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Methods for probabilistic modeling of concentrating solar power plants

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Abstract

Probabilistic modeling of concentrating solar power technologies provides important information regarding uncertainties and sensitivities not available from deterministic models. Benefits of using probabilistic models include quantification of uncertainties inherent in the system and characterization of their impact on system performance and economics. This paper presents the tools necessary to conduct probabilistic modeling of concentrating solar technologies. 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. Models of performance, reliability, and/or cost are then simulated multiple times using the sampled set of parameters. The results yield a cumulative distribution function that can be analyzed to quantify the probability of achieving a particular metric (e.g., net energy output or levelized energy cost) and to rank the importance of the uncertain input parameters.

Keywords: Probabilistic modeling; Uncertainty; Sensitivity; Latin Hypercube Sampling; Concentrating solar

1. Introduction

Modeling system performance and economics of solar thermal power plants has traditionally relied on deterministic analyses. Input parameters are typically entered as specific (point) values rather than distributions of values that honor the inherent uncertainty in many of the system features and processes. As a result, the confidence and uncertainty associated with the results are unknown.

This paper introduces probabilistic tools 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., annual energy produced, 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 determine 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.

2. Modeling approach

The probabilistic modeling approach consists of three primary steps: (1) creating uncertainty distributions for stochastic parameters and sampling the distributions n times, (2) running the performance and/or cost models n times using the sampled variables, and (3) evaluating the distribution of n results to quantify uncertainty and sensitivity. Screening analyses are first conducted to determine a

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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, or professional judgment. 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. Latin Hypercube Sampling requires fewer realizations than Monte Carlo sampling, which is prone to clustering, and allows prescribed correlations among parameters. The ensemble of realizations generates a cumulative probability distribution that can be used to quantify the uncertainty in system performance. A stepwise regression analysis is then performed to determine the input parameters that are most correlated to the simulated performance metric, indicating those parameters or processes that are most important to the system performance. These types of analyses provide additional useful information not available in deterministic analyses (or even parametric analyses where only a few prescribed values are varied in a "one-off" fashion). Additional details of each of the three primary steps is provided in the next few sections.

2.1. Uncertainty distributions and sampling

Many parameters used in models of concentration solar power technologies are not known precisely because of a lack of measurement data, natural variability in the parameter value (e.g., mirror reflectivity), or changes in future behavior (e.g., insolation). To accommodate this inherent uncertainty, parameter distributions can be created to represent a range of values for each uncertain parameter. Latin Hypercube Sampling (LHS) is a way to sample these distributions in a systematic (stratified) way to ensure that values are sampled from across the entire distribution with the chosen number of realizations, n. Fig. 1 shows examples of how parameters with normal and uniform distributions would be stratified for $n = 5$ samples. The cumulative distribution function (CDF) shown on the right side of Fig. 1 is stratified into five equal bins along the y-axis, where the letters along the x-axis represent the values of the parameter. Because a normal distribution has a higher density of values near the mean, the bins are not distributed equally along the x-axis (i.e., a smaller range of values covers a greater range of probability near the mean). In contrast, a uniform distribution yields equally spaced bins throughout the parameter distribution.

A code has been written by Sandia National Laboratories to implement LHS (Wyss and Jorgensen, 1998). After sampling the uncertain variables n times, the code can also produce restricted pairings such that each set of parameters honors correlations (or zero correlations) among the sample variables. For example, the magnitude of the incident flux on the receiver may be inversely correlated to wind speed (wind shakes the collectors and lowers the optical intercept). These correlations can be specified in LHS, and the code will swap the order of the n parameters until the desired correlations exist among the sampled parameters. 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 total number of uncertain variables (Wyss and Jorgensen, 1998).

Typically, the number of samples (realizations) that are used to represent all possible input-parameter combina-

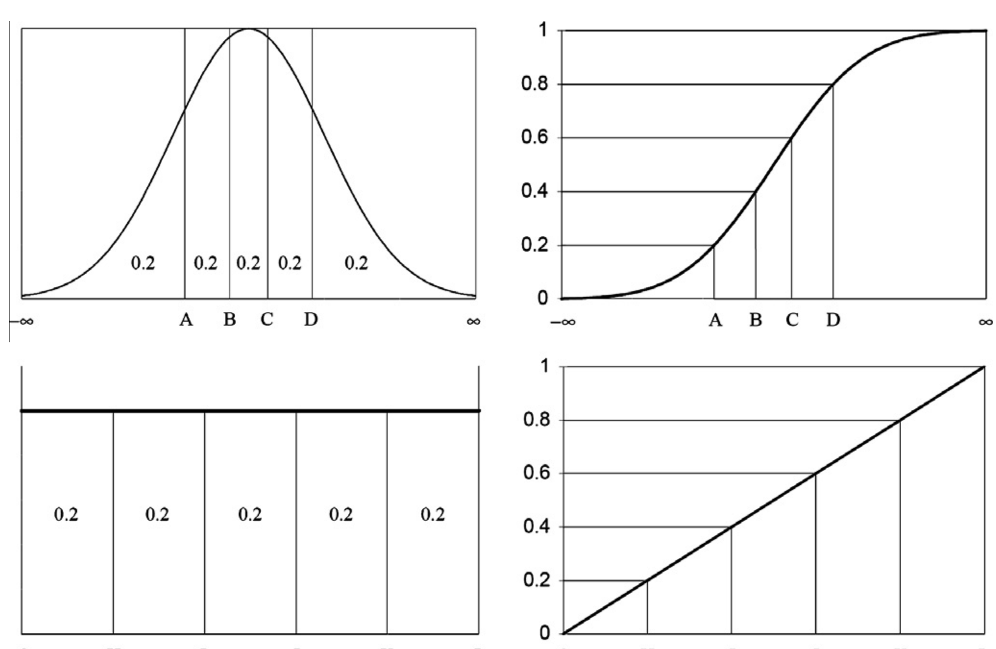

Fig. 1. Histograms (left) and CDFs (right) of parameters with a normal distribution (top) and uniform distribution (bottom) stratified into five equally probable bins (from Wyss and Jorgensen, 1998).