Title
RELIABILITY OF WIND POWER FROM DISPERSED SITES: A PRELIMINARY ASSESSMENT

Author
Kahn, E.

Publication Date
1978-04-01

LBL-6889
UC-60 c.1
TID-4500-R66

Energy and Environment Division

Reliability of Wind Power From Dispersed Sites: A Preliminary Assessment

Edward Kahn

April 1978

Lawrence Berkeley Laboratory University of California/Berkeley

Prepared for the U.S. Department of Energy under Contract No. W-7405-ENG-48

Printed in the United States of America
Available from
National Technical Information Service
U. S. Department of Commerce
5285 Port Royal Road
Springfield, VA 22161
Price: Printed Copy, $ 4.50 Domestic; $ 9.00 Foreign
Microfiche, $ 3.00 Domestic; $ 4.50 Foreign

LBL-6889

RELIABILITY OF WIND POWER FROM DISPERSED SITES: A PRELIMINARY ASSESSMENT

Edward Kahn

April 1978

Energy and Environment Division
Lawrence Berkeley Laboratory
Berkeley, Caifornia 94720

Work performed under the auspices of the U.S. Department of Energy and the California Energy Resources Conservation and Development Commission.

ACKNOWLEDGEMENTS

This work was supported by the UC-LBL Distributed Technology Project and the California Energy Commission. I would like to thank Paul Craig, Mark Levine, Meir Carasso and Kish Sharma for their encouragement. An earlier version of this report was considerably improved by the comments of Richard Sextro, who also provided computational help, Carl Blumstein, C.G. Justus, Amory Lovins and Neil Woodley. Responsibility for remaining errors is the author's.

Table of Contents

List of Figures

List of Tables

1. INTRODUCTION

This paper addresses itself to the reliability benefit of geographically dispersed wind turbine generators. Electricity produced from wind machines experiences wide fluctuations of output at a given site. Yet the value of electricity is a function of its reliability. We typically want electricity available at demand. Pricing schedules have traditionally valued firm power, that is, reliably available power, much more highly than "dump power;" that is, power which is available intermittently on an "if and when" basis. The conventional wisdom on wind power suggests that it is unrealistic to expect that wind generation will be sufficiently reliable to displace conventional capacity. For example, a recent report expresses the situation as follows:

> Because it is not possible to accurately predict when wind energy will be available, it is usually not practical to assign capacity credit to wind units ... For the majority of utilities, it will be necessary to provide conventional generating facilities as backup ... (21)

While such conclusions may be valid for analysis of individual sites, the main thesis of this paper is that geographical dispersal improves aggregate reliability. If the wind is calm at some sites, we can count on it blowing at others. This means that capacity credit, that is, the displacement of conventional capacity, is reasonable to expect from an array of wind generators spread over a large region.

To examine this thesis we need to outline the methodology required for such assessments and examine data to estimate the magnitude of the dispersal benefit. It is important to emphasize that the analyses presented here are preliminary. The limitations in data and methodology will be discussed at some length. The greatest uncertainties are due to lack of adequate wind resource data. In particular, we need to know how dependent the wind speed at one site is on the wind speed at another. This dependence is called the statistical correlation. In general the lower this dependence, the more reliable an array of dispersed wind generators will be. At present we do not know too much about the wind speed correlations, so our analysis can only present a stylized vision of the subject that is limited to a small number of sites. Nonetheless there is enough data to allow the formulation of interesting questions and the statement of preliminary results.

There are also significant problems of method. To address our problem we must marry statistical meteorology with utility methods of assessing power generation reliability. If we do not make some simplifying assumptions, our analysis will drown in a sea of data requirements and endless computation. For conceptual purposes as well, we must find ways of identifying the major variables and labelling our final results.

We will find that reliability is gained from geographical dispersal, but that there are several limitations on this benefit. Two of the most important limitations are the saturation of regional wind diversity and the barrier of large penetrations. The first effect, saturation of diversity, says that as the region examined increases in size, the marginal benefit decreases. For our data we will find that northern California sites aggregate to only slightly poorer reliability than arrays which encompass the entire Pacific Coast region. This is consistent with a similar study of German data which found diminishing marginal benefit of larger and larger wind regimes.(15)

The second limitation, the barrier of large penetrations, results from the statistical fact that wind speed correlations never diminish entirely. This fact means that an array of wind generators will act as a single unit in some sense. As more and more such generators are added to a system, i.e., as the penetration increases, the array requires a larger and larger backup. Since the array reliability is never perfect, large penetrations will be marginally less effective in meeting demand. In a sense this diseconomy of scale which has plagued some of the large-unit conventional technologies will also limit wind arrays.(13) For our data we will find this barrier appearing when wind is roughly 25 percent of the generator mix.

Because this subject is complex and not widely understood, we will begin with a quick tour through the methodology. This will simplify the real problems but provide some perspective on the analysis required. After this we will discuss California data. The limitations of the data will allow us to highlight some additional methodology questions and give estimates of the magnitude of dispersal benefits.

2. METHODOLOGY: FROM WIND POWER FREQUENCY TO LOSS-OF-LOAD PROBABILITY AND BACK AGAIN

2.1 The Basic Steps

Wind energy is available intermittently. To represent the variability in some compact form, it is useful to use a cumulative frequency distribution. In Figure 1 we show such a graph for a single site and a large array. A given point on such a graph associates to a certain level of power the frequency with which power up to that level is available. Thus the median value for the single site in Figure 1 is about 300 kW for 2000 kW of generating capacity. For comparison the array value for a frequency of 50 percent (the median) is about 650 kW per 2000 kW of capacity. Notice that we can only compare array output over the number of sites in the array.

The data represented in Figure 1 are the first kind of input for a capacity credit analysis. There are many problems associated with getting such data. First, the wind speed data which are presently available are typically collected at heights below that proposed for large wind generators. They must be scaled up for analysis, and that is an uncertain process. For array output curves such as that shown in Figure 1 we need data on the correlation of wind speed among sites. A brute force calculation can be done if there are good data for all sites. There are also some relatively simple approximations which can be made to array performance. One such technique, developed by C.G. Justus and associates at Georgia Institute of Technology, will be employed in our data analysis for California.(11)

Assuming that wind power frequency data for an array are available, the next step in the process is the convolution of this resource with the generators used in the utility system of interest. The calculation of capacity credit is done in the context of a power system generation reliability model. The most common of such models is the Loss-of-Load Probability (LOLP) calculation. This index measures the probability of load being in excess of resources. Generators are represented probabilistically in such models by means of a single unavailability parameter, the forced outage rate. This is a reasonable portrayal of conventional unit

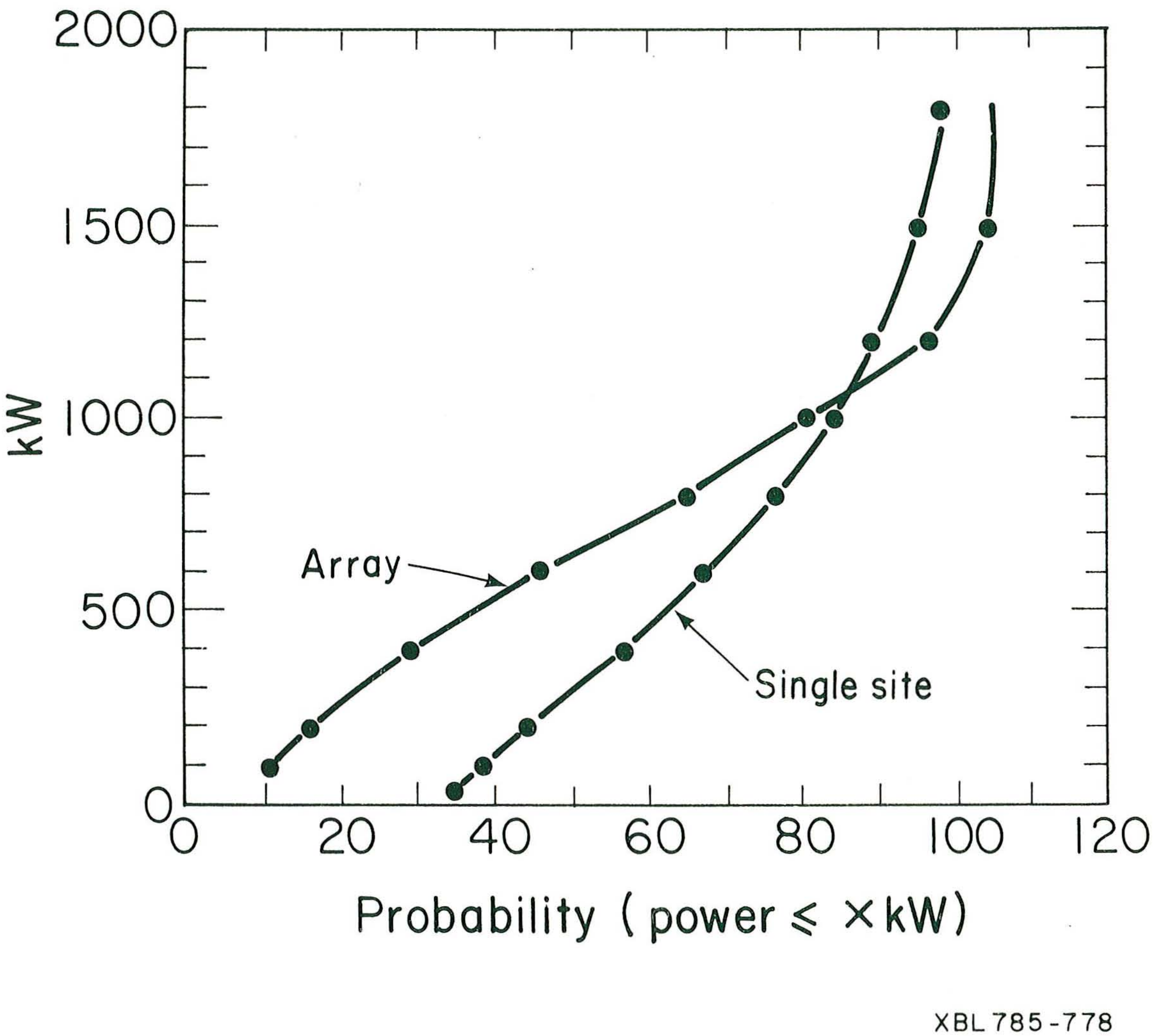
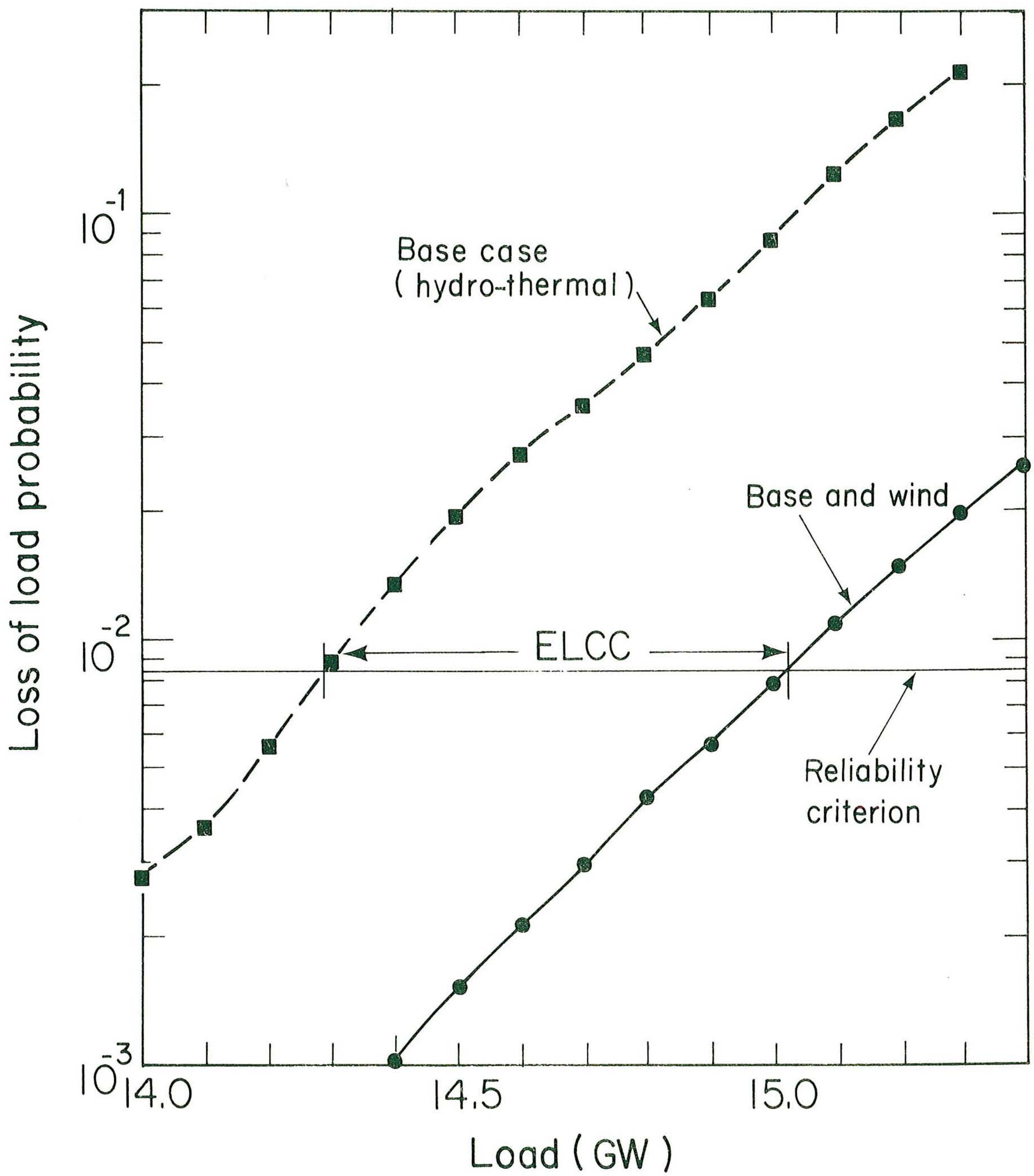


Figure 1. Power Frequency Distribution:
Array vs. Single Site

performance; either they are on or off. More recently this representation has been augmented to allow for partial unavailability which can be frequent but usually involves only a small fraction of unit capacity. The curves of Figure 1 are not easily made compatible with the standard generator models. To capture the full variability of wind power, many "states of availability" and their probabilities are required. Moreover, the wind power from an array will act as an aggregate. Each wind unit cannot be treated as an independent random variable. In the LOLP calculation each conventional unit is assumed independent. Since the wind generation is correlated, its representation in the LOLP analysis must show this.

After the wind power is given a many-state power availability representation, it can be included with conventional resources to calculate LOLP. An example calculation is shown graphically in Figure 2. In this graph we plot LOLP as a function of load for a base case and a case with a large penetration of dispersed wind generators. For utility planning purposes an LOLP objective, the reliability constraint, is imposed. When forecasted load exceeds this specified level, it is a signal for additional capacity requirements. The criterion shown in Figure 2 is one version of the ubiquitous but unmotivated "one day in ten years" rule of thumb.

To address the question of capacity credit for wind arrays, we need a common currency in which we can trade off different types of generation. The most useful numeraire for such purposes is a notion known in the technical literature as the Effective Load Carrying Capability (ELCC). This is just the distance between the base case maximum load and the load for the case with wind generation measured at the LOLP equal to the risk criterion. Any unit added to a base system will shift the risk curve to the right. The magnitude of the shift (ELCC) is a function of unit size, forced outage rate, and system characteristics. We can say that one supply alternative displaces another if the ELCC for each is the same. There are, of course, other ways to achieve capacity displacement at constant reliability. These involve backup generation. For example, wind machines can be added in some array configuration displacing other resources with greater ELCC, then gas turbines can be added to the system to restore equal ELCC for the two options. This will involve a greater economic burden than the simple case with just pure dispersal.



XBL 785-777

Figure 2. Effective Load Carrying Capability Defined

2.2 Optimization of Various Kinds

Starting with the basic tools of a wind power frequency curve and LOLP model one can ask a variety of questions. Clearly there is more than one way to construct a wind array. In the simple calculations to follow we will assume that all sites are weighted equally. As penetration increases we are just adding more machines at the known locations. This is partly a data constraint in our case, but even with what we know array performance could be improved by adding more machines at favorable sites. The problem simply is to identify what favorable means in this context. If we had negatively correlated sites, they would be favorable. Negative correlation means that when it is windy at site A it is calm at B and vice versa. Such perfect complementarity has yet to appear in the data. If it existed, then about half the array capacity should be sited at locations that were negatively correlated with the remaining sites. We will see in section 3 that there is a tradeoff between high mean wind speed and low positive correlation for array design. Our data provide anecdotal but not conclusive insight into this tradeoff.

Wind regimes that are optimal for power reliability may or may not coincide with administrative districts which currently exist. The dispersal benefit suggests that coordination over large areas is desirable. Small municipal utility systems would probably be unable to capture the diversity. The same is probably true for most typical utility service areas. Large geographically diverse service areas, such as that of the Pacific Gas and Electric Company, encompassing most of northern California, may well be near optimal in size from this point of view. In section 4 we will examine the question of whether the wind resource diversity as we know it today provides a justification for integrating all the California utilities into a regional pool. This question is of independent interest.[14,20]

Our discussion of capacity credit and the previous remarks about the inability of municipal utilities to capture a geographical economy of scale are not conclusive arguments for centralized exploitation of wind energy. An institutionally decentralized implementation of wind machines could still benefit from geographical dispersal if an appropriate mechanism for allocating mutual aid or backup responsibility can be found. Existing power pool agreements are a model of such arrangements. Responsibility and benefit are allocated to members on the basis of investment share and the statistical performance of equipment. Similar tools could be brought to bear in the management of a regional "wind pool." More thorough discussion of such arrangements can be found elsewhere.[14] For our purposes it is important to know that a variety of social and institutional configurations can capture the geographical scale economy of dispersal, if an appropriate statistical foundation can be found to characterize the resource.

There are, of course, many other kinds of optimization involved in integrating wind arrays into an electric energy system besides array design and the optimization of social administration of the resource. Machine design, for example, is guided by principles of optimal resource management. It is important from the systems viewpoint, however, to realize that implementing large wind arrays may require redesign of other elements in the power system. In particular these regions with substantial hydro resources may find significant opportunities for matching wind energy output fluctuations with hydro dispatch for a smoother total output. Such an operating strategy would probably justify investment in additional turbines for "shaping" of the hydro resource to fit the wind regime. These issues, which are part of the ultimate integration problem, lie beyond our more simple task of illustrating the dispersal benefit with sample data. It is to that task that we now must turn.

3. WIND DATA AND MODELS FOR ARRAY CHARACTERIZATION

3.1 Introduction

Our study of wind diversity in California derives almost entirely from the research of C. G. Justus and associates at Georgia Institute of Technology.[10,11,12] The scope and limitations of this work are important to understand before particular results are discussed. Justus has attempted to model the performance of large wind turbine generators such as those proposed by the Department of Energy. To develop a profile of wind speed frequency distribution at the sites analyzed, the data from

6m must be scaled up to the 60m hub-height of the proposed DOE machines. Justus does this by means of some empirical scaling laws associated with the parameters of the Weibull probability distribution. This distribution is particularly useful for wind power analysis, but one must rely on ersatz data for the task at hand. To estimate the error in the scaling laws, a sensitivity analysis should be done using additional upper air data. Our method uses estimates of array reliability that are conservative.

Justus uses data for Pacific Coast sites listed in Table 1; seasonal variation in mean wind speed is given in Table 2. Among the California sites, five of the six are in Pacific Gas and Electric Company's service area. Although there are some data for more promising sites than those studied by Justus (Pt. Arena and San Gorgonio Pass, see reference 3), and it was recorded at more appropriate heights, only six months of data are available. This compares to five years for most of the Justus sites. Since our primary interest is in geograhpical correlations, we must rely upon the larger data set. Because there is a large number of data points, we can have reasonable confidence in the correlation coefficients. In Table 3, we summarize data on the summer average correlation among California station pairs. Recall that the correlation coefficient is a measure of linear dependence that varies between +1 (perfect correlation) and -1 (complete inverse correlation). For comparison we also tabulate average monthly spatial cross correlations for the entire Pacific Coast array. More detailed data are given in Appendix 1.

As we might expect, Table 3 shows rather high correlation among sites that are close geograhpically. Thus Sacramento and Stockton show summer correlations of .49. Conversely sites which are relatively remote from one another show lower correlation. San Francisco and Red Bluff have correlations of .23. The southern California site, Sandburg, shows low correlations with the northern California stations. In the summer these average about .10.

3.2 Weibull Approximation Model

It would be useful to have a simple model that uses the correlation coefficient and a few other parameters to characterize wind arrays.

Table 1

West Coast Sites

ACV	Arcata, CA	SAC	Sacramento, CA
AST	Astoria, OR	SCK	Stockton, CA
BFL	Bakersfield, CA	SDB	Sandberg, CA
EUG	Eugene, OR	SEA	Seattle/Tacoma, WA
MHS	Mt. Shasta, CA	SFO	San Francisco, CA
NUO	Sunnyvale, CA	SLE	Salem, OR
OTH	North Bend, OR	SMP	Stampede Pass, WA
PDX	Portland, OR	SMX	Santa Maria, CA
RBL	Red Bluff, CA	SXT	Sexton Summit, OR
RDM	Redmon, OR		

Note: California correlation data available only for BFL, SAC, SFO, SCK, RBL, SDB.

Table 2

Mean Wind Speed (m/s) at 60 m (197 ft) Hub-Height for Pacific Sites

	Winter	Spring	Summer	Fall	Annual
AST	7.2	5.6	6.1	6.0	5.8
BFL	4.8	6.0	6.0	5.1	5.5
EUG	6.4	5.5	6.0	5.8	5.5
OTH	7.1	6.3	7.9	6.7	6.3
RBL	6.6	6.2	6.3	6.3	5.8
RDM	6.2	5.2	6.0	5.8	5.2
SAC	5.1	5.7	6.5	4.9	5.7
SCK	5.8	6.6	7.0	5.7	6.3
SDB	9.0	9.5	7.6	8.0	8.5
SEA	6.8	6.1	5.8	6.1	6.2
SFO	5.8	8.1	8.5	6.7	7.3
SMP	7.9	7.4	7.2	7.2	7.5
SMX	5.7	4.8	-	5.7	4.9
SXT	7.9	7.3	6.2	6.8	7.8
AVG	6.5	6.5	6.7	6.1	6.2

Table 3

Average Spatial Cross Correlation of Wind Speed: California Sites*

	BFL	SAC	SFO	SCK	RBL	SDB
BFL		.35	.40	.37	.32	.17
SAC			.30	.49	.29	.01
SFO				.44	.23	.19
SCK					.30	.08
RBL						.07
SDB						

*See Appendix 1, July and August values averaged.

Pacific Coast Array Summer Correlation averages .25.

One such model has been developed by Justus. It approximates array performance based on data for a single representative site. For our analysis we rely on data for Sacramento. Individual sites and arrays are characterized by the two parameters of the Weibull distribution, a shape factor, k, and a scale factor, c. Once these parameters are specified, the probability of power output less than or equal to some value P_j is given by

$$Pr[P \leq P_j] = 1 - \exp[-(V_j/c)^k] \quad , \qquad (1)$$

where V_j is defined by

$$V_j = [(P_j/P_r) - a]V_r/b \qquad (2)$$

for P_r = rated power of wind turbine generator
V_r = rated speed of wind turbine generator, and where parameters a and b are empirical constants estimated by Justus[11] for the Pacific Coast region to be $a = -0.42$ and $b = 1.14$.

In our numerical calculations we use data for machines characterized by $P_r = 2000$ kW, $V_r = 10.6$ m/s. Equation (2) is just a linear approximation to the cubic power curve.

To use this model to test for the sensitivity of dispersal benefit to the region considered, we need an expression for the dependence of the array Weibull parameters on correlation coefficient. This is given by (3) and (4) below. Equation (3) expresses the relationship between the standard deviation of array wind speed frequency and both the standard deviation of the representative site speed distribution and the average array correlation coefficient.

$$\sigma_A = \{\sigma_T^2[1 + (n - 1)\bar{\rho}]/n\}^{1/2} \quad , \qquad (3)$$

where σ_A = standard deviation of array wind speed distribution
σ_T = standard deviation of representative site wind speed distribution
$\bar{\rho}$ = average array wind speed cross correlation coefficient
n = number of sites in array

Equation (4) relates the Weibull shape factor k to σ and $\overline{v}$, the mean wind speed. This relation holds for both arrays and individual sites,

$$k = (\sigma/\overline{v})^{-1.086} , \qquad (4)$$

Equation (4) is an empirical approximation to the theoretical relationship between k and $\sigma/\overline{v}$ given by

$$(\sigma/v)^2 = [\Gamma(1 + 2/k)/\Gamma^2(1 + 1/k)] - 1 .$$

For the sake of completeness, we write down an expression for the Weibull scale factor c as a function of k and $\overline{v}$, as follows

$$c = \gamma\overline{v}/\Gamma(1 + 1/k) , \qquad (5)$$

where γ is an empirical adjustment factor found to be about 1.02-1.03.

3.3 Fitting the Weibull Model to Pacific Coast Array

We begin using equations (1) and (2) to characterize the performance of Justus' Pacific Coast wind turbine array. We want to know if the simple model is a good approximation to numerical simulation of large arrays. In Table 4 we list data for summer diurnal variations in array output. The data on mean power and mean wind speed are simulated; they comes from reference 11. We also tabulate array Weibull parameters. These parameters used in equations (1) and (2) ought to be able to reproduce approximately the mean power and wind speed results from numerical calculation.

We make the test indirectly. If the Weibull distribution were symmetric, then the mean power would have probability equal to .50, i.e., the mean and median coincide. Bury[(2)] shows that the Weibull is symmetric for k = 3.6, which is quite close to our values. We can use a simple formula to calculate the median wind speed, $\overset{o}{v}$; namely

$$\overset{o}{v} = c(\ln 2)^{1/k} .$$

Table 4

Pacific Coast Array - Diurnal Power Variations: Summer

		Hour 13	16	19	Data Source
Mean Power		840 kW	1054	805	Table C-6[11]
Mean Wind Speed		8.0 m/s	8.8	7.8	Table 7[12]
Weibull Parameters by Month					
July 73	c	9.21	10.11	9.29	
	k	3.13	3.77	3.53	
July 75	c		10.27	9.42	
	k		3.78	3.86	
August 71	c	9.00	9.85	8.61	
	k	3.52	3.99	3.67	
August 72	c	9.40	9.99	9.08	
	k	3.34	3.86	3.55	
August 74	c	9.21	9.68	8.77	
	k	3.13	3.78	2.87	
August 75	c	9.30	9.76	8.65	
	k	3.33	3.36	2.99	
Summer Average	c	9.22	9.94	8.97	
	k	3.29	3.36	3.41	
$Pr[x \leq \mu]$		.47	.47	.46	
Median Wind Speed: (estimated)		8.3 m/s	8.9 m/s	8.1 m/s	

Putting in our parameters we find median wind speeds that are 1 to 4 percent higher than the mean. Since our Weibull shape parameter k takes values less than 3.6, the distribution is skewed slightly to the right. Hence the median should be less than the mean, but only slightly.[2] Our data also show that the cumulative probability of the mean power ranges from .46 to .47. The combination of these errors could be as much as 10 percent. For our purposes later we will rely principally on the 4:00 p.m. data, where the error is about 5 percent. This can give us reasonable confidence in the accuracy of (1) and (2) at least in this region.

It is more difficult to assess the accuracy of the Weibull model in the tail of the distribution. In some sense this is a more critical region for LOLP calculations. At this point we can only point out a potential difficulty in accuracy, but we do not have the tools to assess its import. Clearly this question can be answered by more simulation studies.

It is worth observing in passing that the diurnal variation data shows rather large output for afternoon performance. The range of 800-1000 kW per 2000 kW of capacity is 40-50 percent of rated capacity. This will be important in our capacity credit calculations. For now it remains to explore the use of equations (3)-(5) in the construction of various array power distributions. This is the subject to which we know turn.

3.4 California Arrays: Building Up from the Bottom and Down from the Top

In Figure 1 we show two power output frequency distributions, one representing average conditions at Sacramento, California, the other representing the summer average performance of Justus' Pacific Coast array. It is useful in understanding the dispersal effect to build up arrays incrementally. This will illustrate how reliability increases and helps develop intuition for the tradeoffs involved. In the calculations which follow attention is focused on summer conditions. The rationale for this limitation will be discussed more fully in section 4, but it is based primarily on the summer peaking electric demand behavior which is characteristic of California.(16)

Our procedure is to use Sacramento as the "representative site" and gradually add additional sites to our arrays. From estimates developed in (10) we have Weibull parameters for Sacramento of k = 1.98, c = 6.32. This is scaled up to 60 m. From equation (4) we can calculate a standard deviation of the wind speed distribution at this site. For array construction we use equation (3) and Table 3 to scale the array wind speed standard deviation. Then the data in Table 2 allow us to calculate $\bar{v}$, the mean array wind speed. This goes back into equations (4) and (5) to yield array Weibull parameters. Then equations (1) and (2) allow us to calculate a table of cumulative power frequency. This can be displayed graphically as in Figure 1. The table corresponding to the single site curve in Figure 1, Sacramento, is given in Table 5 below.

Table 5
Sacramento: Power Output Variations

Pr[P ≤ 1000 kW]	=	.84
Pr[P ≤ 800 kW]	=	.77
Pr[P ≤ 600 kW]	=	.67
Pr[P ≤ 400 kW]	=	.57
Pr[P ≤ 200 kW]	=	.44
Pr[P ≤ 100 kW]	=	.38

In Table 6 we tabulate average power frequency distributions for seven array configurations during the summer. In general, as the number of sites increases, so does reliability. We will see that for utility system planning purposes, it is the behavior at lower power output levels which is crucial. In this regard it is interesting to pay particular attention to Case 7, the entire Pacific Coast Array. The mean summer wind speed over the whole array is less than that of most combinations of California sites. But the behavior at low output levels is better. This is due to low correlation among a significant number of sites.

Table 6

California Sub-Arrays: Average Summer Power Frequency Distribution

Case 1					
Sacramento	$\overline{v}$	= 6.75 m/s	Pr[P $\leq$ 1000 kW]	=	.72
Stockton	$\overline{\rho}$	= .49	800	=	.62
	k	= 2.42	600	=	.50
	c	= 7.77	400	=	.38
			100	=	.22
			50	=	.20
Case 2					
Bakersfield	$\overline{v}$	= 6.5 m/s	Pr[P $\leq$ 1000 kW]	=	.76
Stockton	$\overline{\rho}$	= .40	800	=	.65
Sacramento	k	= 2.61	600	=	.53
	c	= 7.46	400	=	.40
			200	=	.27
Case 3					
Stockton	$\overline{v}$	= 7.3 m/s	Pr[P $\leq$ 1000 kW]	=	.66
Sacramento	$\overline{\rho}$	= .41	800	=	.53
San Francisco	k	= 2.96	600	=	.40
	c	= 8.38	400	=	.28
			200	=	.18
Case 4					
Bakersfield	$\overline{v}$	= 7.0 m/s	Pr[P $\leq$ 1000 kW]	=	.71
Stockton	$\overline{\rho}$	= .39	800	=	.58
Sacramento	k	= 2.98	600	=	.44
San Francisco	c	= 8.00	400	=	.31
			200	=	.20

Table 6 (continued)

California Sub-Arrays: Average Summer Power Frequency Distribution

Case 5			
Red Bluff	$\bar{v}$ = 7.1 m/s	Pr[P $\leq$ 1000 kW]	= .70
San Francisco	$\bar{\rho}$ = .34	800	= .56
Sacramento	k = 3.15	600	= .42
Stockton	c = 8.09	400	= .29
		200	= .18
Case 6			
Red Bluff	$\bar{v}$ = 6.9 m/s	Pr[P $\leq$ 1000 kW]	= .73
Sacramento	$\bar{\rho}$ = .35	800	= .60
Stockton	k = 3.15	600	= .45
Bakersfield	c = 7.86	400	= .31
San Francisco		200	= .19
Case 7			
Pacific Coast Array (13 sites)	$\bar{v}$ = 6.7 m/s	Pr[P $\leq$ 1000 kW]	= .80
	$\bar{\rho}$ = .25	800	= .65
	k = 3.88	600	= .47
	c = 7.55	400	= .30
		200	= .16
		100	= .11

Detailed examination of Table 6 shows the tradeoff between array mean wind speed ($\bar{v}$) and average correlation coefficient ($\bar{\rho}$). Consider cases (3) and (4). Case (3) involves three sites (Stockton, Sacramento and San Francisco). The power frequency distribution shows a little better reliability than the array composed of the same three sites plus Bakersfield, which is case (4). Adding Bakersfield to the case (3) array reduces both mean wind speed and average correlation coefficient. The former decreases by about 4 percent, the latter by about 5 percent. Looking at case (5) we find slightly better availability than case (3). In case (5) we add Red Bluff to the case (3) array instead of Bakersfield. In this case mean wind speed falls only about 3 percent, and correlation coefficient falls about 17 percent.

It would also be useful to characterize California array performance with respect to diurnal variation in output as Table 4 does for the whole Pacific Coast array. To do this we must scale down from the large system to the smaller ones of interest. We cannot use the "building up" approach which we used for our summer average calculations because there is no base case data on a single representative site. Nonetheless equations (1)-(5) are sufficiently flexible so that a simple scaling procedure is possible. This procedure is outlined and sample calculations are presented in Table 7.

A summary of selected distributions is shown in Figure 3. Our next problem is to decide how to use our abundance of data for capacity credit calculations.

4.0 CAPACITY CREDIT FOR WIND ARRAYS: FORMULATING THE PROBLEM

4.1 The Coincidence Hypothesis

Our first problem in array analysis is the selection of the appropriate data. Do we use averages? What is the limitation of restricting attention to the summer period? What guidelines are there to help us avoid just simulating all available data with brute force methods? The principle we will follow is essentially the conventional wisdom in power system studies. What matters for power system reliability is the coincidence in the power availability and the peak demand. Let us call this principle the coincidence hypothesis.

Table 7

Power Frequency Distribution
4:00 p.m. Summer

Case 1				
Pacific Coast Array (Table 4)	$\bar{v}$ = 8.8 m/s	Pr[P $\leq$ 1400 kW]	=	.70
	k = 3.76	1200	=	.57
	c = 9.94	1000	=	.43
		800	=	.31
		600	=	.20
		400	=	.12
		200	=	.06
Case 2				
Pacific Gas and Electric Company Sites	$\bar{v}$ = 9.0 m/s	Pr[P $\leq$ 1000 kW]	=	.44
	k = 3.03	800	=	.33
	c = 10.28	600	=	.24
		400	=	.16
		200	=	.10
Case 3				
All Caifornia Sites	$\bar{v}$ = 9.17 m/s	Pr[P $\leq$ 1000 kW]	=	.40
	k = 3.45	800	=	.29
	c = 10.40	600	=	.20
		400	=	.12
		200	=	.07

Scaling Methodology. From equation (3) we know the ratio of an array wind speed standard deviation to that of a representative site. This is expressed in terms of the pair of numbers $(n,\bar{\rho})$, where n is the number of array sites and $\bar{\rho}$ is the average correlation coefficient. We calculate this ratio for the Pacific Coast Array (n=13, $\bar{\rho}$=.25) and get the value 0.555. Doing the same for case 2 (n=5, $\bar{\rho}$=.35) we get the value .693. Therefore we know that

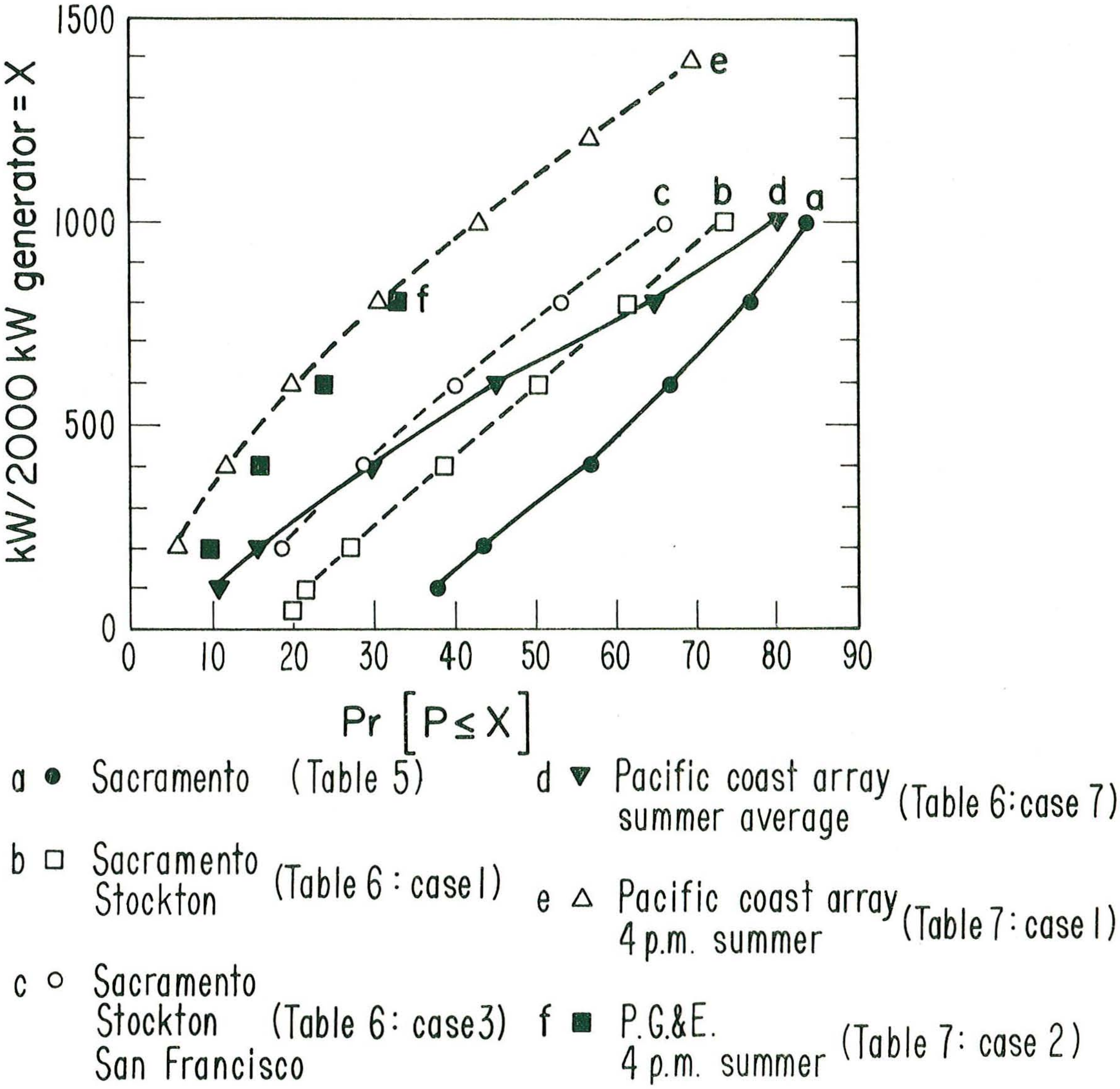
$$\sigma_{PG\&E}/\sigma_{\text{Pacific Coast Array}} = .693/.555 = 1.249 .$$

We calculate $\sigma_{\text{Pacific Coast Array}}$ from equation (4) using the known values of k=3.76 and $\bar{v}$=8.8. This gives $\sigma_{\text{Pacific Coast Array}} = 2.60$, and therefore $\sigma_{PG\&E} = 3.246$. We calculate the value of the Weibull parameter k using equation (4) again, but this time we reestimate $\bar{v}$ for the sites in question. This is done by averaging the mean values

Table 7 Footnote (continued)

in Table 2. For PG&E data this yields $\overline{v}$ = 6.86 compared to the array average 6.7 m/s. Using a linear scaling ratio we get a 4:00 p.m. $\overline{v} = (6.86/6.7)8.8 = 9.0$ m/s. Now returning to equation (4) we get $k = (9.0/3.246)^{1.086} = 3.03$. From equation (5) we get $c = 10.28$.

A similar procedure is used to derive the parameters for case 3. For this case $n = 6$, $\overline{\rho} = .27$. The latter value is calculated from Table 3.



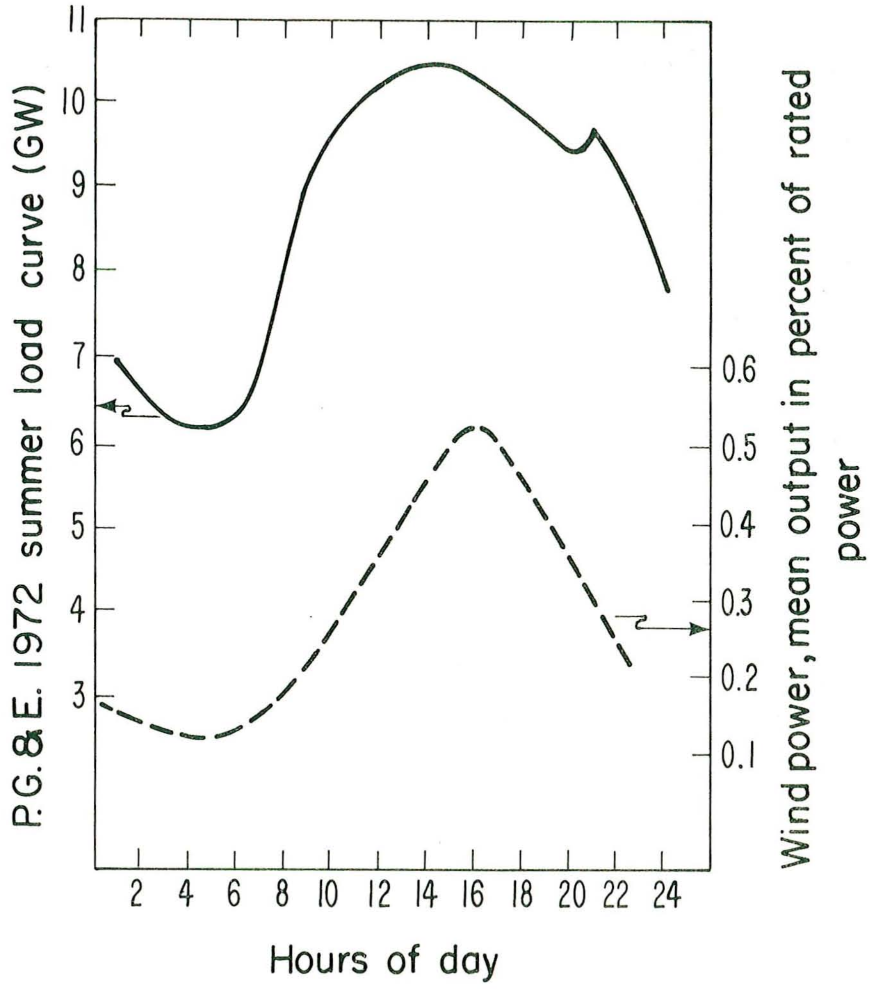
XBL 784-2462

Figure 3. Power Frequency Distribution: Various Configurations

The coincidence hypothesis is more than just folklore. Recent studies of other intermittent electric technologies have verified the importance of this measure. General Electric Company, in a study of photovoltaic power plants, found that degree of coincidence in peak load and insolation was a significant parameter.[8] This coincidence requirement refers to hourly correspondences. Seasonal coincidence is assumed. This is the rationale for our looking at summer data only. But the hourly scale requires that we focus on diurnal variation. Therefore the daily average data of Table 6 is too coarse a measure. For our purposes the appropriate data is given in Table 7. The summer time peak in California is typically around 3:00 p.m.[16] The diurnal variations in array output are compared to the demand curve of the Pacific Gas and Electric Company in Figure 4. This shows good coincidence with our 4:00 p.m. data.

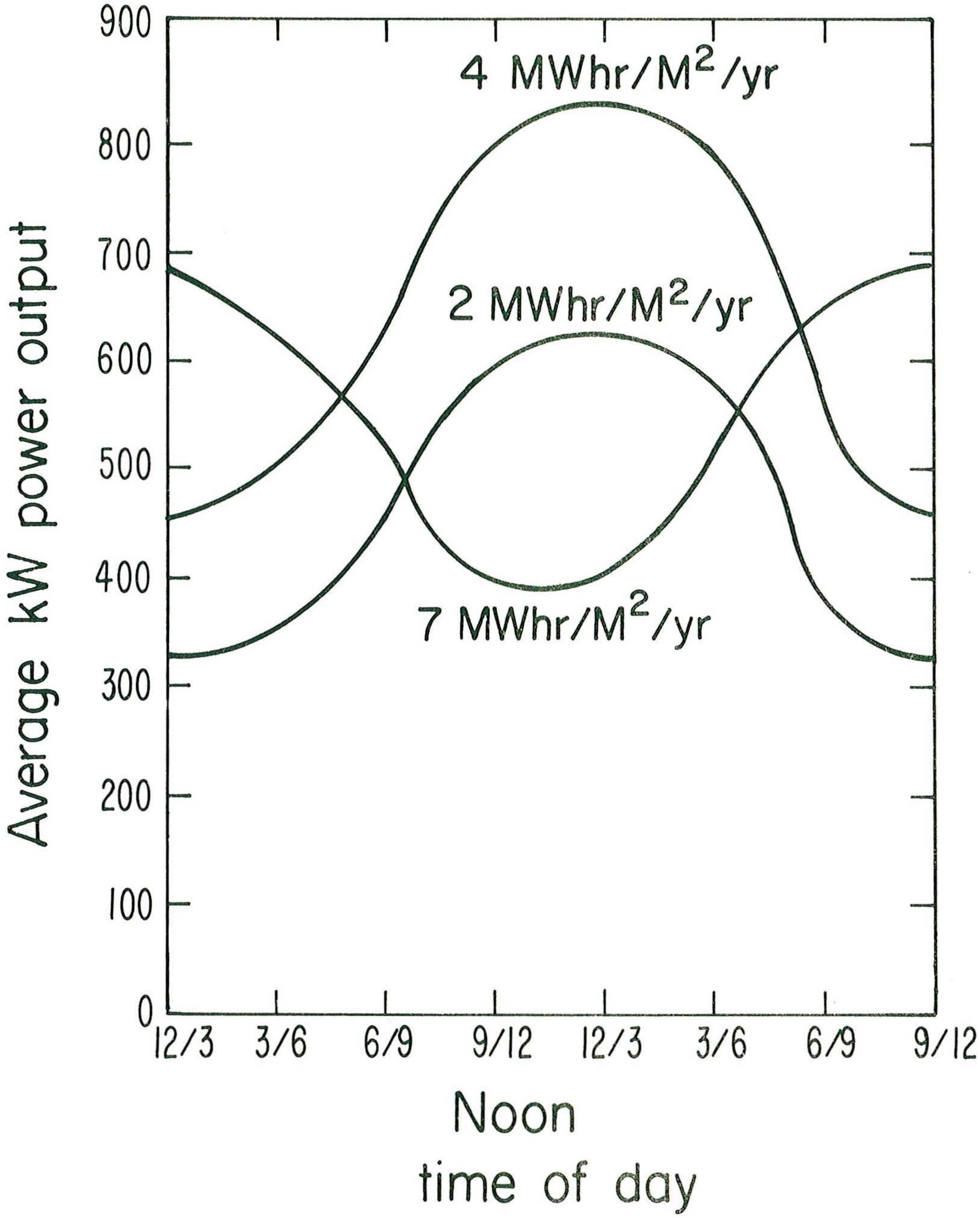
This choice of power frequency distribution is reasonable provided we believe that significant mismatch between loads and resources would not emerge at some other time. There are a number of potential problems here. For example, Figure 4 shows a growing gap between 9:00 p.m. and midnight. This mismatch is probably not inherent in the wind regime and could be ameliorated with more sophisticated siting. Data for the San Bernardino Mountains, for example, shows virtually an antisymmetric wind pattern to Figure 4 with a minimum at 4:00 p.m., increasing in the evening.[18] Moreover, General Electric in another study[7] suggests that high wind speed regimes typically have a diurnal pattern which complements the lower wind speed pattern we have illustrated in Figure 2. Figure 5 shows this change as average energy increases. Thus for the purposes of illustration it is not unreasonable to accept the 4:00 p.m. power frequency distribution as the basic data to be used in analysis of summer conditions.

An interesting potential problem is the emergence of a winter peak shortfall. Table 2 shows that the northern California sites have a somewhat lower mean wind speed in winter compared to summer (5.6 m/s vs. 6.9 m/s). An estimate of when a problem might emerge can be derived from a comparison of the summer/winter peak load differential and the effective load-carrying capability of a wind array. In section 4.3 below we will present results on ELCC for various penetrations of wind



XBL 783-2461

Figure 4. Coincidence of Demand and Wind Resource



Source: General Electric

XBL 784-2463

Figure 5. Dirunal Power Output Variations for Three Wind Regimes

turbines. If these values of ELCC were greater than the difference between summer and winter peak loads, then poorer performance in winter would threaten reliability at the winter peak. For the Pacific Gas and Electric Company service area, the winter peak is typically more than 2000 MW below the summer peak. Our results in section 4.3 will show that ELCC in this system will not be likely to exceed such a number. Therefore winter risks would not emerge under our assumptions. Of course, the question deserves more analysis than these brief remarks. But that is beyond the scope of the present effort.

4.2 A Map from Power Frequency to Generator Models

We have argued briefly in section 2.1 that the translation of a wind power frequency distribution into a representation for LOLP analysis is non-trivial. The basic problem is that the power behavior of wind generators cannot be captured in two or three discrete states which is the typical model for thermal units. Indeed, it has been shown that even for thermal units LOLP accuracy is improved by using a multi-state model rather than collapsing behavior into an "on-off" model.[1,13] The general rule here is a version of "the-more-the-merrier." That is, accuracy improves as the number of states increases. There is, of course, a point of diminishing returns. To limit computational complexity we will use an eight-state model which is described below. In Appendix 2 we present data which supports this choice.

Before describing our transformation from a continuous distribution to the eight-state model, it is worth emphasizing that we need to model the low output end of the distribution more finely than the high output side. This thesis is also supported by data discussed in Appendix 2. However, there is an intuitive rationale for our procedure that is useful to discuss. LOLP, our measure of risk and reliability, is naturally more sensitive to big failures than small ones. The risk of using wind power for electricity is the risk of lulls in the wind. Even slight winds are better than no winds at all. The thesis which states that low output is critical captures the importance of marginal winds. At a time of risk anything is a whole lot better than nothing. For a numerical argument supporting this thesis, see Appendix 2.

Let us consider case 2 from Table 7. We will select eight states from the infinite possibilities and use interval estimates to characterize the probability of the state at the bottom of the interval. For example, if we use the case 2, Table 7 data and look at the interval between 200 and 400 kW, we find that the probability of power in this interval is .06. This is just the difference between $Pr[P \leq 400]$ and $Pr[P \leq 200]$ or .16 - .10 = .06. This rule is conservative. It throws out all output between 200 and 400 kW and counts it all as just 200 kW. In Table 8 below we show our generator model for this case.

Table 8

PG&E 4:00 p.m. Summer Wind Generator Model

State (X_i)	$Pr[P \leq X_i]$	$Prob[State\ X_i] = Pr[X_i \leq P \leq X_{i+1}]$
0	.05	.07
100	.07	.03
200	.10	.06
400	.16	.08
600	.24	.09
800	.33	.11
1000	.44	.30
1600	.74	.26

A final note should be addressed to the question of the penetration of the wind array in the power system. In our analysis we scale the generator representation linearly with penetration. Thus a 2000 MW penetration in PG&E would be modelled by the states listed in Table 8 where each state had units of megawatts. For a 4000 MW penetration each state would have units of twice that number of megawatts. As the penetration grows the gap between states gets larger; that is, the grain of the representation gets coarser. This plus the linear scaling assumption may introduce problems that require further research.

4.3 Results from LOLP Calculations

We have asked the following question about California wind arrays. Does the better reliability of the statewide wind resource (Table 7, case 3) compared to PG&E area (Table 7, case 2) mean more capacity credit for statewide implementation? To answer this question we first must calculate ELCC. We use a standard LOLP model[22] and data on the characteristics of the California electric generation system.[19] The results of these calculations are presented in Table 9.

Table 9

Wind Array ELCC

PG&E				
(1)	Wind turbine capacity	2000 MW	4000 MW	5000 MW
(2)	ELCC	530 MW	700 MW	740 MW
(3)	Base hydro-thermal capacity = 16,354 MW			
(4)	Penetration (= 1/(1 + 3))	11%	20%	23%
(5)	Ratio of (2) to (1)	.265	.175	.148
California Utilities Pooled				
(1)	Wind turbine capacity	4000 MW	8000 MW	10000 MW
(2)	ELCC	680 MW	1190 MW	1240 MW
(3)	Base hydro-thermal capacity = 39,492 MW			
(4)	Penetration (= 1/(1 + 3))	9%	17%	20%
(5)	Ratio of (2) to (1)	.170	.149	.124

The data in Table 9 do not provide an unambiguous answer to our question. Clearly the hypothetical California pool can carry more load with wind turbines than the PG&E service area alone. However, the ratio of ELCC to wind turbine capacity is better for PG&E. This measure is a better indicator of effectiveness than just ELCC. The results suggest the conclusion we began with; namely, that for these data the diversity benefit reaches diminishing returns when we go beyond northern California. This result is not conclusive, of course. Better array design, more and better wind correlation data, and so on could change the outcome. The methodological conclusion of interest is that even when wind output reliability is better in one region, ELCC is dependent on the characteristics of the systems in question.

4.4 Capacity Credit

Capacity credit in our case means the amount of conventional capacity which can be displaced by wind generation. Our ELCC calculations form the basis for making this comparison. What we need to know is the ELCC of competing alternatives. As should be clear by now ELCC is a function of unit size, forced outage rate and the power system in question. We will consider 800 MW coal plants in the PG&E system first, since these are being proposed. PG&E forecasts a .12 forced outage rate for such units when they mature (after 4 years).(17) Using that value, ELCC would be about 475 MW. EPRI, however, estimates a forced outage rate of .197.(5) At that level of performance, ELCC would be approximately 380 MW. An intermediate value of .15 yields ELCC of 430 MW. These numbers are derived in Appendix 3.

Another way to view the question is to ask what kind of thermal generator do the arrays act like. This question is answered by using the LOLP output and fitting a thermal model to it. We do this also in Appendix 3. From that analysis we find that our Table 9 results are approximated by assuming that 2000 MW of wind turbines behaves in this context like an 800 MW generator with a .10 forced outage rate. This says that one of PG&E's coal plants could be displaced by a large wind array. Depending on actual performance of such plants, i.e., if they were as bad as the EPRI estimate, both of the proposed Fossil 1 and 2 units could be displaced.

These results change when we look at a hypothetical pool of all California utilities. For this purpose let us consider a 1000 MW plant with a forced outage rate of .15. From Appendix 3 we find that such a unit would have ELCC equal to about 606 MW. Two such units would be displaced by about 8000 MW of wind turbine capacity. The ratio of wind generator capacity to conventional capacity displaced is thus about four to one in this case. That compares to something less than three to one in the PG&E case. This is another way of seeing the diminishing returns to implementing statewide pooling of the wind resource. Perhaps with better data this conclusion would change.

Finally it should be noticed that Table 9 illustrates the barrier of large penetrations. The PG&E data show an increase of only 40 MW in ELCC for the last 1000 MW of wind turbine capacity. On a relative basis the situation is worse for the statewide case. These results suggest that we are near a limit. It is not clear if the limit is inherent in the resource or only in our limited data. Even if it is the latter, it is likely that this barrier will remain; only its frontier will recede.

5.0 THE RESEARCH HORIZON

Modelling the reliability of wind arrays is still a primitive subject. There is a great need for additional wind resource data. We need to know the time variation of correlations, more details on different wind regimes, and the influence of differing machine parameters. Even with our present scanty knowledge, it seems plausible to assert that our main thesis has been supported. Wind arrays can displace conventional capacity with reliability.

The present inquiry forms part of a larger subject, the integration of intermittent resource technologies into an electric energy system. Our discussion has focused only on the problem of relatively small penetrations. Large penetration analysis will require a look at hydro optimization, other resource complementarities and the role of storage. This is a large and fruitful area of study which will help determine the future of economic viability of emerging technologies.

REFERENCES

1. Billinton, R.A.V. Jain and C. MacGowan, "Effect of Partial Outage Representation in Generation System Planning Studies," IEEE PAS-93, pp. 1252-59, 1974.

2. Bury, Karl, Statistical Models in Applied Science, New York: John Wiley and Sons, 1975.

3. Cliff, W., The Effect of Generalized Wind Characteristics on Annual Power Estimates from Wind Turbine Generators, PNL-2436, October 1977.

4. Corotis, R.B., A. Sigl and M. Cohen, "Variance Analysis of Wind Characteristics for Energy Conversion," J. Appl. Met., V. 16, pp. 1149-57, November 1977.

5. Electrical Power Research Institute, Technical Assessment Guide, August 1977.

6. Garver, L.L., "Effective Load Carrying Capability of Generating Units," IEEE PAS-85, pp. 910-19, 1966.

7. General Electric Company, Wind Energy Mission Analysis, C00/2578-1/2, February 17, 1977.

8. General Electric Company, Requirements Assessment of Photovoltaic Power in Electric Utility Systems, EPRI RP 651-1, Summary Report, February 1978.

9. Henessey, J.P., "Some Aspects of Wind Power Statistics," J. of Appl. Met., V. 16, pp. 119-28, February 1977.

10. Justus, C.G., W.R. Hargraves and Amir Mikhail, Reference Wind Speed Distributions and Height Profiles for Wind Turbine Design and Performance Evaluation Applications, Georgia Tech., ORO/5108-76/4, August 1976.

11. Justus, C.G. and W.R. Hargraves, Wind Energy Statistics for Large Array of Wind Turbines (Great Lakes and Pacific Coast Regions), Georgia Tech., RLO/2439-77/2, May 1977.

12. Justus, C.G., personal communication, 1978.

13. Kahn, E., Testimony before New Jersey PUC, Construction Docket 762-194, filed June 1977.

14. Kahn, E., An Assessment of the Potential for Full Coordination of the California Electric Utilities, LBL-5941, January 1977.

15. Molly, J.P., "Balancing Power Supply from Wind Energy Converting Systems," Wind Engineering, Vol. 1, pp. 57-66, 1977.

16. Morse, David E., Technical Documentation of Staff Procedures for Establishing Peak Demand, ERCDC, October 1976.

17. Pacific Gas and Electric Company, Fossil 1 and 2 NOI, December 1977.

18. Ryan, Bill C., "A Mathematical Model for Diagnosis and Prediction of Surface Winds in Mountainous Terrain," J. of Apply. Met., V. 16, pp. 571-84, June 1977.

19. Sathaye, J. et al., Potential Electricity Impacts of a 1978 California Drought, LBL-6871, January 1978.

20. Sheehy, Kevin, Legal and Institutional Factors Affecting the Implementation of Power Pooling Within California, CERCDC, 1978.

21. Stanford Research Institute International, A Comparative Evaluation of Solar Alternatives: Implications for Federal RD&D, Vol. 1, Menlo Park, CA, January 1978.

22. Sullivan, Robert, Power System Planning, New York: McGraw Hill Company, 1977.

APPENDIX 1

MONTHLY AVERAGE SPATIAL CROSS CORRELATIONS OF WIND SPEED

January

	BFL	SAC	SFO	SCK	SMX	RBL
BFL		.182	.180	.153	.137	.109
SAC			.499	.608	.306	.465
SFO				.472	.247	.359
SCK					.307	.388
SMX						.239
RBL						
SDB	.190	.243	.229	.188	.231	.183

February

	SDB	SAC	SFO	SCK	SMX	RBL
BFL	.110	.193	.204	.280	.319	.141
SAC	.257		.421	.581	.339	.458
SFO	.233			.479	.425	.312
SCK	.263				.414	.343
SMX	.093					.200
RBL	.169					
SDB						

March

BFL		.266	.272	.282	.260	.137
SAC			.377	.586	.409	.398
SFO				.470	.388	.267
SCK					.480	.254
SMX						.213
RBL						
SDG	.172	.143	.102	.212	.122	.117

April

BFL	.115	.171	.286	.244	.355	.152
SAC	.120		.263	.591	.257	.431
SFO	.177			.434	.475	.159
SCK	.203				.406	.397
SMX						.156
RBL	.136					
SDG						

APPENDIX 1
(continued)

	May						June					
	BFL	SAC	SFO	SCK	SMX	RBL	SDB	SAC	SFO	SCK	SMX	RBL
BFL		.325	.328	.393		.245	.091	.369	.381	.381		.235
SAC			.374	.578		.263	.068		.326	.538		.317
SFO				.493		.173	.087			.434		.151
SCK						.306	.088					.303
SMX												
RBL							.151					
SDB	.118	.012	.117	.126		.097						

	July						August					
BFL		.409	.414	.403		.321	.175	.288	.382	.339		.328
SAC			.321	.517		.329			.277	.456		.254
SFO				.468		.208				.417		.253
SCK						.313						.283
SMX												
RBL												
SDB	.158	.016	.161	.062		.045		.003	.221	.092		.088

APPENDIX 1
(continued)

September

	BFL	SAC	SFO	SCK	SMX	RBL
BFL		.244	.325	.316		.237
SAC			.228	.485		.235
SFO				.378		.062
SCK						.185
SMX						
RBL						
SDB	.108	.068	.081	.083		

October

	SDB	SAC	SFO	SCK	SMX	RBL
BFL	.165	.207	.293	.269		.126
SAC	.300		.333	.624		.372
SFO	.174			.405		.211
SCK	.294					.383
SMX						
RBL	.231					
SDB						

November

BFL		.230	.285	.263	.228	.124
SAC			.373	.587	.263	.440
SFO				.438	.289	.249
SCK					.282	.366
SMX						.138
RBL						
SDB	.154	.177	.162	206	.154	.106

December

BFL	.155	.256	.272	.250	.207	.184
SAC	.132		.461	.596	.335	.494
SFO	.151			.490	.283	.350
SCK	.160				.324	.376
SMX	.238					.202
RBL	.092					
SDB						

APPENDIX 2
GENERATOR MODELS FOR WIND ARRAYS

With the introduction of large generators into power systems, there has been increasing interest in modelling the performance of such units by more sophisticated methods than the two-state, "on-off" models. It has been found that generator representations which use the weighted average or equivalent forced outage rate produce results which understate reliability.[1,13] Therefore multi-state models have been found more preferable. These results have significance for modelling wind arrays because such configurations tend to act like large generators. Their output characteristics are even more "spread out" than the big thermal units; i.e., they operate at partial capacity most of the time.

To evaluate the accuracy of the eight-state model displayed in Table 8, we ran some sensitivity cases. These were designed to test the significance of adding more states to the representation and to estimate the impact of using many states on the low output side. The two alternate representations are given in Table A.

Table A

Alternate Models of PG&E Array: Summer 4:00 p.m.

Eleven-State Model		Eight-State Model High Output Sensitivity	
State	Probability	State	Probability
0	.07	0	.16
100	.06	300	.11
300	.07	600	.14
500	.08	900	.16
700	.10	1200	.15
900	.11	1500	.09
1100	.11	1700	.07
1300	.09	1900	.15
1500	.09		
1700	.07		
1900	.15		

We present the results of the LOLP calculations in Table B for the base case (no wind array) and the three models of a 2000 MW array. The program used is a standard calculation based on the algorithm described in reference 22. The data on the base system is characterized in reference 19. The results confirm the thesis that the representation of the low output side is critical. Both the eight-state model from Table 8 and the eleven-state model agree well. The eight-state model which is sensitive to high output performance but aggregates on the low side is about 100 MW more conservative. This model does the kind of averaging which has been shown to have conservative bias. The difference between the two other models is insignificant. It is less than 10 percent in LOLP, which corresponds to about 5 MW.

Table B

LOLP Results

Load (GW)	Base Case (no wind)	Table 8	11-State	8-State High Side Sensitivity
14.00	2.38×10^{-3}	3.18×10^{-4}	3.36×10^{-4}	4.79×10^{-4}
14.10	3.65×10^{-3}	4.90×10^{-4}	5.19×10^{-4}	7.43×10^{-4}
14.20	5.75×10^{-3}	7.46×10^{-4}	8.12×10^{-4}	1.17×10^{-3}
14.30	8.99×10^{-3}	1.20×10^{-3}	1.27×10^{-3}	1.82×10^{-3}
14.40	1.36×10^{-2}	1.85×10^{-3}	1.96×10^{-3}	2.78×10^{-3}
14.50	1.98×10^{-2}	2.80×10^{-3}	2.94×10^{-3}	4.11×10^{-3}
14.60	2.71×10^{-2}	4.08×10^{-3}	4.23×10^{-3}	5.78×10^{-3}
14.70	3.54×10^{-2}	5.75×10^{-3}	5.88×10^{-3}	7.89×10^{-3}
14.80	4.66×10^{-2}	7.93×10^{-3}	8.06×10^{-3}	1.08×10^{-2}
14.90	6.38×10^{-2}	1.09×10^{-2}	1.11×10^{-2}	1.49×10^{-2}
15.00	8.94×10^{-2}	1.52×10^{-2}	1.56×10^{-2}	2.09×10^{-2}
15.10	1.24×10^{-1}	2.12×10^{-2}	2.17×10^{-2}	2.90×10^{-2}
15.20	1.67×10^{-1}	2.95×10^{-2}	2.98×10^{-2}	3.95×10^{-2}
15.30	2.13×10^{-1}	3.98×10^{-2}	3.98×10^{-2}	5.18×10^{-2}
15.40	2.56×10^{-1}	5.22×10^{-2}	5.14×10^{-2}	6.55×10^{-2}
15.50	2.96×10^{-1}	6.64×10^{-2}	6.45×10^{-2}	8.07×10^{-2}
15.60	3.41×10^{-1}	8.25×10^{-2}	7.98×10^{-2}	9.88×10^{-2}
15.70	4.03×10^{-1}	1.02×10^{-1}	9.84×10^{-2}	1.21×10^{-1}

APPENDIX 3
GARVER'S SLOPE-m TECHNIQUE: A LINEAR APPROXIMATION TO ELCC

A useful tool for evaluating ELCC where some simulation has already been done is the linear approximation to LOLP introduced in reference 6. This technique has achieved widespread acceptance in the power industry. We write down the equation, define the variables and apply it to some of our results. The main parameter to be estimated in this equation is the slope of the risk (LOLP) curve. Garver derives the following expression

$$\text{ELCC} = C - m \ln[(1 - r) + re^{c/m}] \quad ,$$

where c = nominal generator rating
m = characteristic slope of LOLP curve
r = generator forced outage rate .

To calculate m we look at a curve of LOLP vs. load and find the distance in MW between the risk criterion (1 day in 10 years) and e = 2.718 times that risk. Recalling that 1 day in 10 years has the interpretation of 8.5×10^{-3}, we can interpolate from Table B, Appendix 2 and find that m = 260 for the base PG&E system. Now we can use Garver's equation to calculate ELCC for an 800 MW unit on the PG&E system as a function of forecasted forced outage rate. In section 4.4 we considered three projected forced outage rates. Table C shows the ELCC corresponding to each.

Table C
ELCC for PG&E 800 MW Unit

FOR	ELCC
.12	475
.15	430
.197	380

Simulation of a hypothetical pool of all California generation resources yields a value of m = 400 MW at the same risk level (8.5×10^{-3}). We find that a 1000 MW unit in such a system with FOR = .15 will have ELCC = 606 MW.

It is difficult to apply Garver's equation to wind arrays because we would have to collapse the behavior to a single forced outage rate. Appendix 2 argues that this is likely to be biased conservatively. We can, however, use Garver's equation in a post-facto way to give conceptual insight into the performanceof arrays. By this I mean we can take the results of simulation and find values of c and r which fit those results. This will yield the thermal equivalent referred to in 4.4. An important further reason why the Garver equation cannot be used predictively is that the value of the parameter m changes with wind penetration. In Table D we give these changes in m for the PG&E system, repeat the data from Table 9 on ELCC and show the ELCC values calculated by fitting c and r to these results.

Table D

Two-State Linear Approximation to ELCC

Wind Turbine Capacity	2000 MW	4000 MW	5000 MW
ELCC (simulated)	530 MW	700 MW	740 MW
Slope-m value	310 MW	320 MW	340 MW
Equivalent Unit Size	800 MW	1600 MW	2000 MW
Estimated FOR	.10	.10	.10
Estimated ELCC	553 MW	718 MW	731 MW