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STOCHASTIC MODELING OF POWER TOWERS AND EVALUATION OF TECHNICAL IMPROVEMENT OPPORTUNITIES

Nolan S. Finch[1] and Clifford K. Ho[2]

[1] Sandia National Laboratories, Concentrating Solar Technologies Department, P.O. Box 5800, Albuquerque, NM 87185-1127, USA, +1 (505) 284-5190, nsfinch@sandia.gov

[2] Ph.D., Sandia National Laboratories, Concentrating Solar Technologies Department

Abstract

In March 2010, the U.S. Department of Energy (DOE) hosted a power tower technology roadmap meeting attended by members of industry, laboratory, and government [1]. The meeting resulted in a list of technology improvement opportunities (TIOs) which were categorized within four power tower subsystems: solar collector field, solar receiver, thermal storage, and power block /balance of plant. Baseline values and future goals for each TIO were identified. The roadmap also included a performance model of a 100 MW_e (540 MW_t) central receiver power plant (molten salt) with thermal storage developed in the System Advisor Model (SAM). Assuming all TIOs and other assumptions described in [1] were successfully met, the model deterministically predicted the plant's levelized cost of energy (LCOE) would be less than 10¢/kWh H – down from the current-day baseline of nearly 16¢/kWh.

In this study, stochastic modeling results of the same central receiver power plant model are presented. Levelized cost of electricity (LCOE) was treated as a function of uncertain input parameters. The uncertain input parameters were the TIOs identified in the roadmap and were assigned uniform uncertainty distributions between current values and agreed upon goals. In addition to the TIOs outlined in the tower roadmap, investment tax credit (ITC) was treated as an uncertain input in the stochastic model. The stochastic performance model showed that the LCOE for a 100 MWe molten salt power tower with storage would have a 95% probability of falling between 9.5-17.6¢/kWh. Thermodynamic cycle efficiency, investment tax credit, and heliostat field cost had the largest impacts on this result.

1. Introduction

Interest in power towers has increased over the past several years for many reasons. Power towers offer high efficiencies which potentially translate into opportunities for low-cost electricity. In addition, power towers can readily integrate thermal energy storage (TES) to achieve high capacity factors which can enable cost-effective, dispatchable electricity to intermediate and baseload power markets [1].

With the aim of developing a plan to guide future research and development, the U.S. Department of Energy (DOE) and Sandia National Laboratories hosted a workshop that included participants from industry, DOE, and national laboratories. The workshop resulted in aggressive plant performance and cost targets that, if realized, would make electricity generated by power towers (sized on the order of 100MWe) cost competitive with newly constructed conventional fossil-fired power plants. Figure 1 (next page) illustrates the hypothetical molten-salt central receiver system (with storage) that is the focus of this study.

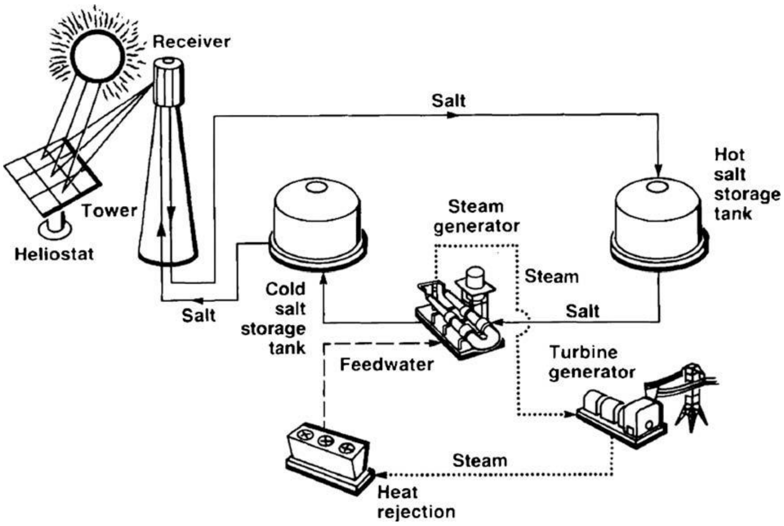

Figure 1. Illustration of a hypothetical molten-salt central receiver system which includes thermal storage (from Ho et. al., 2010)

To help organize the power tower research and development goals, the power tower plant was divided into four subsystems: solar collector field, solar receiver, thermal storage, and power block/balance of plant. Within each of the four subsystems, baseline cost and performance values were assessed for present-day towers to facilitate discussion on future goals. Once baselines were agreed upon, technology improvement opportunities (TIOs) were identified. Discussions between attendees assessed the basis for each TIO and set specific out-year targets and priorities for each which was then compiled in a multi-year research and development portfolio. Table 1 below shows current-day and projected price estimates for electrical power produced by a 100 MWe power tower plant. Projected price estimates reflect incremental performance enhancements and cost savings garnered from successful implementation of TIOs identified in the roadmap [1].

Table 1. Current and projected LCOEs detailed in the power tower roadmap

Real LCOE (¢/kWh)	2013, 30 % Investment Tax Credit	2013, 10 % Investment Tax Credit	2017, 10 % Investment Tax Credit	2020, 10 % Investment Tax Credit
	12.9	15.7	11.8	8.1

As mentioned above, TIOs were compiled for each of four power tower subsystems – starting with solar collector field. Solar collector field cost drivers are tied to heliostat size. For large heliostats, cost is dominated by four major items: drives, manufacturing, mirror modules, and mirror support structure/foundation. Cost for small heliostats, on the other hand, is dominated by drives, manufacturing, field wiring/controls, and mirror modules. Since there is no consensus among power tower developers on optimal heliostat size, the power tower roadmap identified TIOs that would benefit both small and large heliostat development. Table 2 (next page) shows the improvement opportunities identified for the solar collector field.

Solar receiver cost is driven by the tower and the receiver itself. TIOs identified for the solar receiver subsystem included developing high-temperature receiver materials that would allow integration with a higher-efficiency power block, developing solar selective absorbers and coatings, minimizing thermal losses by developing rigorous flux measurement techniques, and working to minimize the cost of tall towers (structural and permitting) as commercial power tower projects will need to employ towers taller than 100 meters. Compiled TIOs for the solar receiver subsystem can also be seen in Table 2.

Table 2. Technical Improvement Opportunities (TIOs) identified in the power tower roadmap [1]

	Technical Improvement Opportunity (TIO)	Generalized Performance Goal From Roadmap		Current Value	Goal Value
Solar Collector Field	Heliostat Drives	-10%	$/m^2	200	120
	Wind Load Measurement & Mitigation	-10%			
	Heliostat Manufacturing	-10%			
	Heliostat Structure Optimization	-10%			
	Anti-Soiling/Cleanliness of Mirrors	+2.5%	reflectivity	0.935	0.96
	Optical Methods and Testing	-20%	mrad optical error	1.53	1.25
Solar Receiver	High Temperature Receivers	+13%	efficiency	0.43	0.48
	Receiver Materials Testing & Database	-10%	$/kW$_t$	200	150
	Selective Absorbers	-50%	emissivity	0.88	0.44
	Flux Measurements	-20%	mrad optical error	1.53	1.25
Thermal Storage	Valves and Non-Welded Flanges	+4%	plant availability	0.90	0.94
	High Temperature Storage	-15%	$/kWH$_t$	30	20
	Single Tank Thermocline Storage	-15%			
Power Block & Balance of Plant	High-Efficiency Hybrid Configurations	-25%	$/kW$_e$	1000	800
	Supercritical Steam Cycles	+13%	efficiency	0.43	0.48
	Supercritical CO_2/Advanced Cycles	+13%			
	Parasitic Load Reduction	-25%	Gross/Net Annual Production	1.10	1.075
O&M	Cost Reduction Measures	-23%	$/kW-yr	65	50

The thermal storage subsystem cost is driven by salt media and tanks. TIOs identified for the thermal storage subsystem include improved salt valves/hardware, high-temperature storage for increased efficiency, high-temperature single tank storage to reduce tank costs, and high-temperature heat transfer fluids to enable higher-efficiency power cycles. Thermal storage TIO specifics can also be seen above in Table 2.

Power block/balance of plant TIOs revolved around integrating tower systems with advanced power cycles and minimizing parasitic losses. Advanced power cycles provide higher-efficiency operation but require high-temperature operation. This improvement need drove development goals in the other plant subsystems as well. In addition to increased cycle efficiency and minimal parasitic losses, dry cooling and natural gas hybridization were other development opportunities identified for this subsystem. Power block/balance of plant TIO specifics are also included in Table 2.

Operation and maintenance (O&M) goals were also addressed in the roadmap. Due to the limited number of power towers in operation in the world, limited O&M data for towers are available. Discussions with industry operators of tower plants and trough plants indicated operational/maintenance costs for each were very similar [1]. As such, O&M costs for existing tower and trough plants were analyzed to set a reasonable baseline with future goals set as seen in Table 2.

2. Modeling Approach

Table 1 above shows deterministic SAM modeling results from the roadmap for point design cases. The 2020 case represents a fully-successful implementation of all roadmap TIOs. As it is improbable to fully realize every one of these aggressive goals in the short term, it is important to understand, in a probabilistic sense, the affect each of these parameters has on LCOE. Understanding this end effect will not only help set realistic performance expectations but, moreover, can help focus research and development efforts.

To quantify the relationship between uncertain inputs and power tower LCOE, a probabilistic model, based on the deterministic models used in the roadmap, was created. TIOs delineated in the roadmap were mapped to appropriate SAM inputs and assigned uncertainty distributions. As mentioned above, the inputs were conservatively assigned uniform distributions centered between present day values and roadmap goals. Table 3 (next page) shows the SAM inputs and their distributions.

Table 3. The SAM embodiment of TIOs shown in Table 2. All inputs were assigned uniform uncertainty distributions between present day and future goal values.

SAM Input (TIO)		Present Day	Future Goal
Availability	(%)	90	94
Balance of Plant (BOP) Cost	(\$/kWe)	350	250
Cycle Efficiency	(%)	42.5	48
EPC and and Owner Cost	(%)	25	15
Fixed Costs by Capacity	(\$/kW-yr)	65	50
Image Error	(mrad)	1.53	1.25
Investment Tax Credit (ITC)	(%)	30	10
Mirror Reflectance and Soiling	(%)	89.3	92.6
Powerblock Cost	(\$/kWe)	1000	800
Receiver Emissivity	(%)	88	44
Receiver Cost Scaling Exponent	-	0.7	0.53
Solar Collector Field Cost	(\$/m^2)	200	120
Storage Cost	(\$/kWt)	30	20

Table 3 also includes investment tax credit as an uncertain input though it was not formally identified as an opportunity in the roadmap. It is included here to gain a better understanding of its overall affect on LCOE. Conversely, solar input is not included in Table 3. Previous studies [2] have already demonstrated the affect an uncertain solar input has on plant performance and, as such, solar input uncertainty is not included in this study.

Note that the inputs shown in Table 3 were the independent, uncorrelated inputs analyzed in the study. However, SAM required other inputs that depended on the independent inputs shown here. Such dependant inputs included initial salt temperatures (hot and cold), receiver fluid outlet temperature, thermal energy storage hours, solar multiple, power block inlet temperature, and power block design power rating. Since these dependant variables were not linearly independent of the SAM inputs included in Table 3, they were not included in the sensitivity/uncertainty analysis presented later in the paper.

Once inputs were identified and assigned uncertainty distributions, Latin Hypercube Sampling methodology was used to create input variable combinations. Latin Hypercube Sampling breaks each input distribution into equally probable regions and then pulls equal numbers of samples from each region [3]. Figure 2 below illustrates this concept for one random variable with a uniform probability density function – like the inputs presented in this study.

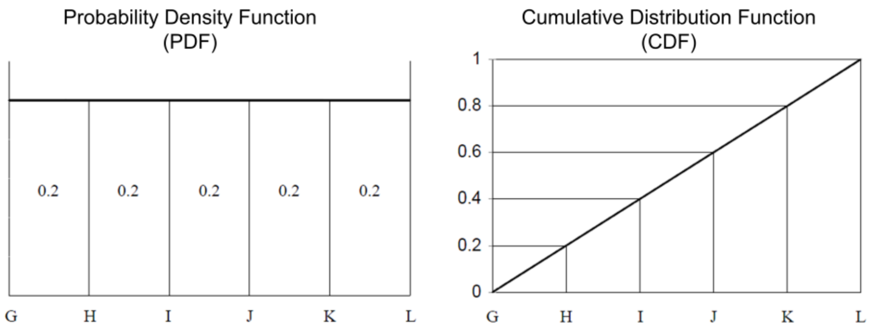

Figure 2. Equiprobable sampling regions for a uniformly distributed random variable: historgram (left) and cumulative distribtion function (right) (from Wyss and Jorgensen, 1998)

One sample pulled from one input variable distribution and combined with one sample from every other input variable distribution (and other calculated dependant inputs as mentioned above) resulted in one input deck. This input deck was then entered into SAM and subsequently processed to produce one output – an LCOE value. The combination of the input deck and output value is termed one model realization. Though SAM does have statistical capabilities that would allow a set of inputs sampled via Latin Hypercube to be batch processed, the particular study presented here required the heliostat field to be re-optimized for every input deck – a feature not included in the GUI version of SAM. As such, a SAM User Language script was written that read pre-sampled input decks from a file, optimized the heliostat field layout, simulated the plant, and then wrote the LCOE value for the input deck to another file.

The goal of stochastic modeling is to process uncertain input parameters through a representative model and create a sample output distribution which, in this case, is LCOE. However, it is important to show that sampled LCOE from the stochastic model closely matches its population distribution. To do this, increasing numbers of model realizations were processed until it could be shown with 95% confidence that the sample LCOE mean was within ± 1% of its population mean per the method described in [2]. In the study presented here, 1300 realizations provided 96.5% confidence that LCOE sample and population means were with ± 1% of each other.

Once all realizations had been processed, the LCOE output distribution was analyzed. Specifically, a CDF of LCOE was produced which allowed confidence intervals to be assessed. Moreover, the CDF allows one to appreciate the overall affect of input uncertainty on LCOE uncertainty.

After composite uncertainty was assessed, a sensitivity and uncertainty analysis was performed. To do this, a multiple regression model was formed to fit the full set of SAM data. Specifically, a linear model shown in (1) was used to fit modeled LCOE results to the inputs (x_i) sampled above.

$$(1) \qquad LCOE = b_0 + b_1 x_1 + b_2 x_2 + ... + b_n x_n$$

The non-standardized regression coefficients (b_i) shown in (1) were calculated by finding the least squares fit of the output LCOE data to the input samples. Calculating standardized regression coefficients (β_i) required a least-squares fit be applied to normalized inputs and outputs as seen in (2) and (3).

$$(2) \qquad LC\hat{O}E = \beta_0 + \beta_1 \hat{x}_1 + \beta_2 \hat{x}_2 + ... + \beta_n \hat{x}_n$$

$$(3) \qquad \text{Where:} \quad LC\hat{O}E = \frac{LCOE - mean(LCOE)}{\sigma_{LCOE}} \quad \text{and} \quad \hat{x}_i = \frac{x_i - \overline{x}_i}{\sigma_{x_i}}$$

The standardized regression coefficient (β) is a statistical measure that evaluates the relative contribution (on a normalized basis) of each input parameter to the magnitude of the dependant variable (LCOE in this case). The sign of each β also gives its direction of correlation with the output. In short, standardized regression coefficients quantify the sensitivity of the output with respect to each input.

In addition to sensitivity, it is also good to know how much each input affects the uncertainty of LCOE. The coefficient of determination (R^2) describes how well a model, like the one shown above, fits measured output data. Values for R^2 range from zero to one with one representing a “perfect” fit (though not necessarily perfect in a causal sense). In order to assess how much each input contributes to the overall output uncertainty, the change in coefficient of determination (ΔR^2) is calculated between the best fit model, which includes all of the input terms, and a series of models that incrementally drops one input at a time. The importance ranking of the input variables using either ΔR^2 or β is typically the same.

3. Results

The results of uncertain TIO inputs on LCOE can be seen below in Figure 3. While deterministic modeling results ranged from 8.1-15.7 ¢/kWh for point designs detailed in the tower roadmap, probabilistic results shown here indicate a 95% confidence level for LCOE of 9.5-17.6 ¢/kWh.

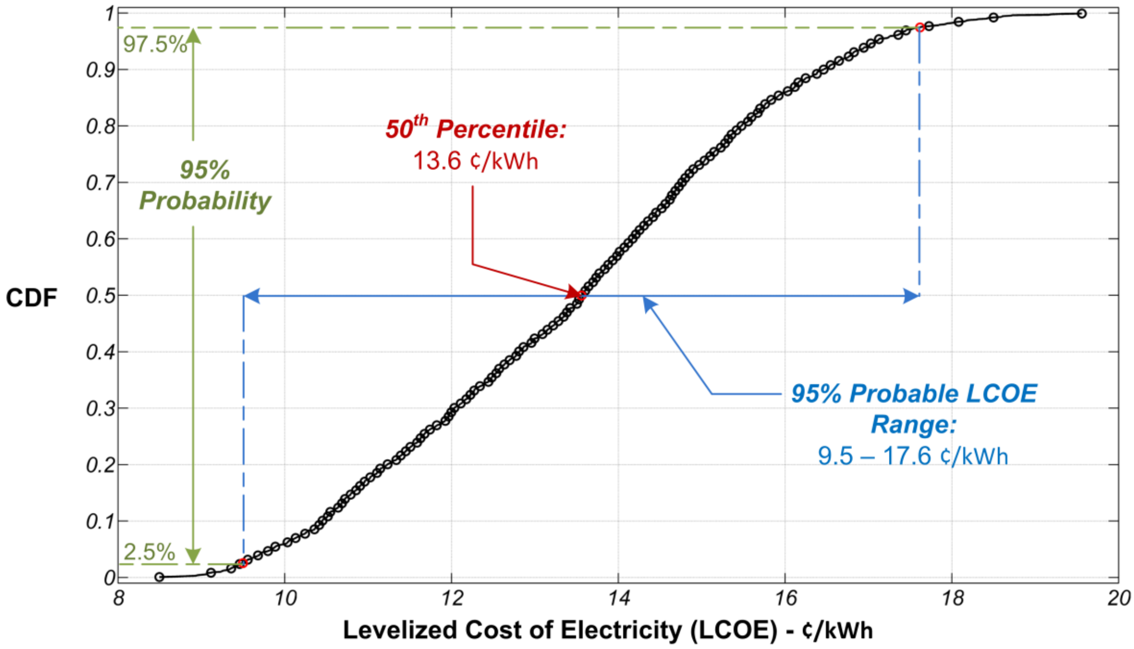

Figure 3. CDF of real LCOE resultant from uncertain input parameters (TIOs)

Though LCOE results shown in Figure 3 are considerably higher than the ~8¢/kWh target presented in the tower roadmap, it is important to keep in mind the assumptions this model is built on. This model assumes all TIOs are uniformly distributed random variables meaning it is as likely for there to be no progress on a particular goal (TIO) as there is to realize complete success on any particularly model realization. This may appear to be an overly conservative approach but, in the absence of real data, it is a good method to bound expected performance for an inherently uncertain development process.

Sensitivity (standardized regression coefficients), can be seen below in Figure 4. Not surprisingly, cycle efficiency had the largest affect on LCOE and was positively correlated. Investment tax credit also had a large effect and was negatively correlated with LCOE (e.g. bigger tax credits resulted in smaller LCOE results). Solar collector field costs also had large positive impact on the magnitude of LCOE.

ΔR^2 results for LCOE are also displayed in Figure 4. ΔR^2 quanitifies how much each input affects the uncertainty of LCOE. For this model, the sum of all ΔR^2 contributions equals 0.972. As such, cycle efficiency uncertainty contributes 76% (0.74/0.972) of all LCOE uncertainty. Similarly, investment tax credit (ITC) uncertainty contributes 12.6% and solar field cost uncertainty 7.5%. All other inputs were minor contributors.

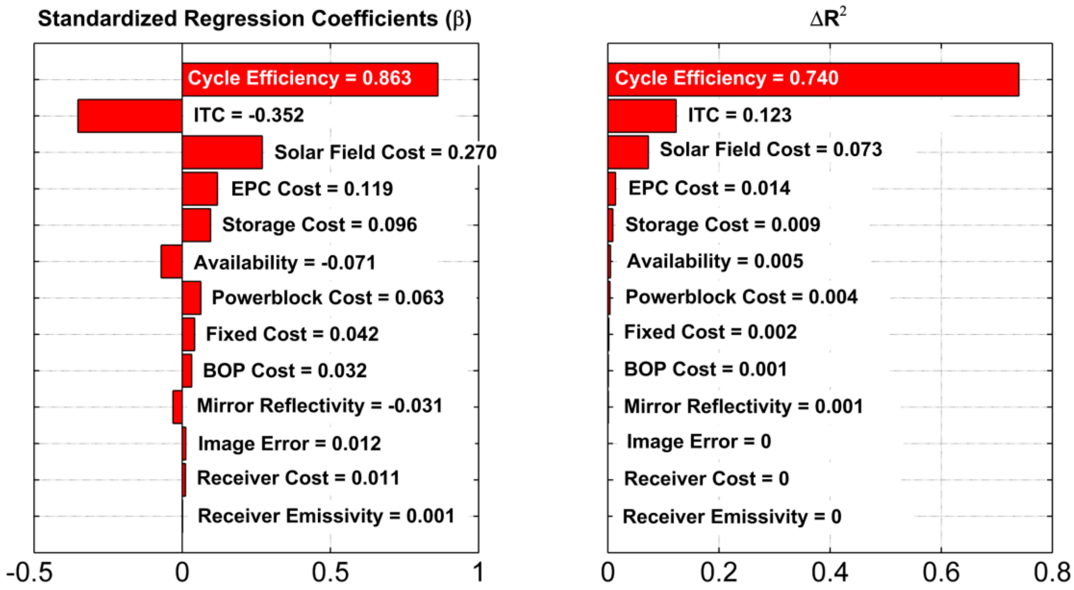

Figure 4. Sensitivity analysis of uncertain parameters on simulated LCOE using standardized regression coefficients (left) and ΔR^2 (right).

4. Conclusions

By assigning conservative uncertainty distributions to TIOs identified in the power tower roadmap, a stochastic model was created to probabilistically determine the impact of uncertain TIOs on LCOE. The uncertain TIOs were treated as random inputs into a modeled 100 MWe molten salt solar power with thermal storage. The inputs were sampled according to Latin Hypercube methodology to ensure equal numbers of samples were taken from equally probable regions of each input's uncertainty distribution. Results from the model showed that the 95% confidence interval for LCOE is 9.5-13.6¢/kWh which assumes uniform distributions for all TIOs centered between current day values and future goals outlined in the power tower roadmap. Cycle efficiency, investment tax credit, and solar field cost had the largest affect on LCOE magnitude and, similarly, on LCOE uncertainty. Investment tax credit, unlike cycle efficiency and solar field cost, was negatively correlated with power tower LCOE.

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