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INCORPORATING UNCERTAINTY INTO PROBABILISTIC PERFORMANCE MODELS OF CONCENTRATING SOLAR POWER PLANTS

Clifford K. Ho and Gregory J. Kolb
Solar Technologies Department, Sandia National Laboratories
P.O. Box, 5800, Albuquerque, NM 87185-1127, USA
(505) 844-2384, ckho@sandia.gov

ABSTRACT

A method for applying probabilistic models to concentrating solar thermal power plants is described in this paper. Benefits of using probabilistic models include quantification of uncertainties inherent in the system and characterization of their impact on system performance and economics. Sensitivity studies using stepwise regression analysis can identify and rank the most important parameters and processes as a means to prioritize future research and activities. The probabilistic method begins with the identification of uncertain variables and the assignment of appropriate distributions for those variables. Those parameters are then sampled using a stratified method (Latin Hypercube Sampling) to ensure complete and representative sampling from each distribution. Existing models of performance, reliability, and cost are then simulated multiple times using the sampled set of parameters. The results yield a cumulative distribution function that can be used to quantify the probability of exceeding (or being less than) a particular value. Two examples, a simple cost model and a more detailed performance model of a hypothetical 100 MW_e power tower, are provided to illustrate the methods.

1. INTRODUCTION

Modeling the performance and economics of solar power plants based on technologies such as power towers and parabolic troughs has evolved over several decades. Yet nearly all of the modeling performed previously implement deterministic evaluations of the system or component performance. Input parameters are typically entered as specific values rather than distributions of values that honor the inherent uncertainty in many of the system features and processes. As a result, the confidence of the deterministic result and uncertainty associated with the results are unknown.

This paper presents a probabilistic method to yield uncertainty analyses that can quantify the impact of system uncertainties on the simulated performance metrics. The confidence and likelihood of the simulated metric (e.g., levelized energy cost) being above or below a particular value or within a given range can be readily assessed and presented using these probabilistic methods. In addition, sensitivity analyses can be used with probabilistic analyses to rank and quantify the most important components, features, and/or processes that impact the simulated performance. This information can be used to guide and prioritize future research and characterization activities that are truly important to the relevant performance metrics.

Probabilistic methods are used widely in many fields including risk assessments and waste management, and they are required by the Nuclear Regulatory Commission for performance assessments of nuclear waste repositories [1]. Becker and Klimas [2] implemented a probabilistic method for simulating a hypothetical 100 MW_e power tower using the levelized energy cost as a metric. This work extends the work of Becker and Klimas [2] and investigates additional examples and performance metrics (e.g., net annual energy production). Direct costs are also updated to reflect inflation factors from 1990 to 2008.

2. MODELING APPROACHES

Models and codes used to model solar thermal power plants can be grouped according to a total-system modeling pyramid, which describes a natural hierarchy for modeling complex systems (Figure 1). At the top, total-system models are used to evaluate overall performance metrics such as levelized energy cost or power output. These total-
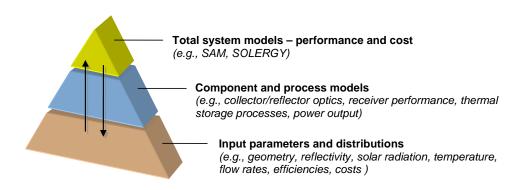
Figure 1. The total-system modeling pyramid.

system models rely on input from more detailed process models that provide information regarding the performance of individual components within the total system. The process models require input parameters and distributions (for uncertainty and sensitivity analyses) that are acquired through various means such as testing, literature, surveys, and/or professional judgment. This modeling pyramid is often used as the framework for modeling complex systems because it provides a logical flow and organization of the information and modeling activities.

In addition to passing information up from the detailed process models and parameters, the framework calls for information being passed down from the top to assist in prioritizing modeling and characterization efforts in areas that have been shown in the models to significantly impact the relevant cost and performance metrics.

2.1 Deterministic Modeling

Deterministic models use single (or central) value estimates for each input parameter. For each state or scenario of the physical system that is modeled, a unique set of input parameters and boundary conditions is applied. Therefore, deterministic models yield a single result for each scenario modeled, and the uncertainty associated with the result is not quantified. Sensitivity analyses can be performed parametrically by selectively varying input parameter values to determine the potential impact on the simulated metric. However, this process can be arduous with more than a few parameters, and sensitivities can be confounded by interactions among parameters that have dependencies on one another.

2.2 Probabilistic Modeling

In contrast to deterministic models, probabilistic models allow for a quantification of the uncertainty inherent in the input parameters and processes being modeled. Probabilistic models provide an estimate of confidence and reliability in the predicted results, along with more rigorous sensitivity analyses that identify the parameters and processes that are most important to the simulated metrics.

Screening analyses are first conducted to determine a subset of input parameters that are to be assigned

uncertainty distributions as opposed to deterministic point values. The uncertainty distributions (e.g., uniform, normal) can be based on actual data, literature values, professional judgment, etc. Monte Carlo or Latin Hypercube sampling methods are then implemented in the model to generate many different (but equally probable) realizations of the system performance. The ensemble of realizations generates a cumulative probability distribution that can be used to quantify the uncertainty in system performance.

It should be noted that the number of runs (or realizations) necessary for a random probabilistic (Monte Carlo) simulation, which is prone to sample clustering, increases as the number of uncertain input variables increases. Latin hypercube sampling (LHS) is a stratified sampling method that reduces the number of necessary realizations by ensuring that values are sampled from across the entire input distribution. LHS software has been developed at Sandia National Laboratories that implements this method and allows for correlations among input variables [3]. The minimum number of samples required to implement a restricted pairing among the sampled variables (either to correlate variables or to minimize correlation) is approximately $4k/3$, where k is the number of uncertain variables [4].

A stepwise regression analysis is then performed to determine the input parameters that are most correlated to the variability of the simulated performance metric, indicating those parameters or processes that are most important to the system performance. The sensitivity of the probabilistic model to uncertain input variables can be determined using regression analysis. Multiple regression analysis involves construction of a linear regression model of the simulated output (the dependent variable) and the stochastic input variables (independent variables) using a least-squares procedure. Stepwise linear (rank) regression is a modified version of multiple regression that selectively adds input parameters to the regression model in successive steps [5]. In this method, a sequence of regression models is constructed that successively adds the most important input parameters to the regression to improve the overall correlation. In the end, the sensitivity analysis identifies

those parameters that are significantly correlated to the performance metric, and omits those parameters that are not.

3. ANALYSIS AND DISCUSSION

3.1 Simple Cost Example

As an illustrative example, Figure 2 shows a plot of the levelized energy cost (LEC) for a hypothetical solar thermal power plant calculated using both probabilistic and deterministic methods. In both methods, the LEC was calculated using the simplified equation from Becker and Klimas [2]:

$$LEC = \frac{Annualized\ Capital\ Costs + Annual\ O\&M\ Costs}{(Annual\ Energy\ Generated)(Availability)} \quad (1)$$

In the probabilistic model, each of the four variables in Equation (1) was treated as an uncertain parameter (see Table 1). Each variable is represented by a distribution of values that can be based on data, literature, model results, and/or professional judgment. In this example, a hypothetical uniform distribution was used for each input parameter based loosely on values reported in Becker and Klimas [2]. Equation (1) was calculated 300 times (300 realizations) using randomly sampled values from the distribution of input parameters to yield a distribution of equally probable LEC values. The distribution of calculated LEC values ranged from approximately \$0.08/kWh to \$0.16/kWh.

Figure 2 shows these results as a cumulative distribution function (CDF), or cumulative probability. This plot can be used to predict the probability of the LEC being less (or more) than a particular value, or between two values. For example, in this hypothetical example, there is approximately a 95% probability that the LEC will be less than ~\$0.14/kWhe and a 5% probability that the LEC will be greater than ~\$0.14/kWhe. There is approximately a 0.9 – 0.2 = 0.7 (70%) probability that the LEC will be between \$0.10/kWhe and \$0.14/kWhe.

Table 1. Uncertainty parameter distributions for simple cost example.

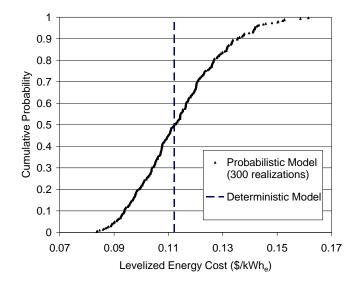| Parameter	Distribution (30 year life)
Capital Costs ($M)	Uniform 28.4 – 37.3
O&M Costs ($M)	Uniform 3.6 – 5.4
Annual Energy (kWh)	Uniform 2.96E+08 – 4.44E+08
Availability	Uniform 0.85 – 0.95

Figure 2. Cumulative distribution function of LEC for simple cost example.

The deterministic model, using average or "central" values for the uncertain input parameters, predicts an LEC of just over \$0.11/kWhe, which happens to be the median (50th percentile) of the probabilistic model. This single value does not provide any indication of the amount of uncertainty in the output (e.g., that there is a 50% probability that the LEC will be greater than \$0.11/kWhe in this hypothetical example). Also, the deterministic LEC value may shift left or right in Figure 2 depending on the nature of the distributions used for the input parameters (e.g., uniform, normal, log-normal). For example, if most of the input distributions were log-normally distributed, the deterministic LEC value may fall in the 20th to 30th percentile instead of the 50th percentile.

Figure 3 shows the results of a stepwise linear regression sensitivity analysis using the 300 hypothetical realizations shown in Figure 2. The vertical axis is represented by ΔR^2, the change in the coefficient of determination when a new independent variable is added to the model. The value of ΔR^2 describes the percentage of the uncertainty or variability in the simulated LEC (or other simulated metric) that is caused by the uncertainty in each input variable. The cumulative ΔR^2 for this example is 0.98, which indicates a good overall correlation using the multiple rank regression model.

The sensitivity analysis shows that the simulated LEC is most sensitive to the annual energy produced (over 70% of the uncertainty in simulated LEC can be explained by the uncertainty in annual energy produced), followed by the annualized capital costs. The availability and annual O&M costs are much less important in this hypothetical example. Therefore, further characterization and research efforts could be focused on those components and processes that affect the annual energy produced and capital costs, which are shown to have the most impact on simulated LEC in this hypothetical example.
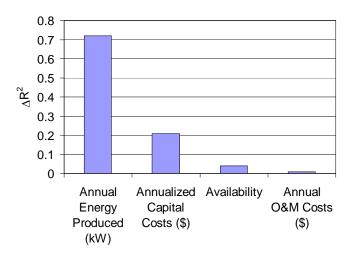
Figure 3. Sensitivity analysis showing relative importance of uncertain input parameters on simulated LEC for simple cost example.

In addition to ΔR^2, the standardized regression coefficient (β) is another statistical measure that evaluates the relative contributions of each input parameter to the magnitude of the dependent variable (as opposed to the variability of the dependent variable). The sign of β also gives the direction of correlation. The importance ranking of the independent variables using either ΔR^2 or β are typically the same.

In an actual uncertainty and sensitivity analysis, the uncertainty of detailed lower level components and processes (e.g., collector performance, flow rates, heat loss, storage, turbine output, etc.) should be included in the model. In this hypothetical example, the uncertainties of the detailed components and processes are rolled into one of the four high-level parameters defined in Equation (1). For example, all of the uncertainties associated with detailed performance modeling are rolled into the "Annual Energy Produced," and all of the uncertainties associated with component reliability are rolled into the "Availability." Another example with more detailed consideration of these subcomponents and processes is provided in the next section.

3.2 Hypothetical 100 MW$_e$ Power Tower

A hypothetical 100 MW$_e$ molten-salt central receiver power-tower system with thermal storage (Figure 4) was simulated using a power-tower performance code (SOLERGY), a reliability model, and a simple cost model. The models assumed a plant life of 30 years, a storage capacity of 7 hours, and used the 1977 weather data for Barstow, CA, which yielded a direct normal insolation of 2.7 MWh/m^2/yr. Other deterministic parameters used in the models were taken from [2].

After an initial screening, a total of 33 parameters were assigned uncertainty distributions to represent the inherent uncertainty in values associated with costs, the heliostat field, receiver, storage, and power-block components. The uncertain input parameters are summarized in the Appendix

(Table 2, Table 3, and Table 4; 32 parameters are defined in the tables, and the 33rd (O&M costs) is defined in Section 3.2.1). The following sections provide a brief overview of the models and uncertainties implemented in the analysis.
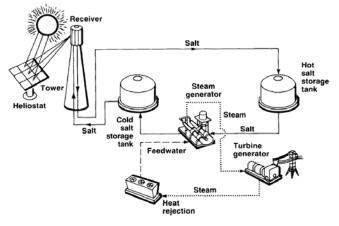

Figure 4. Schematic of hypothetical molten-salt central receiver system with thermal storage (from Falcone [6]).

3.2.1 Cost Model

The cost model that was used is the same as in Eq. (1), but additional parameters were used to account for indirect charges and financing. The following equation was used to calculate the annualized capital costs used in Eq. (1):

Annualized capital costs =
$$FCR*DC*(1+INDC)*(1+AFUDC) \qquad (2)$$

where   FCR = constant-dollar fixed charge rate = 7.4%
(derived from [7])
DC = total direct costs
INDC = indirect charges = 17% (from [2])
AFUDC = allowed funds during construction to cover interest charges = 6.57% (from [2])

Uncertain cost parameters used in the model are summarized in Table 2 in the Appendix. It should be noted that the direct costs reported in [2] were multiplied by an inflation cost index to reflect increases in direct costs from 1990 to 2008. The annual operating and maintenance (O&M) costs were assumed to be a percentage (uniformly distributed between 2-3%) of the direct costs.

3.2.2 SOLERGY Model

SOLERGY [8] simulates the annual energy output of a solar thermal power plant and has been validated using data from Solar One [9]. It utilizes actual or simulated weather data at time intervals of 15 minutes and calculates the net electrical energy output at every time step throughout an entire year. Input to the code is entered via user-specified text files.

Factors include energy losses in each component of the system, delays incurred during start-up, weather conditions,

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storage strategies, and power limitations for each component. Table 3 summarizes the uncertainty distributions used in SOLERGY for this analysis. The deterministic value of the total annual energy output (348,018 MWh) was calculated using the central values in Table 3.

3.2.3 Reliability Model

The reliability model assumes that all of the components act in series (if one component goes down, the entire system goes down). The following equation is used to calculate the overall availability, A, of the system with n components based on the mean time between failure ($MTBF$) and mean down time (MDT) of each component, i:

$$A = \prod_{i=1}^{n} \frac{MTBF_i}{\left(MTBF_i + MDT_i\right)} \tag{3}$$

Table 4 in the Appendix summarizes the uncertainty distributions used in the reliability model. The deterministic value for the total availability (0.905) was calculated using the central values listed in Table 4 and Table 5.

3.2.4 Results

A total of 64 realizations were implemented using Latin Hypercube Sampling of the uncertain parameters defined in Table 2, Table 3, and Table 4 in the Appendix. The 33 parameters were assumed to be independent, and the sample pairings were restricted to minimize the correlations within the LHS model. The number of realizations was sufficient to implement the restricted pairings in LHS ($64 > 4k/3$) and to produce reasonable distributions (between the 5th and 95th percentiles) for this illustrative example.

SOLERGY was run 64 times using the sampled sets of input parameters. The availability model defined by Eq. (3) was also run 64 times using the 64 sets of parameters sampled from the parameters in Table 4. Finally, the cost model defined by Eqs. (1) and (2) was run 64 times using the results from SOLERGY, the availability model, and the cost parameters listed in Table 2.

Figure 5 shows the cumulative probability for the simulated annual SOLERGY net energy output, which ranges from 328 – 370 GWh. The deterministic result (348 GWh) is also shown in the plot and corresponds to a cumulative probability of 0.6. This indicates that there is a 60% probability that the actual net energy output will be less than the deterministic value of 348 GWh in this hypothetical power-tower simulation. It is interesting to note that although the uncertain parameters used in SOLERGY were all uniformly distributed, the deterministic result is not at the 50% percentile of the cumulative probability (it is at 60%). This is due to the nonlinear models and responses in SOLERGY.

Figure 6 shows the results of a stepwise linear regression analysis of the SOLERGY results. The uncertain input parameters were used as the independent variables,

and the SOLERGY net energy output was used as the dependent variable. Results show that all six of the parameters chosen to be represented by uncertainty distributions were statistically significant, but the parasitics, receiver heat loss, heliostat cleanliness, and receiver absorption were most important. Uncertainty in the heliostat availability and receiver start-up time were less important. The cumulative ΔR^2 was 0.96 for the multiple rank regression of simulated net energy output.
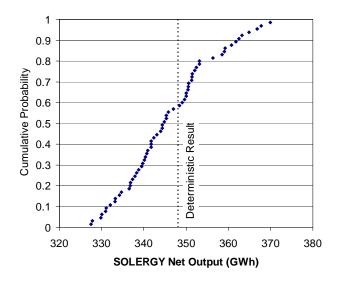

Figure 5. Cumulative probability for annual SOLERGY net energy output.

Figure 7 shows the cumulative probability for the LEC using the SOLERGY, reliability, and cost models. The simulated LEC ranges from approximately $0.11/kWh to $0.15/kWh for the uncertainty distributions used in the models. The deterministic result of just over $0.12/kWh has a cumulative probability of 0.45. Therefore, there is a 45% probability that the LEC will be less than the deterministic value (between ~$0.10/kWh and $0.123/kWh) and a 55% probability that the LEC will be greater than the deterministic value (between $0.123/kWh and ~$0.15/kWh) in this simulation.

Figure 8 shows the sensitivity study using a stepwise linear regression analysis of the LEC simulation. All of the uncertain input parameters used in the SOLERGY, reliability, and cost models were used as the independent variables, and the simulated LEC was used as the dependent variable. The cumulative ΔR^2 was 0.97 for the multiple rank regression of simulated LEC.

The sensitivity analysis shows that the simulated LEC is most sensitive to the heliostat (collector) costs (nearly 60% of the simulated LEC variability is explained by the variability in heliostat costs), followed by the O&M costs. Specific processes associated with the performance of the system were also found to be important to the LEC, including reliability of the components, parasitics, receiver absorption, and heliostat performance. Therefore, to reduce

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costs, further characterization and research efforts could be focused on these components and processes, which were shown to have the most impact on simulated LEC in this analysis of a hypothetical 100 MW_e power tower. It should be noted that additional uncertainties pertaining to weather, the power cycle, and other processes that were not included in this example may also significantly impact the simulated performance and cost metrics. In addition, the distributions used in the analysis of this power-tower example were different than those used in the simple cost example (Section 3.1), so results are not directly comparable.
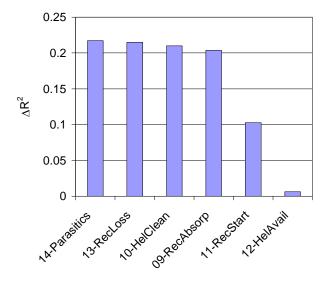

Figure 6. Sensitivity analysis using SOLERGY net energy output as the metric and the uncertain parameters in Table 3 as inputs.
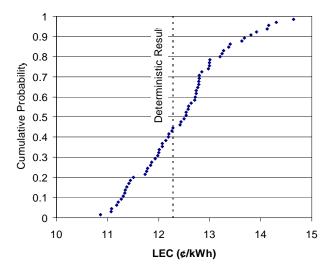

Figure 7. Cumulative probability for levelized energy cost using SOLERGY, reliability, and cost models.

4. CONCLUSIONS AND FUTURE WORK

This paper described a probabilistic approach for modeling solar thermal power plants. Two examples were provided utilizing a simple cost model and a more detailed performance model. The following summarizes the major points and conclusions, as well as future directions:

- Probabilistic modeling can provide a rigorous quantification of uncertainty in simulated performance and economics of solar thermal power plants. The probability that a simulated metric (e.g., LEC, net energy output) will be greater than and/or less than a particular value can be readily assessed.

- Stepwise multiple regression models provide sensitivity analyses that identify the most important parameters that impact system performance and economics. This information can be used to identify and prioritize research to better characterize and improve system components and processes that most impact the performance and cost.

- Incorporation of these probabilistic methods into total-system models such as SAM [10] and SOLERGY [8] will provide additional reliability and confidence in the results through quantification of the inherent uncertainties and their impact on the system.
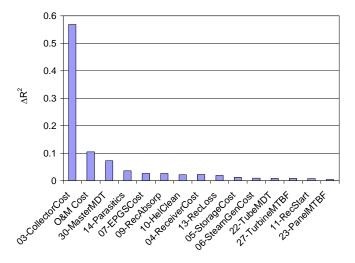

Figure 8. Sensitivity analysis using LEC as the metric and all 33 parameters as inputs.

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APPENDIX: UNCERTAIN PARAMETER DISTRIBUTIONS FOR HYPOTHETICAL 100 MW$_E$ POWER TOWER

The following tables of uncertain parameter distributions are taken from Becker and Klimas [2].

Table 2. Uncertainty distributions for cost parameters [2].

No.	Parameter[1]	Central Value[2] ($M)	Distribution	Rationale
1	Land	1.4	Uniform ±15% about the central value	Central value was a consensus guideline and was based on the utility study. The uncertainty is based on the cost of land varying by $0.03/m^2. Utility Study variation was -10 to +30%.
2	Structures & Improvements	3.7	Uniform ±15% about the central value	Central value was a consensus guideline and was based on the utility study. The lower bound is based on the consensus discussion and the costs estimated from PHOEBUS.[3]

No.	Parameter[1]	Central Value[2] ($M)	Distribution	Rationale
3	Collector System	92.2	Uniform ±18% about the central value	Central value and range based on discussion in Section 6.3.1 of [2]. Estimates are based on SAIC and SKI analysis and include film replacement.
4	Receiver System	25.6	Uniform ±18% about the central value	Central value is based on a semi-detailed costing of the individual components in the receiver, tower, and heat transport system. The costing is on the same level as the utility study estimates (without the detailed design). Bounds are based on stacking the bounds from each of the individual systems. Receiver cost is $13.2 M (includes contingency), tower cost is 6.3, and heat transfer system cost is 6.1 (both include contingency). Uncertainties on the receiver, tower, and H.T. systems are 20, 15, and 20% respectively. The upper bound for each system was based on the utility study receiver system (escalated, with competitive bids, downsized for this plant). The lower bound is assumed to be symmetric to the upper bound.
5	Thermal Storage System	23.9	Uniform ±14% about the central value	Central estimate is based on an average of the CBI and PDM costs used in the utility studies. The salt cost is an average of the utility study cost and natural salts from Chile. All the costs are escalated for inflation. The lower bound is based on the utility study CBI costs with the low cost (Chile) salt and the upper bound is based on the PDM costs with the utility salt.
6	Steam Gen. System	10.6	Uniform ±23% about the central value	Central value is based on an average of the B&W design from the utility study and a scaled-up CE Lummus. Both costs are escalated. The upper and lower bounds are based on B&W and CE Lummus, respectively.
7	EPGS - Electric Power Generating System	42.0	Uniform ±14% about the central value	Central is based on the average of a cost estimate from LUZ (obtained from CEC) scaled-up to 100-MW$_e$ and an estimate from H. Fricker (derived at the 3/90 meeting and based on ABB data). The upper and lower bounds are based on the Fricker and LUZ estimates, respectively.
8	Master Control System	2.7	Uniform ±10% about the central value	Central estimate is based on a consensus from the 4/90 meeting. The consensus was based on cost of the control system for the 30-MW$_e$ plant, which Interatom (for PHOEBUS[3]) has costed to be $2 M and Sandia had costed to be $1.8 M. We agreed on a $2.0 M. The 100-MW$_e$ cost is scaled-up using the 0.3 factor. The uncertainty bound is based on the utility study estimate.

[1]O&M Costs are uniformly distributed between 2 – 3% of the total capital costs.
[2]In this study, the sampled capital costs are multiplied by 1.63, the consumer price index inflation factor from 1990 to 2008 (http://data.bls.gov/cgi-bin/cpicalc.pl). The values in this table are the 1990 values.
[3]PHOEBUS was an industrial consortium in the 1990's that investigated commercialization opportunities for solar-thermal power-plant technologies.

Table 3. Uncertainty distributions for SOLERGY parameters [2].

No.	Parameter	Central Value	Distribution	Rationale
9	Receiver Absorptance	0.93	Uniform .91-.95	Upper bound was measured at Solar One during its final 3 years [11]. Lower bound is plausible because salt receiver has higher flux level and Themis had problems maintaining Pyromark on 316 SS [12].
10	Heliostat Cleanliness	0.95	Uniform .93-.97	Central value provided by LUZ for their mirror assemblies. Upper bound may be achievable with more frequent washes than employed by LUZ. Lower bound assumed symmetric to upper bound.
11	Receiver Start Time	0.75 hr	Uniform ±33%	Central value based on data from salt receivers tested at Sandia [13]. It is feasible that a more aggressive startup procedure and an optimized heliostat field could shorten startup by .25 hr. Temperature ramp rate limits, however, may lengthen startup by approximately the same amount.
12	Heliostat Availability	0.99	Uniform	Central value and range based on Solar One data [11]

					.985-.995	and projections of plant personnel during the final 3 years of operation.
13	Receiver Thermal Losses	26.2 MW			Uniform ±24%	Uncertainty in radiation estimates were estimated to be +/- 20% on the Sandia salt receiver analysis and tests [14]. Convective correlations are estimated to be +/- 35% [15]. Stacking radiation and convection bounds given a 75/25 split between radiation and convection losses yields +/- 24%.
14	Parasitic Multiplier	1			Uniform ±20%	Since SOLERGY parasitic power models were based on generic information, it was judged they could be in error by +/- 20%.

Table 4. Uncertainty distributions for reliability parameters [2].

No.	Parameter[1]	Central Value (hrs)	Distribution	Number of Units	Rationale
15	Hot and Cold Salt Pumps MTBF	2800	Uniform ±60%	4 (2 hot, 2 cold)	Central estimate from pump and valve loop data [16]. Lower bound based on Themis salt pump data (-60%) [17] and Solar One receiver pump [18]. This value is similar to 90% confidence level for hot pump from pump and valve loop. Upper bound assumed to be symmetric to lower bound (+60%).
16	Hot and Cold Salt Pumps MDT[2]	6.5	Uniform ±70%	4 (2 hot, 2 cold)	Central value based on judgments from Sandia pump and valve loop personnel. Lower bound based on mean value for Solar One receiver pump (-70%) [18]. Upper bound assumed to be symmetric to lower bound (+70%).
17	Flow Control Valve MTBF	3460	Uniform ±20%	4 pumps 5 others	Bounds are the 10% and 90% confidence levels from FCV data at Solar One (31 failures in 104,000 valve hours) [18]. Limited FCV failure data from Sandia pump and valve loop is consistent with Solar One data.
18	Flow Control Valve MDT[2]	2.9	Discrete probability distribution	4 pumps 5 others	Discrete probability distribution based on repair of 31 valves at Solar One [18]. Repair times for salt valves are expected to be similar. Discrete probability distribution: 0.5hr/29%, 1.5hr/19.4%, 2.5hr/16%, 3.5hr/13%, 4.5hr/3.2%, 6.5hr/6.5%, 7.5hr/6.5%, 8.5hr/6.5%.
19	Heliostat Array Control MTBF	1284	Uniform ±82%	1	Lower bound based on data from Solar One [18]. Solar One believed to be pessimistic because redundancy was compromised due to identified problems. Upper bound is based on Solar One data as well, but assumes most of Solar One's problems are corrected and redundant backup occurs 90% of the time (typical value).
20	Heliostat Array Control MDT	3.3	Discrete probability distribution	1	Discrete probability distribution based on repair of 25 HAC failures at Solar One [18]. Discrete probability distribution: 1hr/36%, 3hr/32%, 5hr/24%, 9hr/4%, 13hr/4%.
21	Receiver Tube Leak MTBF	4166	Uniform ±50%	1	Central estimate based on 3000 hours of leak-free operation at Themis [17]. Central value is the 50% confidence. Bounds based on judgment with lower bound representing possible age effects.
22	Receiver Tube Leak MDT	14	Discrete probability distribution	1	Discrete probability distribution based on 10 severe tube leaks repaired during unscheduled outages at Solar One [18]. Repair time for salt tubes expected to be similar. Discrete probability distribution: 0hr/40%, 0.7hr/10%, 3hr/10%, 8hr/20%, 13hr/10%, 108hr/10%.
23	Warped Receiver Panel MTBF	10,000	Uniform ±80%	1	Bounds are the 10% and 90% confidence levels from panel warp data at Solar One [18] (1 failure in 10,000 receiver hours). Due to differences in design of water/steam and salt panels, these values are believed to be conservative for a salt plant.
24	Warped Receiver Panel MDT	46	Uniform ±80%	1	Range based on judgment. Depending on the design of receiver panels and attachments it may take 1-2 days to replace the panel (lower bound) or close to two weeks (upper bound).
25	Steam Generator System	9500	Uniform ±90%	1	Central value based on 3 years of no forced outages at SEGS IV [19] (50% confidence of 0 failures in 7000 hrs). Lower bound based on heat recovery steam generator data [20] and may be

No.	Parameter[1]	Central Value (hrs)	Distribution	Number of Units	Rationale
	MTBF				indicative of thermal cycling problems that occur several years after plant startup. SEGS III-VII have had 10 years with no forced outages. Upper bound assumes SEGS III-VII data can be combined with thermal cycling problems.
26	Steam Generator System MDT	14	Discrete probability distribution	1	Assumed to be the same as the repair time for receiver tube leaks. Since both are tubular heat exchangers, this appears plausible.
27	Turbine Generator System MTBF	319	Uniform ±41%	1	Central value is the mean value for -100-MW turbines reported in the NERC data base that see cyclic service [20]. Lower bound is mean of Solar One turbine data (-41%). Upper bound assumed to be symmetric to lower bound (+41%).
28	Turbine Generator System MDT	3.3	Uniform ±33%	1	Central value is the mean value for 100-MW turbines reported in the NERC data base that see cyclic service [20]. Lower bound is mean of Solar One turbine data (-33%). Upper bound assumed to be symmetric to lower bound (+33%).
29	Master Control System MTBF	165	Uniform ±19%	1	Bounds are the 10% and 90% confidence levels from distributed control system data at Solar One [18] (35 failures in 5774 control system hours).
30	Master Control System MDT	2.7	Discrete probability distribution	1	Discrete probability distribution based on repair of 35 distributed process control system failures at Solar One [18]. Discrete probability distribution: 0.6hr/48.5%, 1.8hr/14.3%, 3.0hr/11.4%, 4.2hr/2.9%, 5.4hr/2.9%, 6.6hr/5.7%, 7.8hr/11.4%, 11.4hr/2.9%.
31	Electric Grid System MTBF	962	Uniform ±45%	1	Bounds are the 10% and 90% confidence levels from on site and offsite electric grid failures at Solar One [18] (failures in 5774 grid hours).
32	Electric Grid System MDT	2.7	Uniform ±93%	1	Bounds based on 6 grid failures repaired during unscheduled outages at Solar One [18]. Due to limited data the upper and lower bounds of these 6 failures were used rather than a discrete probability distribution.

[1]MTBF = Mean time between failure, MDT = Mean down time.
[2]In this study, the sampled mean down time for the pumps and pump valves was divided by two because the mean down time was assumed to be the cumulative down time for two pump trains.

Table 5. Fixed reliability parameters.

Parameter	Mean Time Between Failure (hrs)	Mean Down Time (hrs)	Number of Units
Heat Trace	35,600	6.5	32
Drain/Vent Valves	138,580	5.2	20
Air Binding	1,923	1.5	1
Control Gain Adjust	6,494	1.7	1
Flow Transmitter	6,666	3.5	2
Temperature Transmitter	62,500	2.3	2
Pressure Transmitter	10,000	3.4	2
Scheduled Outages	8,424	336	1