility's present worth savings, expressed as an equivalent capital cost ($/rated kW) of the intermittent source, from reduced operating costs and modified capital additions.

Utilities may desire to use their corporate model instead of FINAM. FINAM requires a base or zero intermittent generation case and up to 10 change or positive intermittent generation cases. It is assumed that the change cases are using the same intermittent generation design and that the difference between the change cases is the assumed amount of alternative generation capacity installed. This section describes the model's performance. Section 6.0 of The User's Guide (Volume II) will fully describe the required inputs and available results as well as define important variables and required computer data files.

7.1 OPTIONS

The first available option is that the user may designate that annual expenditures given as input (operating costs, fuel costs, etc.) are either first-of-year or end-of-year quantities. If end-of-year values are used, they must be discounted to the beginning of the present worth year. This is true even for the case when the first annual expenditure is indicated to be the desired present worth year. The choice of which to use is arbitrary but should be consistent with previous studies and company policy. The DOE and EPRI generally accepted standard is to assume that expenditures occur at the end of the year. Reference 17 describes the calculations performed under this assumption. Section 7.2 discusses the situation if expenditures occur at the beginning of the year.

The second option is the ability to perform sensitivity or parametric studies after initially determining the intermittent generation value for the data provided as input. A sensitivity study is the modification of only one class of input data from the original and the performance of the value calculations again. Examples of classes of input data include fuel costs, capital costs, and operating and maintenance costs, as well as the rates of escalation of these costs. For sensitivity studies, FINAM assumes that the amount of installed capacity and the estimated amount of operation for each conventional generation type does not change from the original. The sensitivity feature can only indicate the relative importance of specific input data in determining the result. Its results should therefore only be used for this purpose, unless it can be verified that the data modification does not alter the optimum conventional generation capacities or electricity production. Sensitivity cases may be performed at the time of original execution or during a subsequent execution without reentering the original data if these data were saved after being validated and stored in a computer file. See the flow diagram of Fig. 7-1.

7.2 CALCULATIONS

Before describing calculations of FINAM, it will be helpful to know what data are required. Since all results are presented in a specific year's present worth dollars, the desired year is needed. The discount rate is also needed to discount to the desired year. All dollar inputs to this model are assumed to be nominal dollars (i.e., including general inflation) in the associated input year. A maximum of 12 conventional generation types (coal, nuclear, hydro, oil-steam, combustion turbines, etc.; not intermittent sources) may be considered and up to 20 years of detailed capacity and operation data (from production cost model simulation or expansion model estimate) may be analyzed. For each conventional generation type and simulation year, data are needed on the fuel cost ($/MBtu) and capital cost ($/rated kW), as well as fixed ($/MW yr) and variable ($/MWh) operating and maintenance (O&M) costs. The capital costs input here are the same as would be provided to a utility expansion planning model--the year of initial operation, present worth equivalent of all capital expenditures. It is assumed that capacity additions are available at the beginning of the year. To approximate the years after the last simulation year by applying an escalation rate, the desired escalation pattern for each of the four cost items listed previously is needed for each generation type.

For the base case and each intermittent generation capacity case, specific additional data are needed for each simulation year. Though the previously listed data would typically also be input to utility expansion planning and production cost models, the data referenced here would be the output from these utility planning models. These data are the capacity of each conventional generation type added and the corresponding estimated total expenditures (in thousands of dollars) for fuel, as well as fixed and variable O&M costs. Total expenditures needed to meet the expected unserved energy for each year can be accounted for in this model if the data are available.

With respect to the intermittent source, limited information is required by FINAM. The total rated capacity is needed for each change case. Also, the assumed operating lifetime and fixed charge rate are needed. The operating lifetime will be used to determine either the last year for which operating cost data must be given or the year to which the last given year of operating data must be extended by the use of escalation rates.

FINAM determines the total present worth of revenue requirements for the base case and each intermittent generation case. The following discussion applies to either the base case or one of the change cases. All calculations are performed for each. The description provided assumes that annual expenditures occur at the beginning of the year.

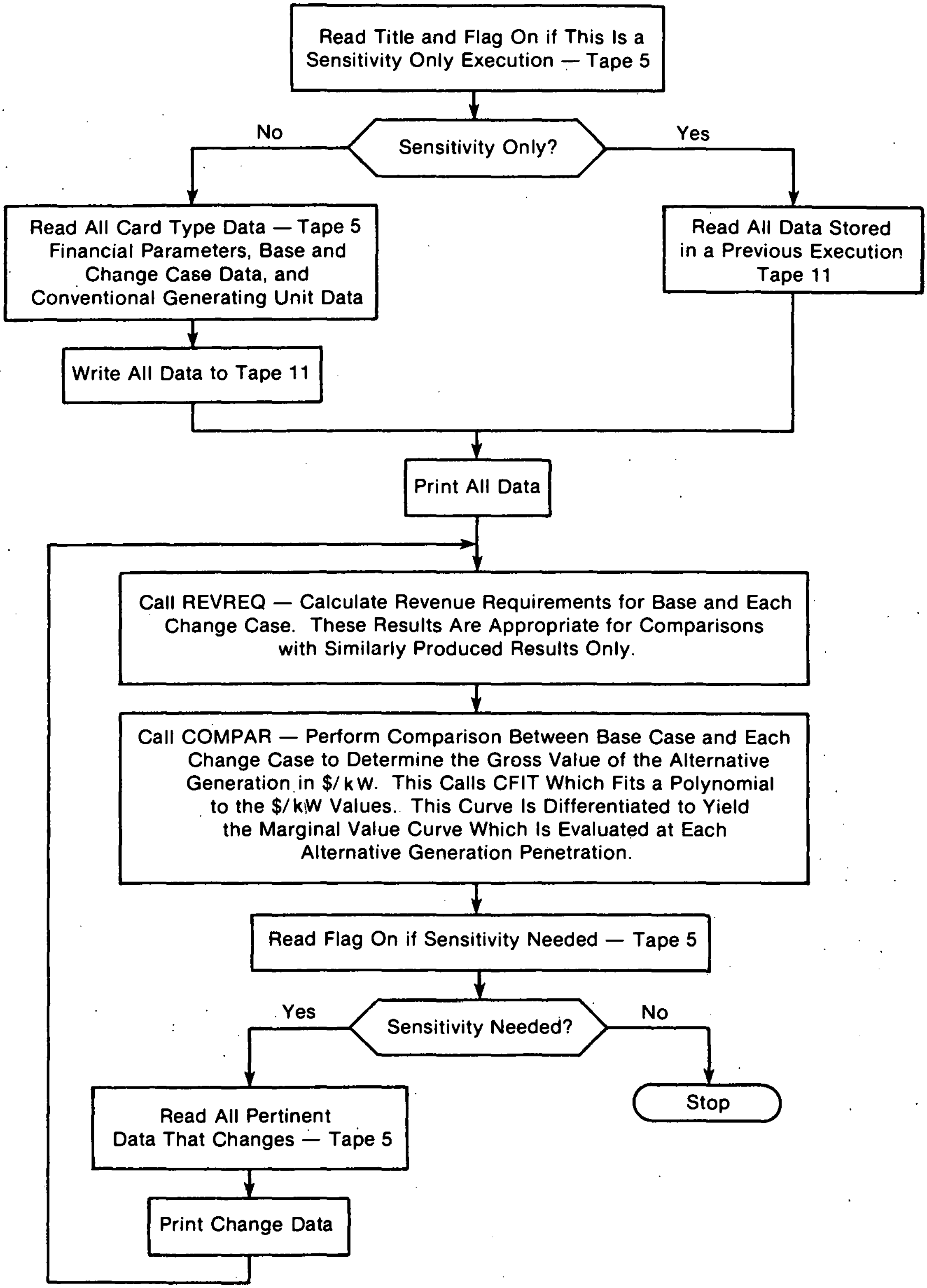

Figure 7-1. FINAM

7.2.1 Present Worth Modifier

The first calculation is the determination of a present worth modifier to be used for each simulation year and for each year that capacity additions are made. The present worth modifier converts expenditures in each year to a present value equivalent in the base year of interest. It is calculated as follows:

$$GNP = (1 + GNPDEF)^{[IYRPW - JYR(1)]} ,$$

$$PWD(J) = GNP \cdot (1 + PWDISC)^{[JYR(1) - JYR(J)]} , \text{ and}$$

$$PWDCC(JJ) = GNP \cdot (1 + PWDISC)^{[JYR(1) - JCAPYR(JJ)]} ;$$

where

J = 1, number of simulation years (NSIM),
JJ = 1, number of capacity addition years (NCAPYR),
PWD(J) = present worth modifier simulation for year J,
PWDCC(JJ) = present worth modifier for capacity addition year JJ,
GNPDEF = gross national product deflator,
PWDISC = present worth discount rate,
IYRPW = base year in which the present value of costs will be reported,
JYR(J) = simulation year J, and
JCAPYR(JJ) = capacity addition year JJ.

As an example, consider the following:

PWDISC = 0.10,
IYRPW = 1980, and
JYR = 1980, 1985, 1990.

Under these assumptions, PWD = 1.0, 0.6209, and 0.3855.

7.2.2 Simulation Year Variable Costs

For each simulation year, total variable costs will be convertd to a present value equivalent for the base year and summed into a total revenue requirements variable. The first simulation year's contribution is the input total variable expenditures multiplied by the first present worth modifier:

$$TREVRQ = TOTVAR(1) \cdot PWD(1) ,$$

where

TREVRQ = total revenue requirements summation variable for this case (1000$), and

TOTVAR(1) = total input variable costs in simulation year (1000$).

The following years are more complicated, since it may be desirable to use simulation years that are not sequential (e.g., 1980, 1985, and 1990). Hence, it is assumed that the total variable costs escalate at an even rate between given simulation years. After calculating this rate, it is applied for each intermediate year, and the escalated total variable costs are discounted to the first of these simulation years. These intermediates are totaled and then discounted to the desired base year. The calculations are presented in the following sequence:

$$\mathrm{DELTAYR} = \mathrm{JYR}(J+1) - \mathrm{JYR}(J) \ ;$$

$$\mathrm{ESC} = \frac{\mathrm{TOTVAR}(J+1)}{\mathrm{TOTVAR}(J)}^{1/\mathrm{DELTAYR}} \ ;$$

$$\mathrm{TR} = \sum \left[\mathrm{TOTVAR}(J) \cdot (\mathrm{ESC})^{I}/(1 + \mathrm{PWDISC})^{I}\right],\ I = 1,\ \mathrm{DELTAYR} \ ; \text{ and}$$

$$\mathrm{TREVRQ} = \mathrm{TREVRQ} + \mathrm{TR} \cdot \mathrm{PWD}(J) \ ;$$

where

J = 1 to (NSIM - 1),
DELTAYR = number of years between simulation years J and J + 1,
ESC = even escalation rate,
PWDISC = present worth discount rate, and
TR = temporary counting variable.

By this procedure, the (J + 1) year total variable cost is produced in the escalation process and need not be handled separately. As can be noted from the above sequence, the procedure will work properly even if the simulation years are given sequentially.

7.2.3 Calculations for Years Beyond the Last Year of Simulation

To approximate the effect of operations after the last simulation year, it is possible to perform extension calculations. Of course, these calculations are not performed if the extension calculation year is less than or equal to the last simulation year. These calculations are performed on the variable cost components (fuel costs as well as fixed and variable operating and maintenance costs) of each conventional generating unit type and the expected system unserved energy cost. These input values (in thousands of dollars) for the last simulation year are escalated individually using the given rate of each for the appropriate number of years. This escalation simultaneously performs a present worth summation into the last simulation year's dollars. This value then must be discounted to the desired base year and summed with the previous total of revenue requirements.

The sum of variable costs after the last simulation year are estimated and discounted to the last year of simulation by the use of a modifier. This modifier is determined by performing the following calculation enough times to cover all needed years [12]:

For K = 1 through NESC,
ELAST1 and ELAST2 initialized to 1.0,
RK = [1 + ESCRTE(K)]/(1 + PWDISC), and
N = IYR2 - IYR2.

$$\text{If RK} = 1.0\text{, then ESCM(K)} = \text{N};$$
$$\text{if RK} \neq 1.0\text{, ESCM(K)} = \text{RK} \cdot \left(1 - \text{RK}^{\text{N}}\right)/\left(1 - \text{RK}\right)\ ,$$
$$\text{ELAST1} = \text{ELAST1} \cdot \text{ESCRTE(K)}^{\text{N}}\text{, and}$$
$$\text{NYRDIS} = \text{IYR2} - \text{JYR(NSIM)}.$$

$$\text{If NYRDIS is} > 1 \text{ or} < 1,$$
$$\text{then ESCM(K)} = \text{ESCM(K)} \cdot \text{ELAST2}/\left(\text{PWDISC}^{\text{NYRDIS}}\right)\ ,$$
$$\text{ELAST2} = \text{ELAST1, and}$$
$$\text{ESCMOD} = \text{ESCMOD} + \text{ESCM(K)};$$

where

ESCMOD = modifier,
ESCRTE = input escalation rate,
IYR1 - first year ESCRTE applied - first usable IYR1 = JYR(NSIM),
IYR2 - last year ESCRTE applied - last usable IYR2 = IYREXT,
IYREXT = extension calculation year = JYR(1) + intermittent source life - 1,
N = number of years to perform partial extension,
NESC = number of escalation rate periods,
ELAST1 = escalation modifier sufficient to raise a cost in the year JYR(NSIM) to IYR2,
ELAST2 = ELAST1 for the last escalation period, and
NYRDIS = number of years that IYR1 is from JYR(NSIM), used to discount to the year JYR(NSIM).

After this modifier is calculated for each individual cost component, it is applied to each last year variable cost and discounted to the desired base year by the following:

$$\text{TREVRQ} = \text{TREVRQ} + \text{PWD(NSIM)} \cdot \text{ESCMOD} \cdot \text{VARCST}\ ,$$

where

VARCST = the last year variable cost (1000$) of fuel as well as fixed and variable O&M for each generation type and system unserved energy cost.

7.2.4 Capital Costs Calculations

FINAM's total of conventional generating unit capital costs are added in the first year of operation and discounted to the desired year. To account for the fact that capital will be expended over a number of years before the unit is operated, the capital cost ($/kW) provided as input must be equal to the installation-year present worth equivalent of the actual stream of previous precommercial operation expenditures. This is the same value needed by most utility expansion planning models.

The calculations performed use an input fixed charge rate together with the capital cost ($/kW) and capacity addition (MW) of each conventional generation type to approximate annual utility expenditures during the initial commercial operation year and all subsequent years. The number of years in which these expenditures are accounted for depends on the number of years used to calculate the fixed charge rate. The calculations performed are as follows:

$$NN = NFCRYR(I) - 1 ,$$

$$CRF = PWDISC/[(1 + PWDISC)^{NN} - 1] ,$$

$$TR = TR + [FCR(I) \cdot CAPCST(I,JJ) \cdot CAPADD(JJ,I)] \cdot [1 + 1/CRF] , \text{ and}$$

$$TREVRQ = TREVRQ + [TR \cdot PWDCC(JJ)] ;$$

where

JJ = 1 to last capacity addition year,

I = 1 to last generation type,

JYR(NSIM) = last simulation year,

NN = number of years of capital payments within the study but not including the commercial operation year,

NFCRYR(I) = number of years that fixed charge rate is based on for generation type I,

CRF = capital recovery factor,

FCR(I) = fixed charge rate for unit I,

CAPCST(I,JJ) = capital cost ($/kW) for unit I in year JJ, and

CAPADD(JJ,I) = capacity addition (MW) in year JJ.

7.2.5 Value Determination

After the total present worth of revenue requirements is calculated for the base and each assumed alternative generation case, a comparison is performed to determine the value of the specific alternative generation source being considered. The first component of this comparison is the total revenue requirement of each intermittent case subtracted from the revenue requirements of the base case, which is the gross total value in thousands of present worth dollars. With the amount of assumed intermittent capacity provided by input, the break-even cost per rated installed kW of intermittent generation is next calculated. This break-even cost is calculated by first multiplying the gross present worth value by a capital recovery factor determined by the use of the discount rate and assumed life of the intermittent capacity. This converts the gross value into an equivalent stream of equal annual payments. Finally, this result is divided by the assumed fixed charge rate of the intermittent capacity to convert a single annual payment into the equivalent first year expenditure. After the break-even cost per kW is determined for each intermittent capacity case (up to 10), the marginal value per rated kW is determined by using a set of routines to fit a polynomial curve to the break-even costs for all cases analyzed. The polynomial equation developed next is differentiated and evaluated at each solar capacity penetration for the marginal values corresponding to the previous break-even costs. The routines used for this are part of the International Mathematics and Statistical Library (IMSL), but any polynomial fitting routines could be used.

7.3 SENSITIVITY ANALYSIS

The sensitivity of the WECS value to certain economic parameters can be roughly determined without rerunning the entire financial portion of the methodology. This is done by changing any of the following in the sensitivity section of FINAM's input data:

- present worth year,
- assumed date that expenditures occur,
- intermittent life and fixed charge rate,
- present worth discount rate,
- fuel costs ($/MBtu),
- capital costs ($/kW),
- fixed O&M costs ($/MW/yr),
- variable O&M costs ($/MWh), and
- expected unserved energy costs ($/MWh).

This FINAM sensitivity feature should be used cautiously, since it assumes that the economic changes do not affect the operation of the conventional generation system as previously simulated in the utility planning models. The result of the FINAM sensitivity feature are intended only to identify the important economic parameters to be investigated further in the utility planning models. Only when the planning models are executed with the sensitive economic parameter can the true importance of this parameter be determined.

SECTION 8.0

USE OF RESULTS

After the analyses described in the preceding sections have been completed, the value of WECS can be compared to its cost. The value of WECS is the present value of savings to the utility of reduced operating costs and modified capital additions. The cost of WECS is the present value of total cost over the machine's lifetime. This total cost must include costs for the machine itself, installation, operation and maintenance, interest on capital, insurance, and property taxes.

Remember that the value calculations are for a particular wind turbine at a specific site and are based on numerous utility system and financial assumptions. Parametric studies help to identify effects of certain scenarios and assumptions on the final results. Recall that FINAM has the ability to perform limited sensitivity studies on financial parameters. The use of analytic intuition by the user will help simplify the sensitivity task. For example, the analyst should initially recognize the importance of parameters such as site, wind, velocity, and fuel cost escalation rates upon the final value result.

The equation of WECS marginal value as a function of WECS capacity, as described in Sec. 7.2.5, is extremely useful to the utility planner. If the marginal value curve is plotted along with the WECS cost curve (Fig. 8-1), then the break-even point (cost/value ratio equals one) of WECS addition to the utility for the specific case considered is indicated by the intersection of the two curves. A useful plot of the cost/value ratio with respect to WECS capacity can also be easily generated.

Because manufacturers of wind machines choose different rated wind velocities for their design, a comparison between values ($/rated kW) of different types of wind machines is not valid. Only an inspection of a specific wind machine's marginal value compared with total cost will indicate its economic viability for this specific utility system.

Besides considering different types of WECS, electric utilities must consider investment options other than WECS. Some options could be installing conventional generating units, purchasing power from neighboring utilities, instituting a load management program, or financing conservation projects. A careful inspection of each of these competing choices must be made before a complete economic evaluation of the situation has been achieved.

If the WECS cost/value ratio is favorable and serious consideration is being given to the WECS option, then the utility planner might also perform a financial analysis by using the utility's corporate model to determine the effects on cash flow, debt requirements, etc.

Also, many factors other than economics will affect a utility's decision regarding WECS installation. Technical questions of WECS not addressed in this analysis include effects upon the transmission and distribution system and on system stability, and cycling effects upon thermal generating units in

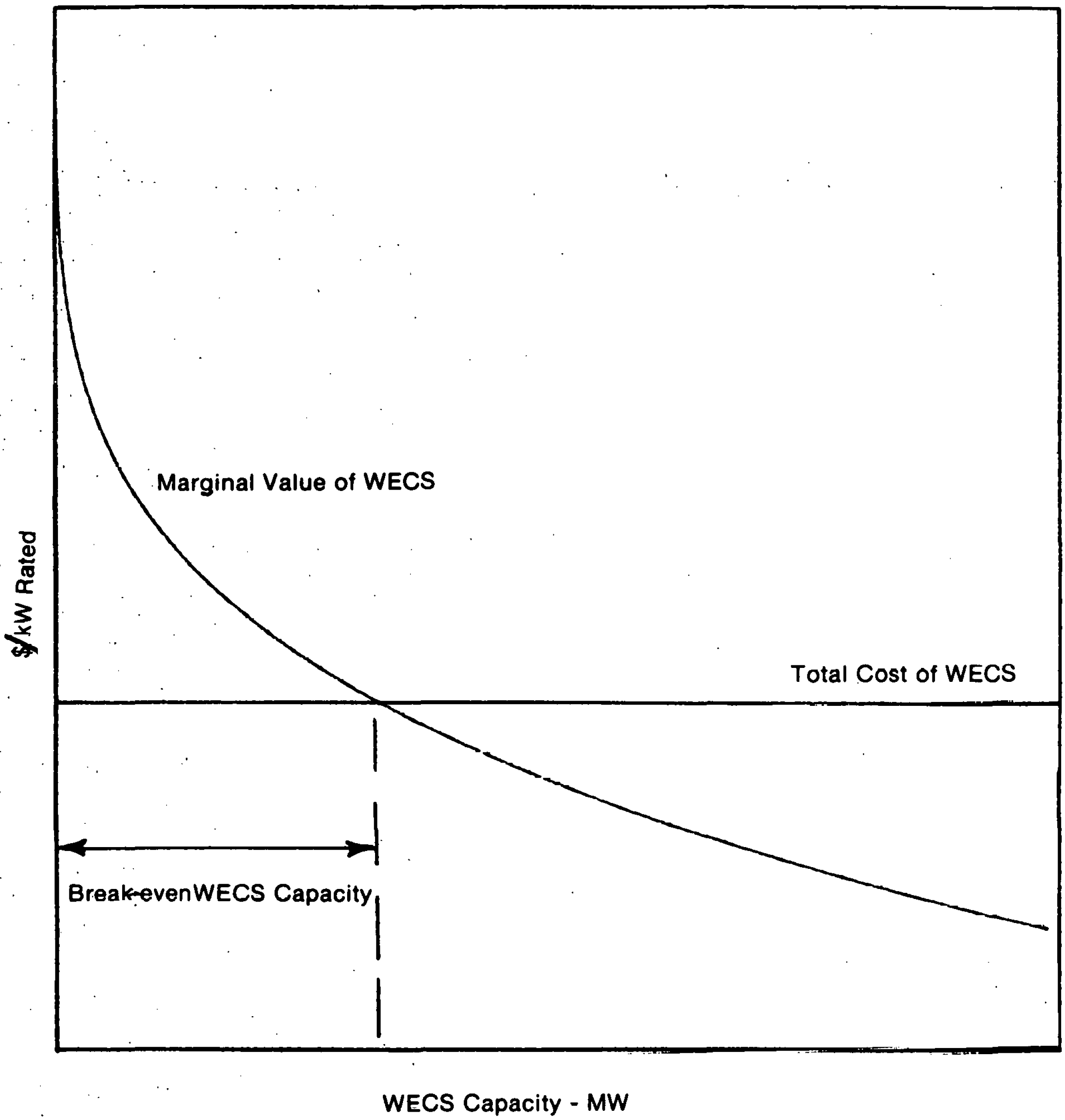

Figure 8-1. WECS Marginal Value Compared with Total Cost

the system. Also, a utility must consider financing, regulation, land use, public acceptance, and energy supply security.

This volume has described the models currently available from SERI to analyze the long-term economic impact of wind systems on electric utilities. Efforts to extend this analysis to photovoltaic and solar thermal systems will include models similar to WEIBUL and ROSEW. SERI is also considering modifications to ULMOD that will include storage dedicated to the solar generation system.

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SECTION 9.0

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APPENDIX A

INTEGRATION OF INTERMITTENT SOURCES INTO BALERIAUX--BOOTH PRODUCTION COST MODELS

SERI/TP-35-375

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INTEGRATION OF INTERMITTENT SOURCES INTO BALERIAUX - BOOTH PRODUCTION COST MODELS

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Abstract - An intermittent generation source is one over which a utility dispatcher has minimal control with regard to the amount of power available at any instant. The power may fluctuate freely over the range from zero to some maximum. Examples of such sources are wind machines, photovoltaic cells and, in some cases, run-of-river hydro. For a utility planner this form of resource presents problems in the determination of reliability and worth. A method of integrating these resources into a utility production cost model is presented; the method should improve approximations in production costing and in the loss-of-load calculation.

INTRODUCTION

In electric utility planning measures of the risk of failure to meet load are extremely important. These measures are used in determining the value of a new source to a system mix and in expansion planning for the system. Historically, the introduction of the Calabrese loss of load calculation (LOLP) was an improvement over the "per cent reserve margin" and hence became a popular reliability measure. With the introduction of production codes based on Baleriaux-Booth theory, the probability of failure to meet load could be obtained directly from an equivalent load duration curve. By multiplying this probability by the hours for which the load duration curve is applicable, one obtains the loss of load hours as the measure of risk. Since an expanded form of the LOLP calculation is equivalent to the Baleriaux-Booth measure, the latter measure has the advantage of giving production cost values and the corresponding loss of load probability from the same computer run.

However, when one examines sources other than those which are conventional fossil or nuclear fueled, one can run into problems with the Baleriaux-Booth codes. In particular, if one is analyzing a source which supplies energy intermittently or in variable amounts within an hour period, then one does not get a true probability of failure to meet load if the input data is based on hourly values. In particular this problem arises with wind or solar sources, and to a lesser extent with a highly variable run-of-river source.

This paper will: (1) demonstrate the equivalency of LOLP methods and the Baleriaux-Booth method for conventional sources, (2) show that the failure of the equivalency to hold in the case of intermittent sources is due to a correlation between load and energy availability and the use of hourly input data, (3) suggest alternative methods for calculating reliability measures for intermittent sources. (These alternate methods would enable one to calculate the economic measure which is commonly called a capacity credit.)

Equivalency Between Measures

The historical Calabrese LOLP calculation used 260 hours for the failure to meet load calculation. The 260 hours consist of the peak hour per day for the five weekdays in fifty-two weeks (1 x 5 x 52). If one expands the calculation hours to every hour of the study interval and if one weights the LOLP value for the hour with the probability of the hour, the equivalency of the Baleriaux-Booth measure can be demonstrated.

For what follows, the following assumptions will be used:

1) loss of load is defined as the failure to meet load due to the failure of generation resources

2) the outage of a source will be patterned after a conventional source, namely that at a given instant we conceive of the plant as being in one of a very limited number of availability states. This is in contrast to the intermittent resource which is often regarded as possessing great variability in output, ranging over zero output to full output in a small time interval.

FORMULATION

The equation for the Baleriaux-Booth measure of reliability is

$$\Pr\left\{\left[\tilde{L} - \sum_{i=1}^{N}\left(CAP_i - \tilde{FO}_i\right)\right] > 0\right\}$$

where

$\Pr$ = probability

$\tilde{L}$ = load regarded as a random variable

CAP_i = capacity in MW regarded as the deterministic nameplate rating of the i-th resource not on maintenance

$\tilde{FO}_i$ = forced outage in MW of the i-th source regarded as a random variable

N = the number of sources on the system

The bases behind Baleriaux-Booth theory are the expression of load as a probability distribution function and the convolution of the distribution of the forced outage random variable with the distribution of the load random variable. The convolution of the distribution of the sources guarantees that all the possible combinations of outages are considered.

The LOLP calculation requires that in comparing the output of all the sources with the load at each hour, one must consider all combinations of outages. If the total output of the sources is less than the load, the probability of the event is the loss of load probability. If one weights this LOLP with the weight of the hour with respect to the interval and sums over all the hours, one gets the identical result as that derived from the Baleriaux-Booth procedure.

The use of a simple example will demonstrate the equivalency.

Table I. Assumptions for the Example

Hour	Load MW	Machine	Nameplate Cap MW	Prob. of Outage
1	50	1	40	.20
2	50	2	70	.20
3	50			
4	100			
5	100			
6	100			

Table II. LOLP Calculations

Hour	Machine States (In/Out)	Prob. of Loss of Load
1	Machine 1 in any state; 2 out	1 x .2 = .2
2	Machine 1 in any state; 2 out	1 x .2 = .2
3	Machine 1 in any state; 2 out	1 x .2 = .2
4	Machine 1 and/or 2 out	$1 - (.8)^2$ = .36
5	Machine 1 and/or 2 out	$1 - (.8)^2$ = .36
6	Machine 1 and/or 2 out	$1 - (.8)^2$ = .36
		1.68

Weighted LOLP = 3(1/6 x .2) + 3(1/6 x .36) =
= .28

The logic behind the loss-of-load probabilities is given below. For hours 1 through 3, machine 2 is essential in carrying the load. Machine 1 cannot carry the load by itself and hence its state is immaterial. A failure to carry load is then described by: machine 1 is on and machine 2 is off (.8 x .2) or machine 1 is out and machine 2 is out (.2 x .2). Hence the calculation can be given as 1 x .2. For hours 4 through 6, machine 1 and 2 are both necessary to carry load. Failure to meet load is then 1 minus the probability of both machines being in the on-state.

A standard LOLP calculation would not weight the LOLP values by the hourly weight but would add up the LOLP values for each value to arrive at the expected number of hours, which is 1.68 hours in this example. However, it is easier to show the equivalency with the weighted value since one reads a probability number and not an expected value from a LDC.

Table III. (a) Pr [Load > L] for original LDC
(b) Pr [Load + Outage > L] for convolved LDC

(a)

L in MW	Pr [Load > L]
0	1.00
50	.50
100	0.0

(b)

L in MW	Pr [Load + Outage > L]
0	1.00
50	.68
90	.60
100	.28
120	.20
140	.12
160	.10
170	.02
210	0.0

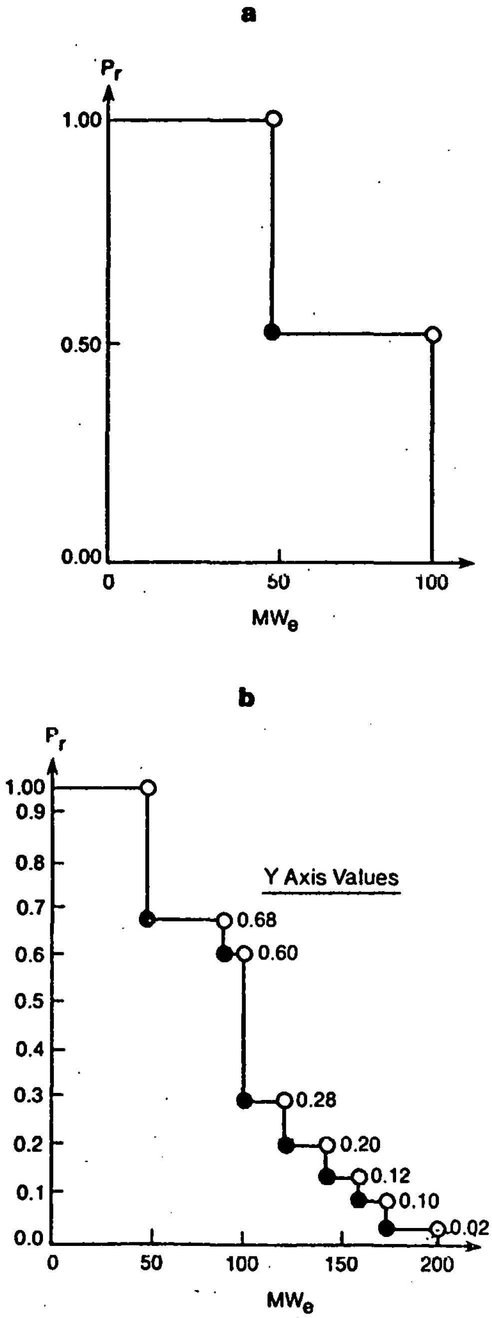

Figure 1. (a) Original Load Duration Curve
(b) Load Duration Curve after the Two Convolutions

The values in the (b) part of Table III may be obtained from the recursive formula for two-state availability

$$F_N(P) = P_N F_{N-1}(P) + (1-P_N) F_{N-1}(P-C_N)$$

where:

F_N is probability distribution after the distribution of the N-th machine has been convolved with F_{N-1}

P_N is the probability of the N-th machine bein available

C_N is the capacity for the N-th machine.

However, for such a simple example one can approach the calculation on an intuitive level. To have the capacity of load and the outages sum to less than or equal to 50 MW, the load must be less than or equal to 50 MW and both machines must be available (.5 x .8 x .8 = .32. Hence the entry in the table is 1 -.32 = .68. To have load and outage sum to a value between 50MW and 90MW, the load must be less than or equal to 50MW, machine 1 must be out, and machine 2 must be available (.5 x .2 x .8 = .08). Hence the entry in the table is .68 - .08 = .60. One can continue through the table matching the physical event with the value in the first column. Sophisticated techniques are called for in more complex situations, but the value of this example is its simplistic form.

From Table III and Figure 1, one sees that for a capacity of 110 MW_e, which is the combined capacity for the two machines, the failure to meet load has a probability of 0.28; if one multiplies this by the time under consideration, 6 hours, one gets the expected number for the hours of loss of load.

The Correlation Between Load and Intermittent Energy

Let us now assume a wind machine with 100 per cent reliability and the energy from a wind regime as given in Table IV.

Table IV. Hourly Load and Wind Energy

Hour	Load MWe	Wind Energy MWH	(Load-Wind) MWe
1	50	20	30
2	50	20	30
3	50	20	30
4	100	0	100
5	100	0	100
6	100	0	100

For the moment we will assume that the wind energy is not intermittent but rather remains constant over the hour. We are also assuming that the load is constant over the hour. Hence we have equivalent values albeit different dimensions for energy and capacity. The last column is the difference of the capacities. With this assumption, we will contrast the construction of a load duration curve (LDC) by means of an hourly construction with that in which energy is given a distribution which has been built up over the entire six hour period.

It is common for production costing purposes to form the LDC for the difference of (LOAD - Wind Capacity). If one subtracts the wind capacity on an hourly basis and forms an LDC, one gets the LDC shown in (a) of Figure 2. However, if one treats each of the two distributions of load and wind capacity as independent distributions with the description given in Table V, one gets the LDC in (b) of Figure 2.

Table V: Distributions for Load and Wind Capacity over the Six Hour Period

L in MW_e	Pr [Load > L]
0	1.00
50	.50
100	0.0

L in MW_e	Pr [Wind > L]
0	.50
20	0.0

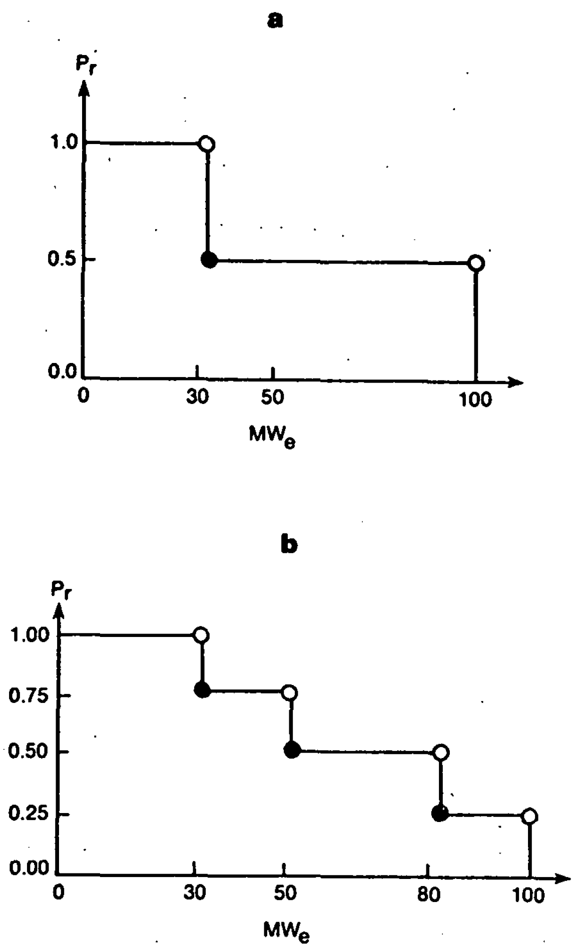

Figure 2. (a) LDC of Load - Wind Energy Subtracted on an Hourly Basis

(b) LDC of Load - Wind Energy with Distributions Treated as Independent

One should note that the expected capacity demand under both the LDC's in Figure 2 are equal, i.e., E [Load - Wind Capacity] = 65 MW_e. However the load shapes are quite different; in fact, if one assumes that the machine from Table I with capacity 40 MW_e is loaded first, its expected energy output over the six hour period in (a) is 168 MWh ((30 MW x 1.0 + 10 x .5) x .80 x 6 hr) while in (b) the expected energy is 180 MWh ((30 MW x 1.0 + 10 x .75) x .80 x 6 hr). It is obvious that costs and reliability measures will be different in the two cases; hence it is essential to decide which method is the more representative one.

If the energy from an intermittent source has a distribution which is independent of the time of day then it is legitimate to convolve the two distributions without consideration of the time of day as was done in (b) of Figure 2. However, if the energy output is a function of time of day, taking the difference in hourly values is the correct procedure.

In this particular example the LDC in (b) would call for a different generation mix than the one in (a). The variety in the load shape would be met by machines which would be more efficient and less costly over the different levels of demand. The two-state demand level in (a) presents simpler planning problems. However, one should not read too much into the present phenomenon; the shapes are a function of the assumed data. Still one can make the generalization that there will always be more demand states under the independent assumption. This is true since a single wind capacity value will be subtracted from all load levels in the convolution. In the hour-by-hour case, a single wind value will be subtracted from a single load value. The implication is that there is more involved in choosing the representative procedure than a reliability calculation; the optimum mix is a function of the choice.

In some of the studies which have considered intermittent energy sources, there has been great care taken to show that there is little correlation between load and intermittent energy in the regions studied [2,3]. What has been shown in these studies is that there is no interrelationship between increasing load and diminishing or increasing intermittent energy in the regions studied. The concept being investigated is whether load goes up as a resource such as wind velocity goes down as might occur in a hot climate or whether load goes up as a resource like wind velocity goes up as might occur in a cold climate. However, it is not this concept of correlation in a directional sense which is at question here. For a resource like wind or solar it is the time of day which is important. As an example, wind energy is highly dependent on the warming and cooling of the land [5]. Since the warming and cooling hours occur at a reasonably predictable time of day, the energy at that time of day is correlated to the load demand at the same hour. The amount of demand is also predictable if one knows the system's chronological load shape.

By way of explanation consider the data in Table VI.

Table VI. Time of Day Loads and Wind Velocity

Hour	Load MW_e	Velocity m/s
1	10	2
2	6	6
3	2	2

Let us assume that the table represents a static situation, i.e., that at the first hour of every day the load will be a constant 10 MW_e and the wind velocity will be a constant 2 m/s for the full hour. The Table implies that there is a relationship between 10 MW_e and 2 m/s, between 6 MW_e and 6 m/s, and between 2 MW_e and 2 m/s. The correlation is traceable through the time of day and, for each hour in this example, the relationship is deterministic. However, across the three hours, if one tries to find a relationship like rising/falling or rising/rising, the correlation coefficient is zero.

It is this time of day correlation which forces one to subtract the energy of the intermittent source from the load on a hourly basis. If this time of day correlation is not true, one can treat the intermittent source as any other source in a Baleriaux-Booth code. There would be no need to subtract energy but rather the standard {Load - (CAP - FO)} equation would work if a sufficient number of availability states are input to adequately model the resource. For an uncorrelated type of resource, the accuracy of the reliability measure depends on the number of availability states and the step-size of the code. However, when correlation exists in the specialized sense we are using here, then time of day relationships must be retained and, as will be shown below, problems arise with the reliability measure due to the hourly input.

Let us consider a source in a more realistic wind profile which will give intermittent or variable energy output over each hour. The problem is that the usual input to a Baleriaux-Booth production cost model is a single value for wind energy. This single value must be subtracted from the hourly load. The following example will show that an expected value for the wind energy will not give the correct loss of load probability.

In the example let us assume that a wind regime is such that a constant output is available for the quarter hour periods so that capacity and energy ha equivalent values and that wind energy is the only e ergy to be considered. Let us also assume that the load is constant over the entire hour. Table VII presents such data.

Table VII. Hourly Load and Wind Energy Data

Time	Load MW_e	MW_e	Max {0, Load - Energy}
:15	5	0	5
:30	5	8	0
:45	5	20	0
1:00	5	32	0
1:15	10	0	10
1:30	10	8	2
1:45	10	20	0
2:00	10	32	0
2:15	15	0	15
2:30	15	8	7
2:45	15	20	0
3:00	15	32	0

The problem with trying to input hourly data is immediately apparent. If one calculates the expected wind capacity for any hour, one gets 15 MW_e. Moreover, if there is a reason to believe that time of day correlation exists and hence the hourly relationship must be maintained, then subtraction of expected hourly wind capacity from load gives a zero load for each hour and hence a zero loss of load probability.

However, if one attempts a standard loss of load calculation using the availability states for wind capacity as 0, 8, 20, 32, each with probability of 1/4, one gets the weighted LOLP of 5/12 (1/3 hrs x 5 hrs x 1/4) and the expected loss of load hours of 5/4 (3 hrs x 5/12). (Note: There are 5 quarter hours in which the wind capacity does not cover the load.)

Due to the extreme values used in this example, it is apparent that neither the reliability value nor any production cost values which would be derived from a Baleriaux-Booth code would be very good approximations if one used the expected hourly values as inputs. However, in a less extreme case than given in this example when one uses a Baleriaux-Booth code, it seems likely that the production cost value might possess a better degree of approximation than the reliability figure. This is merely another way of saying that for small penetrations of intermittent resources, the expected hourly energy might do an adequate job in estimating production costs. However, more than production costs are usually desired. It is important to be able to calculate the total value of the intermittent source. This value consists of production cost savings and capacity credit.

Capacity credit in this context refers to the capital costs which are saved by installing an intermittent resource on a system for a fixed level of reliability; the savings may take the form of savings in reduced interest charges, from the costs of plants deferred by the new installations and/or the substitution of less costly plants as dictated from a reoptimization of future expansion. The method of arriving at this cap ity credit is usually achieved through equating L values for different schedules of sources [2,4,6]. For the determination of LOLP the example above shows that hourly expected value of energy is inadequate. However, if one uses an hourly availability distribution for the intermittent source in the LOLP calculation the LOLP method will lead to an adequate measure. This method, of course, is nothing more than using various levels of availability over the hour interval [3,5].

In summary one method of handling small penetrations of an intermittent source is to use a Baleriaux-Booth code to calculate production costs. Average hourly wind energy is subtracted from the hourly load. The capacity credit is calculated by means of a LOLP using an hourly availability distribution for the intermittent source. The hourly availability could of course be subtracted from the load in the LOLP as long as all availability states with concomitant probabilities are considered. The problem of course is getting the necessary data in order to arrive at the distribution. A suggested solution for this problem is given below.

However, the solution which we would recommend for the reliability and accompanying capacity credit problem is to make direct use of the Baleriaux-Booth codes. As an introduction to this solution, consider running "scenarios", using a different level of available energy from the intermittent source. One could then weight the loss of load probability according to the probability of the level. The problem here is that one is in danger of choosing all the worst "cases" across all hours, and then moving through the scenarios until all the best "cases" are treated [6]. The process would not be exhaustive and quite inefficient with regard to computer usage. This method does, however, suggest a more accurate procedure using Baleriaux-Booth theory.

Using once again the data of Table VII, one can order the quarter hour data in the last column and form a LDC. It is merely an arbitrary convention of most Baleriaux-Booth codes to accept data in hourly fashion. The theory really desires a continuous flow of input values; the normalization with regard to time is not dependent upon the size of the time mesh used for the inputs. So quarter hour inputs, or more generally, any orderable inputs with the proper probability values will do. The resulting LDC is given in Figure 3.

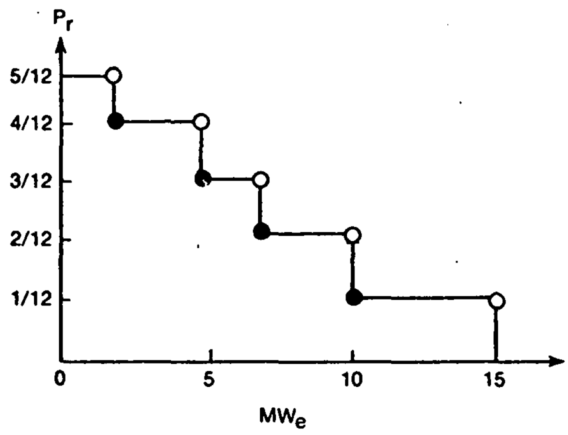

Figure 3. The LDC Based on the Last Column of Table VII

Since we have assumed in this example that only wind energy is to be considered and since the intermittent sources have been included via subtraction, one reads the loss of load probability at 0 MW_e, i.e., 5/12. The expected loss of load hours is 5/4 (5/12 x 3 hrs). These values, of course, are the same as those derived in the LOLP calculation done earlier. Therefore what is needed to make the usual Baleriaux-Booth codes work in this situation is a preprocessor for the data which considers the hourly distribution of intermittent energy, does the subtraction, orders the data according to magnitude, and then chooses data points in a manner consistent with standard input requirements [1,5]. All chronology is lost; chronology, of course, is not necessary for a production cost approximation but some method of restoring chronology is needed if one desires marginal cost estimates. At this time we would recommend the creation and storage of a matrix whose function would be to trace the original hours based on the new LDC inputs.

We have been assuming an intermittent source with 100 per cent reliability. This restriction can be easily removed. What is required is to calculate correctly the probability of each level of availability. For the zero output one must sum the probability of zero wind energy and the product of the probability of non-zero wind energy and the forced outage rate. For the non-zero levels, we need the product of the probability of the level of availability and the probability of being on-line (1 minus forced outage rate).

The purpose of this paper has been to present a methodology to approximate with a fair degree of accuracy the effects of a source which may provide a range from zero output to maximum output, possibly more than once, during the interval of an hour. The reader is perhaps aware that the data for these sources is quite often available only in the form of an hourly observation. With this data the distribution profile is lost. With data in the form of an hourly average, the chance of a zero value over the hour is lowered [7]. This paper has pointed out the effect of this type of data on the reliability measures. In the case of a wind resource one can restore the distribution profile from the average value of the wind velocity.

Ideally if one has multiple years of data, one could reassemble an hourly profile. Lacking this data one could fall back on one of the descriptive distributions which are being suggested in the literature. The Weibull or Rayleigh and the Beta distributions are common ones. One might even consider mixing a discrete weight at a velocity below cut out with one of these continuous distributions. By using estimators for the mean and variance of these distributions, a histogram of wind velocity for each hour could be produced. The histogram can include as many "bins" as the planner believes necessary. This method will produce the various levels of availability with their concomitant probabilities. Unfortunately, we are only aware of descriptive distributions for wind energy; for other intermittent sources the "fitting" distributions are not commonly found in the literature. However, as the resources move closer to commercial feasiblity, we can be certain that their output profiles will be better described. We would also like to emphasize that the "fitting" distribution is no substitute for good data. The better the data, the easier it is to build profiles or to make estimates of the distribution parameters.

We would like to close with comments on some of the problems remaining in system source modeling in general and in Baleriaux-Booth modeling in particular. For large penetrations of intermittent sources, the control problems for system stability are not adequately understood. There are the problems of feasibility of large penetration, cost penalties for the up and down behavior of backup resources with any penetration, possible reallocation of hydro resources, and spinning reserve requirements. There is the problem of actual response time of conventional sources, as the time increment for the intermittent source decreases below that of an hour, the response of replacement energy may not be quick enough for load following. With regard to the Baleriaux-Booth models, the sequential time correlation of the energy from intermittent resources is in danger of being ignored. The output from consecutive hours is correlated and if one uses the hourly averages from a particular year to build distributions, this correlation will be modeled. However, as hourly data from various years are built up, the relationship between distributions from consecutive hours may be lost. However, this loss of hourly correlation may be irremedial in the Baleriaux-Booth model; we see the same phenomenom in the duration aspect of forced outages for conventional sources.

CONCLUSIONS

The use of an average value for an intermittent resource does not give an accurate estimate of the utility system loss-of-load probability or production costs. Therefore, any capacity credit established for the intermittent resource will be in error. The use of a probability distribution over the capacity from the intermittent source will give an improved approximation and is compatible with the theory of Baleriaux-Booth production cost models.

The methodology outlined in this paper is the starting point in an on-going process. The next step is to investigate the formation of daily wind energy profiles. If the construction of common daily profiles, consisting of distributions dependent on time of day and on season of the year, can be constructed for specific sites and/or regions, then system generation modeling can be greatly facilitated. Following the characterization of wind energy, a comparison of the method described in this paper with those of previous studies will be carried out to see the effects of the more accurate modeling endeavor. Finally a comparison of predicted results with the operational data from a system-connected machine will be made in order to establish what further conceptual changes must be effected in order to model more accurately the intermittent resources.

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APPENDIX B

PLANNING FOR ELECTRIC UTILITY SOLAR APPLICATIONS: THE EFFECTS ON RELIABILITY AND PRODUCTION COST ESTIMATES OF THE VARIABILITY IN DEMAND

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Abstract - Previous studies have shown the necessity of the consideration of hourly variability in the output from the intermittent generation source. However, the studies did not take into account the variability in the demand. Major questions concerning the variabilities of demand and intermittent source output are (1) does the demand variability dwarf the intermittent output variability?; (2) can demand variability be handled in the Baleriaux-Booth framework?; and (3) what effect does the demand variability have on the LOLP criterion and the reserve margin? Before attempting answers to these questions, the term variability in demand is clarified by distinguishing between variability due to randomness and variability due to forecasting uncertainty. A result is presented which shows that under general conditions the variability due to randomness can be ignored except in the neighborhood of the peak and minimum demands. The above questions are then addressed in terms of the two types of variability in demand.

INTRODUCTION

Most of the solar applications for the electric utilities' generation system are categorized as intermittent sources; that is, their power output may fluctuate freely from zero to some maximum during small time intervals. In two previous papers [1,2], the authors have claimed that measurements of average output from intermittent sources is inadequate and that the hourly variability in output must be considered. However, there is some inconsistency in this position if one fails to take into account the variability in load or demand. In fact the most often heard objection to our position is "why should we consider the variability of the output from the solar devices when its effects are swamped by the variability of demand?"

This comment gets some theortical support from one of the most widely used formulations of the reliability/production cost problem. The basic equation for the measure of reliability in the Balereaux-Booth formulation is

$$\Pr\{[\tilde{L} - \sum_{i=1}^{N} (Cap_i - \tilde{FO}_i)] > 0\}$$

where

Pr = probability

$\tilde{L}$ = load regarded as a random variable

Cap_i = capacity in MW regarded as the deterministic nameplate rating of the i-th resource not on maintenance

$\tilde{FO}_i$ = force outage in MW of the i-th source regarded as a random variable

N = the number of sources on the system

Now the conceptualization for the random variable L is usually done quite poorly as will be discussed below; the problem in conceptualization is usually due to making a transition from the concept "hours in which a certain load is exceeded" to the concept of probability. However, the observation to be made here is that the load or demand is a random variable; it possesses a nonzero variability. To adequately address the variability of the intermittent output, one must have at least an intuitive handle on the variability in demand.

Once it is recognized that this demand variability must be considered, the question is how shall it be treated. The most common tools used in the evaluation of reliability and production costs are the Calabrese LOLP calculation and the Baleriaux-Booth framework. It has been demonstrated [1] that for reliability calculations the two methods are equivalent. Therefore we will give a procedure for the incorporation of demand variability into the Baleriaux-Booth framework. Its handling in Calabrese-type calculations should follow immediately.

Since it is most common not to recognize load variability in the Baleriaux-Booth framework, the LOLP calculations based in the procedure described in this paper are quite different than those in which the variability is ignored. We will also try to establish some relationship between the LOLP calculation and the reserve margin as a percent of load in the situation in which variability in demand is being considered.

VARIABILITY DUE TO RANDOMNESS VERSUS VARIABILITY DUE TO ASSUMPTIONS

When one seeks to answer the objection that the variability in demand dominates any variability traceable to the output from the intermittent source, one must be certain as to what is meant by variability in demand. At one level, the variability reflects the randomness in demand from excursions due to weather, transitory changes in electric motor usage, and variations due to entertainment habits. To be specific a forecaster makes a prediction for energy and peak demand for the next year on a month by month basis. The forecast interval, of course, could be shorter. If in the realization of that year all the assumptions, which the forecaster made, remain true, the deviation of the actual demand from the forecast will be governed by random events. This deviation we will can random variablity.

At the next level we have variation due to assumptions. We can imagine a forecaster, faced with uncertainty in the economic sector, speculating on possible scenarios for the future, each of which would be weighted by some probability. His econometric model then will produce different demand forecasts consistent with the respective sets of assumptions. The spread of these forecasts for a given year represent what we will call variability due to assumptions or scenarios.

The answer to our mythical objector then depends upon which variability in demand is intended. Both levels of variability can be treated in a Baleriaux-Booth framework but we will argue that it is almost meaningless to handle the variability due to scenario in this fashion. Also the question of dominance is not meaningful if the error distributions of the forecast remain identical in the random variability case.

RANDOM VARIABILITY

In order to examine the random variability we must look at the very nature of $\tilde{L}$, the random variable representing load in the Baleriaux-Booth framework. Booth himself leaves this term ill-defined:

> The probability distribution of the load levels experienced by the power system may conveniently be shown in a load duration curve as that shown in Fig. 1(a). This curve relates the loading levels to the percentage of the total time that each load would be equalled or exceeded [3].

> How we get such a curve is largely immaterial to this explanation, so here we have the probablibity distribution (or density function) for the loads we are to meet [4].

If one looks at the typical method of creating a load duration curve, one gets an insight into the basis of confusion over the random variable $\tilde{L}$. Standard discussions recommend that one plot the percent of time load exceeds a particular load level versus the load level. The percent of time is then interpreted as a probability number. The problem with this is that if one is dealing with historical data and doing calculations over this history, everything is deterministic. There doesn't seem to be any probability questions which can be answered because history has already happened; there is no uncertainty involved. The conceptual trick when dealing with past history is to imagine one is at an unknown time in history; the LDC merely represents the chances of seeing loads in excess of given values. Therefore, since one doesn't know the actual load at that point in history due to the lack of chronological data representation in the LDC, one can ask questions like "what are the chances of exceeding a load of 1000 MW?" The mistake is to regard the LDC as an aggregated history over an interval; one should pretend that one is standing at a unknown instant in that time interval equipped only with information concerning a frequency distribution.

An easier way to conceive of $\tilde{L}$, the random variable for demand or load, is to look at the problem from the forecasting point of view. Let us imagine a forecaster being forced to make hourly forecasts over a given time interval. At each hour the forecaster gives an estimate of the μ (hr) = mean value for the hour. These mean forecasts give a trajectory for the load over this interval. However, the forecaster understands that as history passes and the time interval is actually realized, there are an infinite number of trajectories which could be realized. What the forecaster hopes for is that the actual trajectory will lie in a band around his forecasts of the means. Figure 1 gives a graphical representation of the process.

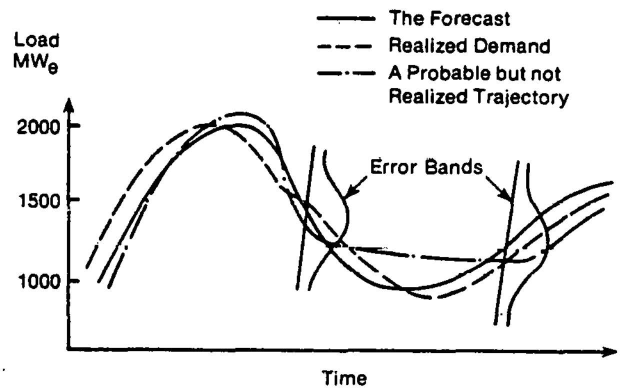


Figure 1. Mean Forecast Vs. Possible Trajectories

In reality the utility forecaster usually gives only a monthly energy and peak forecast rather than hourly forecasts; the argument is the same: he is estimating the μ(= mean) and there are an infinite number of trajectories which can be realized.

Turning our attention from the forecast to past history, one can conceptualize the seemingly deterministic event in an analogous fashion. If one had made an hourly forecast of the demand and the actual demand deviated from the forecast within reasonable limits and without systematic patterns, then one could imagine the forecast as being the mean hourly values for that year and the actual history as a single realization. If the year could be played over and over again, the hourly arithmetic averages would estimate mean values. In fact a utility system which showed little growth or change in load profile from year to year would be in a sense replaying the year. Variations in hourly values would be due to random events, one of which would be weather.

Now if one had not made a forecast for the previous years, one could use the actual demand to estimate the mean values. However, one would try to correct values which were noticeably out of bounds, for instance, a demand reaction to unusually cold weather. Of course this is what is actually done when one attempts to build a typical LDC: the utility planner either corrects for weather or averages normalized shapes over multi-years in an attempt to smooth unusual variations.

BALERIAUX-BOOTH FORMULATION FOR RANDOM VARIABILITY

Before attempting to place random variability into the Baleriaux-Booth context, one should sharpen one's concept of load duration curves (LDC's). As mentioned earlier the transition from building an LDC from realized demand values to a probabilistic interpretation causes some confusion. In Fig. 2 we see how the 8760 hourly values are normalized to give a probability scale.

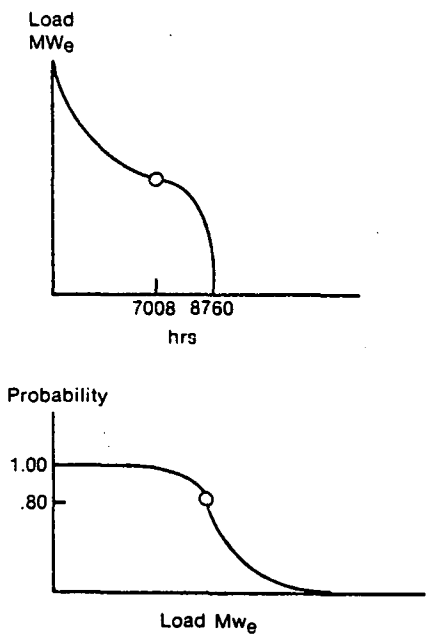


Figure 2. (a) LDC as Percent of Time (hours)
(b) LDC with Time Normalized and Axes Switched

At the point marked in the (a) figure, it is correct to say that 80 per cent of the hours exceeded this value since the LDC represents values realized. At some point, however, one must switch one's thinking from realized values to the estimate of the mean values. Therefore in the (b) figure it is not correct to say that 80 per unit of the values exceeded the marked point. Since we are now conceiving of the LDC as being constructed of mean values it is quite possible that no actual values would lie exactly on the curve; that is, the values given are expected values. In this context it is correct to say that there is an 0.80 probability that the given value will be exceeded; we can also talk about the expectation that 80 per cent of the values will exceed the given one. But to say that 80 per cent of the values will exceed this value is to conceive of the demand as a deterministic event or as a realized set of values rather than as the set of means of random variables.

It is the concept that the individual hourly means do not have to be realized which allows us to incorporate the variability due to randomness directly into the Baleriaux-Booth formulation.

The way LDC's are presently constructed is that if there are n hours in a time interval each hour receives 1/n for a probability weight. Demand values are then ranked and weights accumulated. In the present construction we propose to take the hourly forecast of the mean and the variation and distribute the 1/n weight over a range of values for the hour. These values will then be ranked, weights aggregated, and a LDC formed.

To clarify matters we will use the following simple example

Table I. (a) Hourly Demand Given as Conventional Averages
(b) Pr [Load > L]

(a)		(b)	
HR	Demand (MW)	L (MW)	Pr [Load > L]
1	100	0	1.00
2	150	100	0.50
3	100	150	0.0
4	150		

The probability values in (b) of Table II are arrived at by weighting those probability values in (a) of Table II by the probability of the hours and summing up the weights for each value, i.e. for 70 MW we have 0.20 x 1/4 + 0.20 x 1/4 where 1/4 are the weights for hours 1 and 3. The values are then ranked and the probabilities consecutively substracted from 1.

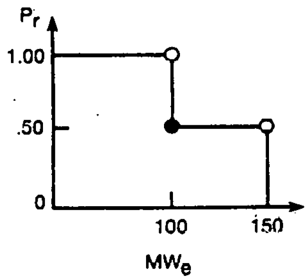
Table II. (a) Actual Forecast Range
(b) Pr [Load >L)

(a)

HR	Demand (MW)	Probability
	130	.20
	115	.20
1	μ=100	.20
	85	.20
	70	.20
	170	.35
2	μ=150	.10
	140	.40
	130	.15
	130	.20
	115	.20
3	μ=100	.20
	85	.20
	70	.20
	170	.35
4	μ=150	.10
	140	.40
	130	.15

(b)

L (MW)	Pr [Load > L]
0	1.00
70	0.90
85	0.80
100	0.70
115	0.60
130	0.425
140	0.225
150	0.175
170	0.0



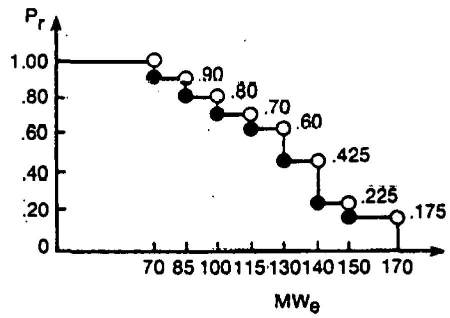


Figure 3. (a) LDC for Conventional Forecast
(b) LDC for Forecast with Uncertainty

In Table I we are given a conventional forecast; that is, hourly averages without uncertainty information for a four hour period. In Table II we are given detailed information concerning the forecast, its range at each hour, and the probability of realizing the particular values in the range.

Table I contains the information of Table II in aggregated form. Figure 3 gives load duration curves for the information in Tables I & II. We wish to note in Table II that we have chosen the distribution within an hour in unrealistic but entirely different manners. For hours 1 and 3 we have symmetric uncertainty ranges with a uniform distribution and a mean value of μ = 100. For hours 2 and 4 we have an asymmetric uncertainty range with a mean value of μ = 150. The fact that the distributions are not identical is extremely important for what is done below.

We would like to call attention to two things concerning the two Load Duration Curves (LDC's) of Fig. 3:

(1) the expected energy for both LDC's are equal;

(2) the second LDC is entirely consistent with the concept of an LDC which we expounded in the beginning of this section.

The fact that the expected energies are equal is immediate on an intuitive level since we are merely doing something quite similar to taking averages of averages. The mathematical justification is that we are applying the distributive law to

$$E[E(\text{forecast}, f), P] = \sum_{i=1}^{4} \sum_{j=1}^{n_i} X_{ij} f_{ij} \quad P=$$

$$\sum_{i=1}^{4} \left(\sum_{j=1}^{n_i} X_{ij} f_{ij} P \right)$$

where

E = the expectation
f = distribution over the forecast
P = distribution over the hour
n_i = number of uncertainty points.

In this case we can consider that P equals 1/n identically, where n is the number of hours.

In our earlier discussion we pointed out that the ordinate values of an LDC should not be thought of as the percentage of time which the load was at value L. The interpretation we desire is that there is some chance or probability that the load will take on this value. To make this idea clear let us look at the load value of 70 MW_e. This number comes from the forecast for hours 1 and 3. The forecaster says that at those hours that load might occur with 0.20 probability. However, there is a 0.80 probability that it will not occur. When looking properly at the LDC, one must imagine oneself at some unknown instant of time in the 4 hour internal; that is, he is unaware of the specific hour. In 2 out of 4 hours he has a 0.20 probability of seeing a load of 70 MW_e. Therefore it is not correct to say that he will not see 70 MW_e 10 per cent of the time; but it is correct to say that he has a .10 probability of seeing 70 MW_e.

We have shown that the probabilistic LDC which is essential to the Baleriaux-Booth framework can handle the random variability in the forecast. Next we would like to show the effect of this uncertainty in demand. Let us continue the example by assuming generation plants with the characteristics given in Table III.

Table III. ASSUMPTIONS OF POWER PLANT CHARACTERISTICS

Machine	Nameplate Cap MW	Probability Outage	$/MWH
1	100	0.0	40
2	50	0.0	60

We have assumed 0.0 for a forced outage rate. The Baleriaux-Booth framework has gained its importance by its ability to handle forced outage in connection with load through the convolution technique. However, at this point we are concentrating on variation in load; any nonzero forced outage rate will only complicate matters and obscure the purpose of the example. Using the values in Fig. 3 and applying economic dispatch we get the following costs and reliability measure

Costs for Figure 3 (a)

L (MW)	
100	1.0 x 100 MW x $40/MWH x 4 HR = $16000
150	.5 x 50 MW x $60/MWH x 4 HR = 6000
	TOTAL COST= $22000

Probability of loss of load = 0.0

Costs for Figure 3 (b)

Cost = Production costs plus cost of expected unserved energy

L(MW)	
70	1.0 x 70 MW x $40/MWH x 4 HR = $11200
85	.9 x 15 MW x $40/MWJ x 4 HR = 2160
100	.8 x 15 MW x $40/MWH x 4 HR = 1920
115	.7 x 15 MW x $60/MWH x 4 HR = 2520
130	.6 x 15 MW x $60/MWH x 4 HR = 2160
140	.425 x 10 MW x $60/MWH x 4 HR = 1020
150	.225 x 10 MW x $60/MWH x 4 HR = 540
	TOTAL PRODUCTION COST = $21520

170 Probability of loss of load
= (0.35 x x 2) = 0.175

Expected unserved energy
= .175 x 20 MW x 4 HRS = 14 MWH

We note that the change in plant usage between Figures 3(a) and 3 (b)is not just in the high cost peaking machine (#2); (#1) also gets less usage because there is some chance that there will be less than 100 MW of demand. The case which used demand averages (a) does not recognize this possibility. We also have the peculiar situation where the costs in (b) are less than those in (a) but the reliability measures are reversed. This is explainable if one considers the extreme: if a system is 100 per cent unreliable there are no incremental fuel costs. So in (b) by fixing a cost for unserved energy greater than $60/MWH, one's intuition concerning reliability and cost is met.

We have shown that both the reliability and the production costs are dependent upon the random variability or uncertainty in the forecast, i.e., average hourly forecasts give different results than the range of values over the hour.

When one considers the position the authors have developed in previous work [1,2], one sees the implications of this result. The standard procedure for the evaluation of the worth of a solar technology is to subtract the hourly solar output from the hourly demand. The authors have shown that for wind machines and other solar sources, especially those without storage, there is a discrepancy between evaluations based on hourly inputs and those based on distributions over the hour. From the example above it appears that demand as a function of the hour and uncertainty in forecast should be expressed as

$$D = \mu_D + \tilde{\xi}_D - (\mu_S + \tilde{\xi}_S)$$

where:

- D = residual forecasted demand
- μ_D = mean of the forecast for the hour
- $\tilde{\xi}_D$ = a random variable representing the range of uncertainty in the demand
- μ_S = mean of the output from the solar source
- $\tilde{\xi}_S$ = a random variable representing the variation in output from the solar devices.

The dimensions are in MWh.

If one were to approximate the range of values in order to handle deviation values for demand for the hour, we would suggest choosing values for $\tilde{\xi}_F$, μ_S, $\tilde{\xi}_S$ as given below:

$$\tilde{\xi}_D = i\,\sigma_D \qquad i = 0,1,2,3$$

$$\tilde{\xi}_S = i/n \text{ (Range of values)} \qquad i = 1,2,\ldots,n$$

$$\mu_S = 0$$

Where σ_D is the standard deviation for the forecast for the hour and n is some reasonable number of bins or intervals for the range.

The combinatorics of the situation imply that we are taking every combination of the reasonably discretized forecast with the discretized range of output from the solar source or 7n cases for each hour.

The increased computer costs when one switches from the difference between hourly average forecast and the hourly average solar output to this combination case are not trivial. However, the pleasant surprise is that it is not necessary to do the 7n calculation for each hour; in most cases one can ignore the random variation in the forecast except at the endpoints of the LDC, the maximum and minimum demand values. The formal lemma which we prove in the Appendix states:

> Lemma: Let f(x) be a probability density defined in [a,b]. For each x in $[a + \varepsilon, b - \varepsilon]$, $(\varepsilon > 0)$, let there be defined one and only one density $g_x(\tau)$ τ in $[x - \varepsilon, x + \varepsilon]$ such that x is the expected value of the distribution defined by $g_x(\tau)$.

$$\text{Define} \qquad h(x) = f(x) \int_a^b g_\tau(x)\, d\tau.$$

> Then h(χ) if and only if $g_\chi(\chi + z) = g_{\chi - z}(\chi)$, for all χ and $(z < \varepsilon)$. That is, the probability mass for h(χ) at each χ in $[a + \varepsilon, b - \varepsilon]$ is the same as that for f(χ) if there exists a distribution $g_{\chi_0}(\tau)$ and all the other $g_\chi(\tau)$ are merely translated copies if that distribution.

In less formal language and in the case of a forecast, the lemma states that if the forecast range at each hour is bounded fairly tightly and if the error distribution is the same at each point in the forecast, then after one ranks the forecast values, one can forget about the variation in the forecast except perhaps at distances from the endpoints of the forecast which equal the range of uncertainty. The conclusion of course depends on the shape of the LDC.

The proof in the Appendix handles the lemma in a more formalistic approach. We would like to present at this point a more intuitive example of the Lemma. Suppose forecasts are being made at the points n = 1,2,3,4,5,6. Suppose that the mean of the forecast is the point itself, i.e., at 4, the mean of the forecast is 4. Further suppose at any interior point the forecast range only includes the adjacent points. Also at the endpoints the forecast is the point itself with probability 0.5 and the adjacent point with probability 0.5. This information is summarized in Table IV.

If one accumulates the probability masses at each point one gets the results in Table V.

From the example one gets an idea of the smoothing effect the forecast distribution has on the interior points. The uncertainty process begins to smooth out the values so they end up with the determistic mass of 1.0 and of course this is due to the uncertainty process borrowing mass from a value only to repay it from the uncertainty surrounding its neighbors.

Table IV. DATA FOR EXAMPLE BASED ON LEMMA

Point	Forecast Range	Probability
1	1	0.5
	2	0.5
2	1	0.25
	2	0.50
	3	0.25
3	2	0.25
	3	0.50
	4	0.25
4	3	0.25
	4	0.50
	5	0.25
5	4	0.25
	5	0.50
	6	0.25
6	5	0.5
	6	0.5

Table V. ACCUMULATION OF PROBABILITY MASSES IN TABLE IV

Point	Probability Mass
1	0.75
2	1.25
3	1.0
4	1.0
5	1.25
6	0.75

It is obvious that the forecasting procedure does not meet the basic assumptions of the Lemma:

(1) the range of uncertainty at any hour is unbounded.

(2) the forecast has different standard deviations (σ's) according to the following regime: when one ranks the forecasts, the extreme values have larger σ's than the interior values.

(3) $f(\chi)$ should be interpreted as the density for the occurrence of demand. In reality we are dealing with the product of probability of demand and the probability of error in forecast; that is

$$\int_a^b f(\tau)\, g_\tau(\chi)\, d\tau \quad .$$

only if $f(\tau)$ is a constant do we get

$$f(\chi) \int_a^b g_\tau(\chi)\, d\tau \quad .$$

(1) can be justified by forecasting theory. The standard assumption in forecasting is that the error of the forecast is normally distributed. Forgetting that negative forecasts are meaningless, we are left with a theoretical range of $(-\infty, \infty)$. However, the application of forecasting leans heavily on the fact that most of the probability distribution lies within 3 standard deviations of the mean; it is this fact which precludes worrying about negative forecasts. Therefore if one is to discretize the range in a rational manner, one might choose bounds of $(\mu - 3\sigma, \mu + 3\sigma)$ for the range of forecast. Since most of the probability mass is located in that region, the approximate range is both adequate and bounded.

The second problem is that there are "seams" in the forecast, areas where the distribution of uncertainty changes. In the example above we have seen the effects of changes in σ (see points 1,2,5,6 in Table V). We can justify this change in σ by examining an LDC. The slope of the LDC is much greater at the endpoints than at the interior values. This implies that there is more probability of an interior interval occuring than one of the extreme values. The obvious reason for this is that more hours have been forecasted to lie around average demands; the neighborhoods of the peak demand and, quite possibly, the minimum demands reflect very few hours and have a greater level of uncertainty. However, the lemma states that one can only dismiss the demand variability in the interior if all the uncertainty distributions are identical. It is our contention that one can make an excellent approximation by assuming constant σ except at the extremes and thereby not worry about the random variability of the forecast except in the region around the maximum and minimum values. The conventional LDC of hourly averages should only be altered then in small intervals around the endpoints. The σ's of the peak and minimum forecasts can be estimated from historical data. Using our earlier concept of a historical realization as a trajectory lying within bands around the mean value of the forecast, one can estimate these σ's. It is also quite likely that the σ for the peak forecast will be greater than that of the minimum. Some personal observations of utility data have resulted in a guess at the σ as being 6 to 9 per cent of the forecast at these points. We would then suggest an alteration of the LDC only in the neighborhood of 1 σ above and below the peak and minimum forecasts respectively. The assumption is that the σ's at other points are identical.

Finally (3) above implies that distribution over demand is uniform. That this is not so can be seen from the S shape of the LDC. However, for most LDC's a straight line can be fit through the inflection point of this S curve; that is, if one disregards intervals around the maximum and minimum points the cumulative distribution function for demand can be fit by a straight line. Therefore this interior section can be approximated by a uniform distribution and $f(\chi)$ can be removed from the integral. It is this section which we wish to approximate. The larger the range of adequate fit to the straight line, the more justification we have for ignoring the random variation in demand. This is a function of the LDC.

The conclusion on the effect of random variability of the demand is that its effects on cost are minimal but its effect on LOLP can be quite important. The increased spike in the LDC due to peak uncertainty can have a major effect. In relationship to the varibility in the output of a solar source, the random variability in demand does not dominate the picture. Rather it is the variation in output which has the major role since at this time there is not evidence which suggests that the hourly distributions over output are identical as would be required by the Lemma. If, of course, the $\tilde{\xi}_S$ were shown to be identically distributed, the use of hourly averages for the output of the solar source could be justified. Finally the combinations needed to represent both random variation in the demand and variability in output are reduced by the need to examine only the endpoints of the LDC.

RESERVE MARGIN VERSUS LOLP

There are two reliability criterion used most frequently in electric utility planning: per cent reserve margin and LOLP. Per cent reserve margin is usually defined as capacity in excess of a certain percent of the forecasted peak demand. The LOLP criterion has been used in this paper and is assumed to be well-known.

Either one of these criteria make an adequate planning goal. In fact many utilities calculate an equivalency between the two criteria, recognizing the fact that the equivalency is a function of time.

There is a curious phenomenon, however; some institutions use the per cent reserve margin as the basis for planning and then make LOLP calculation separately. The reason usually expressed for this is that the per cent reserve margin takes care of any untoward contingency where the LOLP gives the loss of load risk if conditions happen as expected. The concern being expressed here may be due to the fear of the uncertainty in the forecast. If this uncertainty is restricted to random variability, the alteration of the LDC at peak to represent this variability might make the LOLP more palatable as a planning criterion. This measure would then be responsive to mix and random uncertainty.

VARIABILITY DUE TO ASSUMPTIONS

The second level of variability in demand is that due to the basic assumptions upon which the forecast is made; for what follows let us identify this level of uncertainty as scenario variation.

If we imagine a forecaster using some form of econometric forecasting tool, we can understand the demand differential as a function of the myriad of economic assumptions. We are also familiar with the current situation of different forecasts of growth rates that are filed by adversaries in various siting cases. These various growth rates would give rise to different LDC's, different production costs, and different loss of load risks.

We will show that scenario variation can also be handled in the Baleriaux-Booth framework by presenting a simplified example.

Table IV. ASSUMPTIONS FOR EXAMPLE IN VARIATION DUE TO SCENARIO

Hour	Load (MW) Scenario #1	#2	#3	Machine	Nameplate Cap (MW)	Forced Outage Rate	$/MWH
1	100	125	75	1	100	0.0	40
2	150	175	125	2	50	0.0	60
Probability for scenarios	0.2	0.5	0.3				

We are given three point forecasts with no uncertainty bounds; each forecast could be assumed to represent a different rate of growth. The LDC's for the three scenarios are so trivial we will omit them. Table VII summarizes the basic statistics.

Table VII. BASIC STATISTICS OF THE THREE SCENARIOS

Scenario	Expected Energy (MWH)	Cost of Production	LOLP	Unserved Energy (MWH)
1	250	$11,000	0.0	0
2	300	$12,500	0.5	25
3	200	$ 8,500	0.0	0

Expected Values over All Scenarios

Energy = [0.2 (250 MWH) + 0.5 (300 MWH) + 0.3 (200 MWH)] = 260 MWH

Cost = 0.2 ($11,000) + 0.5 ($12,500) + 0.3 ($8,500) = $11,000

LOLP = 0.2 (0) + 0.5 (0.5) + 0.3 (0) = 0.25

Unserved Energy = 0.2 (0 MWH) + 0.5 (25 MWH) + 0.3 (0 MWH) = 12.5 MWH

To show the simplicity of the example we give the calculation of costs for scenario #1:

1.0 x 100 MW x $40/MWH x 2 HRS = $ 8,000

0.5 x 50 MW x $60/MWH x 2 HRS = $ 3,000

$11,000

Now if one regards the three scenarios as forecasts of the amount of demand and the probability of demand for each hour, one gets the following Table.

Table VIII. (a) SCENARIOS TREATED AS FORECASTS (b) PR [LOAD > L] FOR FORECASTS

	(a)		(b)	
HR	Demand (MW)	Probability	L (MW)	Pr [Load > L]
	75	0.3	0	1.00
1	100	0.2	75	0.85
	125	0.5	100	0.75
	125	0.3	125	0.35
2	150	0.2	150	0.25
	175	0.5	175	0.0

In the (a) section of Table VIII we have handled the scenarios just as we did the forecasts earlier, i.e., the values given are the range for the hour. In the (b) part of the table we have weighted the probability by the hourly weight of 1/2 and formed the values for the LDC table given below

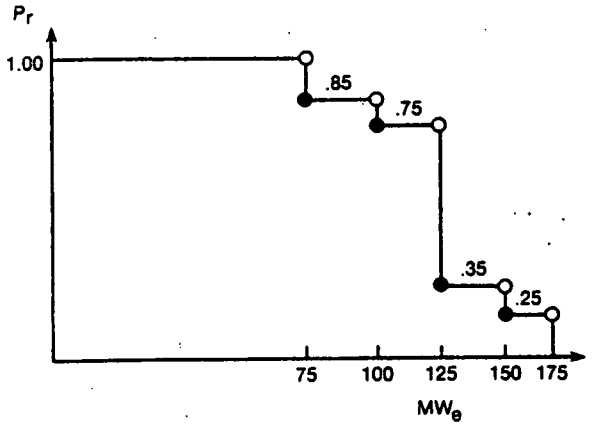


Figure 4. LDC for Scenarios Treated as Forecasts

From the LDC and the machine characteristics we get the following statistics:

Expected Energy =
(1.0 x 75 MW) + (0.85 x 25 MW)
+ (0.75 x 25 MW) + (0.35 x 25
MW) + (0.25 x 25 MW) x 2 HRS
= 260 MWH

Cost = 1.0 x 75 MW x \$40/MWH x 2 HRS =	\$ 6,000
0.85 x 25 MW x \$40/MWH x 2 HRS =	\$ 1,700
0.75 x 25 MW x \$60/MWH x 2 HRS =	\$ 2,250
0.35 x 25 MW x \$60/MWH x 2 HRS =	\$ 1,050
	\$11,000

LOLP = 0.25

Expected Unserved Energy = 0.25 x 25 MW x 2 HR
= 12.5 MWH

These statistics are as expected: from the expected values over the scenarios one gets the same results as taking the distribution over the demand and calculating the expected values. We also note that if one wanted to take into account random variability of forecast given a particular scenario, we would proceed as before. The Baleriaux-Booth framework handles the use of scenario variability as well as random variability. It requires only that one view the LDC as giving probabilities with respect to an instant of time.

While the Baleriaux-Booth framework handles scenario variability, it is questionable whether there is any value in using the technique for this kind of uncertainty. The expected values for cost and reliability are pertinent for random variation. Given a set of assumptions, costs and service failure due to randomness are conditions of life. They can be considered unavoidable risks. However, costs and risks due to scenario construction are a different matter. The individual costs and LOLP for each scenario is important. The planner is concerned with the risks of a planning schedule in the face of demand uncertainties. When one takes expected values over all the scenarios as one does in treating the scenarios as forecasts, one loses the individual results from the scenario. They become aggregated and smoothed by the expectation process. For the planner it's quite important, as shown in our example, that he realize that he may be facing costs of \$12500 and 25 MWH of unserved energy from Scenario #2, the most probable scenario. The smoothing that occurs in the respective expected values of \$11000 and 12.5 MWH could be misleading information.

With regards to the relationship between variation in the output from the intermittent source and that from scenario variation, it is usually stated that large differences in rates of demand growth will dominate if the pentration of the intermittent sources is small in comparison to the growth rates. But this is basically a misleading statement. If one choses to combine all scenarios with appropriate weights as we have done above, scenario variation dominates. However, if the scenarios are placed individually into the Baleriaux-Booth framework then, as was shown in the random variation section of this paper, the variation in the intermittent output is the important concept. If one is interested in evaluating risks in the scenarios, it is important to be concerned about the variability in output.

CONCLUSIONS

The major result of the paper is that if one is concerned with a forecast, which has been ranked or ordered so that chronological order is lost, random variation in the forecast can be ignored except in the neighborhood of this endpoints if the error distributions are identical at every point in the forecast. If it were true that output from intermittent sources were identically distributed and if one subtracted the output from the load on an hourly basis and then ranked the residuals, variation in output could be ignored. However, it is more reasonable to assume that the variation in output of intermittent sources will be a function of the mean of the hourly output; and since the mean will vary diurnally for most intermittent sources, the hourly distributions will not be identical. Therefore the variation of output must be considered. The random variation of the forecast must only be considered near the peak and minimum demands. However, variation in demand due to assumptions can have a major effect on costs and reliability. Unless one is willing to lose the individual results from a scenario through the smoothing effects of expectation, the effect of output variation should still be considered on a scenario by scenario basis.

APPENDIX

Lemma: Let $f(x)$ be a probability density defined on $[a,b]$. For each x in $[a + \varepsilon, b - \varepsilon]$,

($\varepsilon > 0$), let there be defined one and only one density $g_x(\tau)$, τ in $[x - \varepsilon, x + \varepsilon]$ such that x is the expected value of the distribution defined by $g_x(\tau)$. Define:

$$h(x) = f(x) \int_a^b g_\tau(x)\, d\tau$$

Then $h(\chi) = f(\chi)$ if and only if $g_\chi(\chi + z) = g_{\chi - z}(\chi)$, for all χ and ($z < \varepsilon$). That is, the probability mass for $h(\chi)$ at each χ in $[a + \varepsilon, b - \varepsilon]$ is the same as that for $f(\chi)$ if there exists a distribution $g_{\chi_0}(\tau)$ and all the other $g_\chi(\tau)$ are merely translated copies of that distribution.

[Before giving the proof we would like to make a few clarifications on the assumptions of the lemma for the continuous case. For each point in the subinterval we are defining secondary distributions as in the case of forecasting a μ and acknowledging an uncertainty around this μ. Therefore at each x, probability mass is being accumulated from the densities which have expected values in the neighborhood of x. For this given x the accumulation has a magnitude of 1 if the secondary densities (error distributions) are identical except for translation. We also note that only expected values in the $[x - \varepsilon, x + \varepsilon]$ neighborhood of x can contribute probability mass to x].

Proof: we first prove the <u>if</u> part.

Since $g_x(\tau)$ is a density defined on $[x - \varepsilon, \chi + \varepsilon]$, for all x in $[a + \varepsilon, b - \varepsilon]$

$$g_x(\tau) = 0 \qquad \tau \notin (x - \varepsilon, x + \varepsilon)$$

$$\int_{x-\varepsilon}^{x+\varepsilon} g_x(\tau)\, d\tau = 1.$$

Then for all x in $[a + \varepsilon, b - \varepsilon]$

$$h(x) = f(x) \int_a^b g_\tau(\tau)\, d\tau = f(x) \int_{x-\varepsilon}^{x+\varepsilon} g_\tau(\chi)\, d\tau$$

But

$$g_{\chi-z}(\chi) = g_\chi(\chi+z) \text{ for all } z \text{ such that } 0 \le z \le \varepsilon$$

and

$$g_{\chi-z}(\chi) = g_\chi(\chi+z) \text{ for all } z \text{ such that } -\varepsilon \le z \le 0 .$$

Therefore

$$h(x) = f(x) \int_{x-\varepsilon}^{x+\varepsilon} g_\tau(\chi)\, d\tau$$

$$= f(x) \int_{\chi-\varepsilon}^{\chi+\varepsilon} g_\chi(\tau) d\tau = f(\chi)$$

For the <u>only if</u> part we will manufacture a counterexample, showing that if $g_x(\tau)$ is not identical the result does not hold. The counterexample will be for a discrete distribution without any loss of generality since integrals and summations could be interchanged in the above or alternatively the integrals could be interpreted as Riemann-Stieltjes integrals.

Let $f(\eta)$ be a uniform distribution on $\eta = 1,2,..,10$, that is $f(\eta) = 1/10$ $\eta = 1,2,..,10$

Let $\varepsilon = 1$

Let $g_\eta(\tau)$ be defined in the following manner:

for $\eta = 1$	$g_1(1) = 1$
for $\eta = 10$	$g_{10}(10) = 1$
for $\eta = 5$	$g_5(4) = 0.1$
	$g_5(5) = 0.8$
	$g_5(6) = 0.1$
for all other η	$g_\eta(\eta - 1) = 0.25$
	$g_\eta(\eta) = 0.50$
	$g_\eta(\eta + 1) = 0.25$

Since $\varepsilon = 1$ our concern is for the points 2,3,4,..,9. We have defined $g_\eta(\tau)$ identically except for $\eta = 5$.

For 2,3,7,8,9

$$h(x) = f(x)$$

as can be seen in the calculation of h(2):

$$h(2) = f(2) \sum_{i=1}^{3} g_i(2) = f(2)\ (0.25+0.50+0.25)$$
$$= f(2)$$

But for 4,5,6

$$h(x) \neq f(x).$$

For $\eta = 4$

$$h(4) = f(4) \sum_{i=3}^{5} g_i(4) = f(4)\ [.025+0.5+0.1]$$
$$= 0.85\ f(4)$$

$$h(5) = f(5) \sum_{i=4}^{6} g_i(4) = f(5)\ [0.25+0.8+0.25]$$
$$= 1.3\ f(5)$$

$$h(6) = f(6) \sum_{i=5}^{7} g_i(6) = f(6)\ [0.1+0.5+0.25]$$
$$= 0.85\ f(6)$$

[In intuitive terms it is at the seams, the points where the distributions differ, that probability mass starts to accumulate to values other than 1].

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15. Supplementary Notes

Volume I of 2 volumes

16. Abstract (Limit: 200 words)

This report describes a method electric utilities can use to determine the value of wind energy systems. It is performed by a package of computer models available from SERI that can be used with most utility planning models. The final output of these models gives a financial value ($/kW) of the wind energy system under consideration in the specific utility system.

This report, first of two volumes, describes the value determination method and gives detailed discussion on each computer program available from SERI. The second volume is a user's guide for these computer programs.

17. Document Analysis

a. Descriptors Computerized Simulation; Costs; Electric Power; Electric Power Industry; Energy Models; Forecasting:Q1,Q2; Power Demand:T2; Power Generation:T1; Production; Reliability; Wind Power; Wind Power Plants; Energy Sources; Power; Power Plants;

b. Identifiers/Open-Ended Terms Renewable Energy Sources; Simulation

c. UC Categories

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