SolarPACES 2022, 28th International Conference on Concentrating Solar Power and Chemical Energy Systems
Analysis and Simulation of CSP and Hybridized Systems
https://doi.org/10.52825/solarpaces.v1i.809

Published: 21 Dec. 2023

Modeling and Optimizing CSP-PV Hybrid Systems Using the Hybrid Optimization and Performance Platform (HOPP)

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Abstract. The hybridization of concentrating solar power (CSP) with thermal energy storage (TES), photovoltaics (PV), and electrochemical battery energy storage systems (BESS) has the potential to provide continuous, high-capacity-factor energy production at a lower cost than a PV-BESS or CSP with TES alone. Because of the system complexity of CSP technology, it is challenging to evaluate the technological and financial performance of a CSP-PV hybrid system without detailed modeling of annual operations. To address this challenge, we have developed a modeling framework for evaluating the performance and financial viability of CSP systems hybridized with PV and BESS technologies. This modeling effort incorporates CSP tower and trough configurations into an existing modeling tool recently developed by NREL, the Hybrid Optimization and Performance Platform (HOPP). This paper provides a brief overview of our methodology, as well as an example case study. CSP with TES hybridized with PV provides the best benefit-to-cost ratio compared to the other simulated technology combinations. However, for the conditions considered, this configuration only increases the benefit-to-cost ratio by about 1% compared to the CSP with TES configuration. The PV-BESS system provides the lowest benefit-to-cost ratio compared to the other configurations explored because of the relatively low capacity credit received by the system.

Keywords: CSP-PV Hybrids, Performance Simulation, Design Optimization

1. Introduction

As the world increases renewable energy deployment, there is a growing interest in hybridizing various generation and storage technologies to maximize net benefit to the developer and/or off-takers [1]. A particularly interesting combination of renewable technologies is concentrating solar power (CSP) with thermal energy storage (TES), photovoltaics (PV), and electrochemical battery energy storage systems (BESS), shown in Figure 1. The hybridization of CSP with TES, PV, and BESS has the potential to provide continuous high-capacity- factor energy production at a lower cost than a PV-BESS or a CSP-TES system alone [2]. This configuration could service either a grid connection or a remote load that requires minimal variability, e.g., mining operations or hydrogen electrolysis.

Future CSP development must be designed to interact with PV generation. Locations that provide favorable solar resource for CSP deployment will inherently be favorable for PV deployment. In the last decade, the cost of PV has decreased significantly compared to CSP [3] and thus it is difficult for CSP technologies to directly compete with PV generation during the solar day. However, CSP can readily pair with low-cost TES, which enables electricity generation outside of the solar day. While PV system costs are low, storing bulk energy (greater than 2 to 4 hours of capacity) through lithium-ion batteries is not cost competitive [4], [5]. Therefore, hybridizing CSP and PV technologies could provide a cost-effective system to yield high-capacity-factor electricity generation.

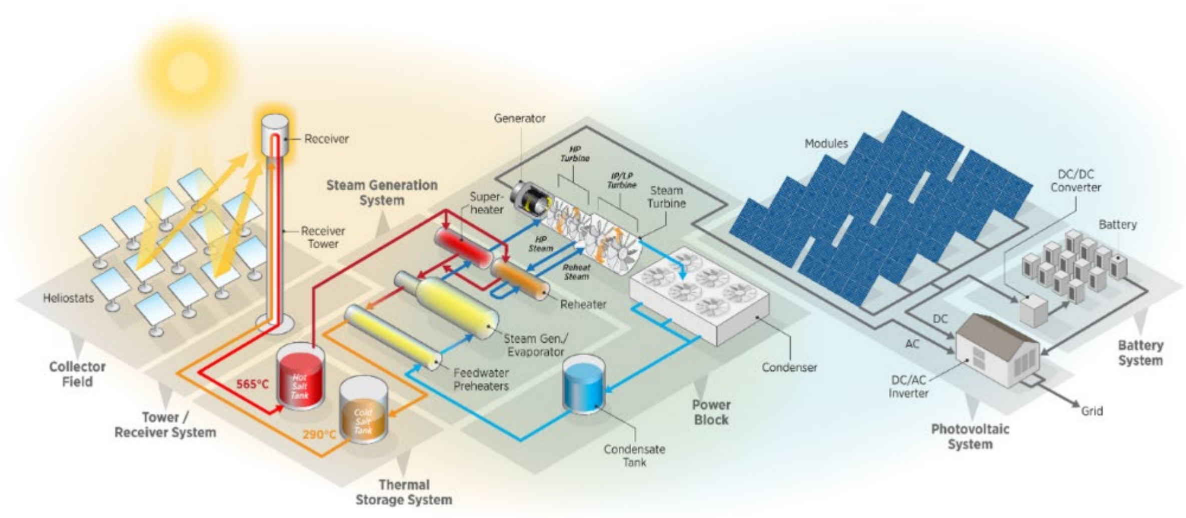

Figure 1. CSP molten-salt tower configuration hybridized with photovoltaics and batteries.

There has been increasing interest in hybridization of CSP and PV technologies in the CSP industry and the CSP research community [2], [6], [7]. However, given the system complexity of CSP technology, it is difficult to evaluate the technological and financial performance of a CSP-PV hybrid system without detailed modeling of annual operations. To address this challenge, we developed a framework for evaluating the performance and financial viability of CSP systems hybridized with PV and BESS technologies. This effort incorporates CSP tower and trough systems into a modeling tool recently developed by NREL, the Hybrid Optimization and Performance Platform (HOPP) [8]. In this paper, we will briefly describe the modelling methodology used within HOPP and present a case study using the software.

2. Hybrid Optimization and Performance Platform (HOPP)

HOPP is an open-source modeling tool that uses a Python-based scripting interface to access and combine underlying single-technology performance models in NREL's System Advisor Model (SAM) to evaluate the performance and financial viability of hybrid renewable energy systems [8], [9]. In this paper, we highlight HOPP's capabilities to evaluate power tower and parabolic trough CSP systems with molten salt TES. Figure 1 depicts a molten-salt tower CSP configuration hybridized with photovoltaics and batteries. In this configuration, the CSP and PV systems are co-located and are assumed to operate behind the same grid interconnect. The PV system power can be dispatched to the grid, stored in the BESS, used to supply CSP parasitic power requirements, or curtailed. CSP and PV technologies can be further hybridized, e.g., using an electric heater to store curtailed PV energy into the TES; however, this configuration is not available through HOPP at this time.

Figure 2a depicts an overview of the HOPP software framework. From the HOPP Python scripting interface, users can provide (i) locational weather data, (ii) market conditions in the form of assumed grid prices, and (iii) any technology-specific performance, cost, or financial parameter assumptions. The HOPP interface provides flexibility to customize analysis with other models, e.g., using HOPP's system electricity output as input to a hydrogen electrolysis model. At the core of HOPP's design evaluation exists the SAM technology and financial modules. HOPP's CSP tower configuration uses SAM's molten-salt power tower technology model, and the trough configuration uses the physical parabolic trough model. Figure 2b presents the information flow for the evaluation of a hybrid system involving a tower CSP configuration and battery technologies.

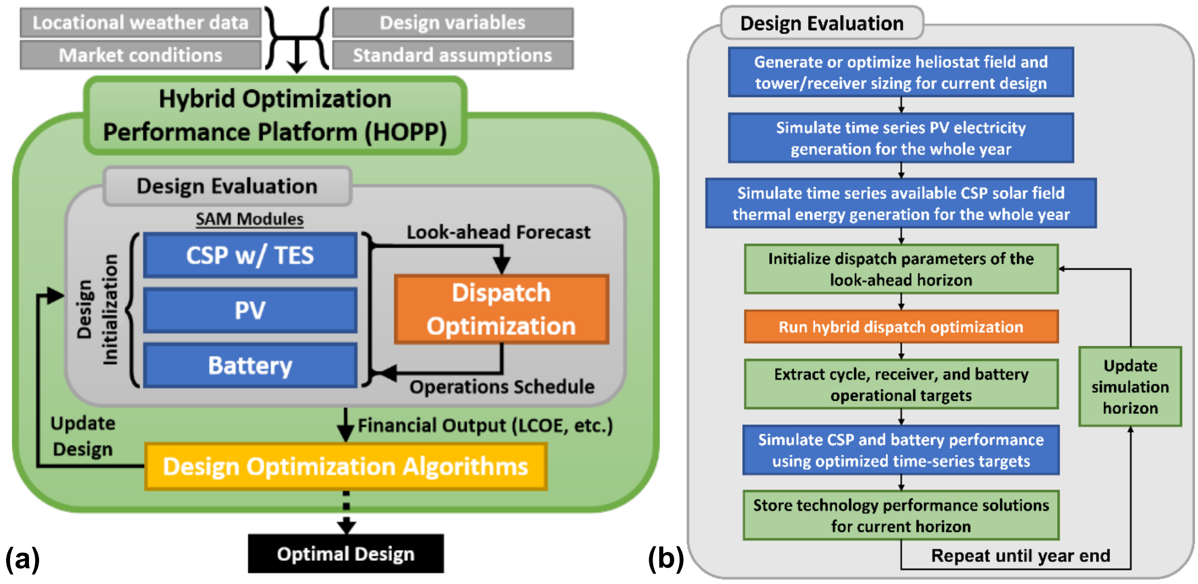

Figure 2. (a) Overview of the HOPP software framework: price-taker dispatch optimization governs time-dependent subsystem operations, and nonlinear optimization algorithms determine the optimal value of high-level design and sizing variables. (b) Information flow for design performance evaluation for a hybrid system involving a tower CSP configuration and battery technologies.

Unlike traditional non-dispatchable renewable energy systems, energy storage assets require operational decisions that maximize the value of the asset, e.g., when and at what rate to charge and discharge the asset. To address this, we implement a price-taker mixed-integer linear program dispatch optimization model (written in Pyomo [10]) that either (i) maximizes the hybrid system *gross profit* while accounting for operational costs, or (ii) minimizes system operating cost while load following. HOPP simulations use a rolling time horizon to step through the year with a 48-hour dispatch look-ahead horizon and 24-hour roll-forward simulation horizon (or the frequency of dispatch re-optimization). After solving the dispatch problem, the operational targets for the CSP cycle, CSP receiver, and BESS are passed to the respective technology performance models as control signals for simulation.

Design analysis methods integrated into HOPP allow the user to iterate on high-level design sizing variables to better understand the specific design space. There is no “set” workflow for exploring and optimizing the hybrid system design. Instead, HOPP provides methods for reducing the required workload to implement parallel simulations, design sampling, and nonlinear derivative-free optimization algorithms. This allows users to customize design analysis workflows. Additional details about (i) the integration of the CSP technology models into HOPP’s simulation framework, (ii) the dispatch optimization model, (iii) the supported design analysis methods, and (iv) representative day clustering simulation are presented in [11].

3. Case study and results

To demonstrate the HOPP modelling framework we conducted a case study based on a hypothetical future grid scenario and the Solar Energy Technologies Office (SETO) 2030 cost targets for PV and CSP, specifically using the “low-cost” scenario [12]. Note that there is a high degree of uncertainty associated with the input data in this case study, and future work will focus on evaluating sensitivity to technology costs and market conditions. HOPP scales PV cost with installed rated DC capacity; therefore, we aggregate the SETO component cost breakdown to a single cost per DC capacity of $586/kW_{dc}$. Table 1 presents the molten-salt power tower single-owner installation cost parameters used to approximate the SETO 2030 cost targets. For BESS costs, we assumed $200/MW and $150/MWh, consistent with 2030 mid-cost projections presented by NREL [13]. Additionally, we assumed an O&M cost equal to the PV system at $4.8/kW-yr, as well as a 10-year replacement period for the BESS.

Table 1. SAM molten-salt power tower single-owner installation cost parameters used to represent the SETO 2030 cost targets. *Engineering, procurement, and construction (EPC)

Parameter	Value	Units
Site improvement cost	10	[$/m^2]
Heliostat field cost	50	[$/m^2]
Tower cost fixed	1,818,300	[$]
Tower cost scaling exponent	0.0113	[-]
Receiver reference cost	62,428,300	[$]
Receiver reference area	1571	[m^2]
Receiver cost scaling exponent	0.7	[-]
Thermal energy storage cost	10	[$/kWh$_t$]
Power cycle cost	700	[$/kW$_e$]
Contingency	7	[%]
*EPC and owner cost	13	[% of direct cost]
Total land cost	10,000	[$/acre]
Sales tax basis	80	[%]
Sale tax rate	5	[%]
O&M fixed cost by capacity	44	[$/kW-yr]
O&M variable cost by generation	3.5	[$/MWh]

NREL's Cambium 2020 database was used to define the hypothetical grid scenario [14]. The database supplies projected load and hourly electricity price (under numerous simplifications) corresponding to NREL's Standard Scenarios [15]. For this study, we used model year 2030 of the Cambium 2020 "Mid-Case" scenario. Figure 3 illustrates model-predicted seasonal distributions of hourly electricity prices in the Southern California balancing area. Shaded bands illustrate the full range and various percentiles of the data set.

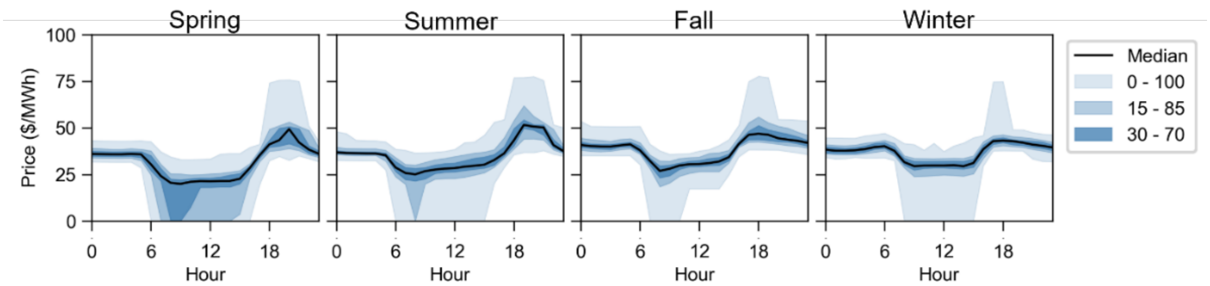

Figure 3. Daily price distributions from the Cambium 2020 mid-case scenario for model year 2030 and balancing area 10 (southern California).

Daggett, California, was selected as the location for the hybrid system and we consider 2012 weather data to be consistent with Cambium prices in Figure 3. For this study, we assumed a capacity payment of $150/kW-yr. The capacity credit was calculated as the ratio of the sum of generation during the top 100 net-load (total load less variable renewable generation) hours divided by the system maximum capacity (i.e., the product of nameplate capacity and 100 hours). These hours occur exclusively in the summer and early fall between the hours of 4 p.m. and 9 p.m. Additionally, this study assumes a 26% investment tax credit, which is consistent with the United States 2022 credit. Removing this investment tax credit would result in higher levelized cost of electricity (LCOE) values than those presented here but would not change the general trends as all configurations are eligible for this credit.

We limited the "dispatchable" power rating to 100 MW_e across four CSP, PV, and BESS configurations which include: (i) CSP-TES, (ii) PV-BESS, (iii) CSP-TES-PV, and (iv) CSP-TES-PV-BESS. The "dispatchable" power rating was defined as the sum of the cycle generator and the BESS rating. Limiting the "dispatchable" power rating forces the configuration to have the capacity to flexibly supply 100 MW_e and enables the design analysis to select the "best" combination of surrounding assets. Additionally, we imposed a 100 MW_e transmission limit for all configurations, thereby requiring the system to effectively use storage assets to maximize revenue. For example, in the CSP-TES-PV configuration, the transmission limit requires CSP to collect during the solar day but dispatch electricity around PV to minimize system curtailment. Lastly, the BESS was restricted to charge only from the PV output and could not charge directly from the grid when electricity prices were low.

We first performed a Latin hypercube sampling consisting of 200 samples, then provided the sample results to three optimization algorithms and conducted local optimization, allowing each algorithm 20 iterations to improve the solution. The algorithms used were *gp_minimize*, *forest_minimize*, and *gbrt_minimize* from the *scikit-optimize* package [16]. Table 2 presents the design variables used in this study and their associated ranges. Cycle capacity and BESS rating were varied only for the CSP-TES-PV-BESS; otherwise, these variables are fixed to 100 MW_e. Because of the way in which HOPP handles PV installed costs, DC-to-AC ratio has no impact on installed costs of PV and only impacts PV system performance. In reality, DC-to-AC ratio impacts the number of inverters required for the PV system, which would impact overall system installed costs.

Table 2. System sizing design variables, associated ranges, and solutions corresponding to maximum benefit-to-cost ratio for each configuration.

Variable	Units	Lower bound	Upper bound	CSP-TES	PV-BESS	CSP-TES-PV	CSP-TES-PV-BESS
CSP with TES							
Hours of TES	[hrs]	6	16	15.1	-	13.2	15.7
Solar multiple	[-]	1	4	2.52	-	2.27	2.78
Cycle capacity	[MW_e]	50[a]	95[a]	100 [b]	-	100 [b]	95[bc]
PV system							
System capacity	[MWdc]	50	325	-	254	53	63
DC-to-AC ratio	[-]	1.0	1.6	-	1.6 *	1.59	1.6[c]
BESS							
Energy capacity	[MWh_e]	50	1,500	-	400	-	50[c]
Power rating	[MW_e]	5[a]	50[a]	-	100[b]	-	5[bc]

[a] Ranges for CSP-TES-PV-BESS, with sum of cycle capacity and BESS rating constrained to 100MWe. All other cases had 100MWe cycle capacity or 100 MWe BESS rating
[b] Values constrained in this analysis
[c] Values correspond with variable bound

We use benefit-to-cost ratio as the design optimization objective function. The benefit-to-cost ratio was defined as the ratio of the sum of annual system benefits (i.e., time-of-delivery electricity pricing and capacity payment) to the annualized costs. This objective tries to overcome the shortcomings of traditional project financial metrics like LCOE, which only account for the system costs and production and ignore revenue streams and time-of-delivery pricing.

Table 2 and Table 3 present the design variable values corresponding to the maximum benefit-to-cost ratio for each configuration and the performance and financial metrics, respectively. The maximum benefit-to-cost ratio in this case study corresponds to the CSP-TES-PV configuration at 1.276, which is only a 1% increase in benefit-to-cost ratio relative to the CSP-TES configuration. This slight improvement appears to be a result of using PV generation during the solar day to cover CSP parasitic loads while simultaneously reducing the CSP solar field size (i.e., solar multiple) compared to the CSP-TES configuration, shown in Table 2. Further hybridization of CSP with PV through an electric TES heater or cost savings could potentially increase the benefit-to-cost ratio of the CSP-TES-PV configuration. These results indicate that co-locating PV with CSP may result in a small improvement in plant financial performance under this future scenario; however, the authors believe more investigation is required to further understand the benefits of hybridizing CSP and PV technologies. The PV-BESS and the CSP-TES configurations resulted in the same LCOE (real) meaning that cost of electricity generation is nearly equal when compared at the same "dispatchable" power generation capacity; however, the CSP-TES configuration provides more "benefit" to the grid by providing more generation and during periods when it is desired, shown in Table 3.

Table 3. Performance and financial metrics corresponding to the maximum benefit-to-cost ratio found for each configuration. Note "^{w}" and "^{b}" superscripts indicate the worst and best values for that metric across the set of simulated technology combinations, respectively.

Metric	CSP-TES	PV-BESS	CSP-TES-PV	CSP-TES-PV-BESS
Benefit-to-cost ratio [-]	1.263	1.108 ^{w}	1.276 ^{b}	1.225
Annual energy [GWh]	520.4	454.0 ^{w}	564.9	643.9 ^{b}
Installed cost [$-million]	336.7	242.6 ^{b}	345.2	386.2 ^{w}
LCOE (real) [$/MWh]	42.0 ^{w}	42.0 ^{w}	38.8	38.0 ^{b}
Capacity credit [%]	89.1 ^{b}	74.3 ^{w}	87.9	86.0

In this future scenario, the PV-BESS configuration resulted in the worst benefit-to-cost ratio compared to the other configurations, largely because of a 15% lower capacity credit than that of the other configurations. From Figure 4, there exist designs with higher capacity credit values, approaching 100% as the BESS duration increases; however, these designs increase system costs more than they increase the benefit of a higher capacity credit. Figure 4 presents an inflection point occurring around 160 MWdc where the capacity credit significantly increases with increasing PV capacity. This inflection point is where BESS stores curtailed energy production and dispatches that energy to high-value time periods. Below this PV capacity, the PV generation rarely needs to be curtailed, and thus BESS operational decisions are based only on the trade-off between increased revenue from time-shifting the PV electricity and BESS operational costs. This results in lower BESS utilization than when the BESS charges from curtailed PV, and thus less likelihood of BESS dispatch during the hours contributing to capacity credit.

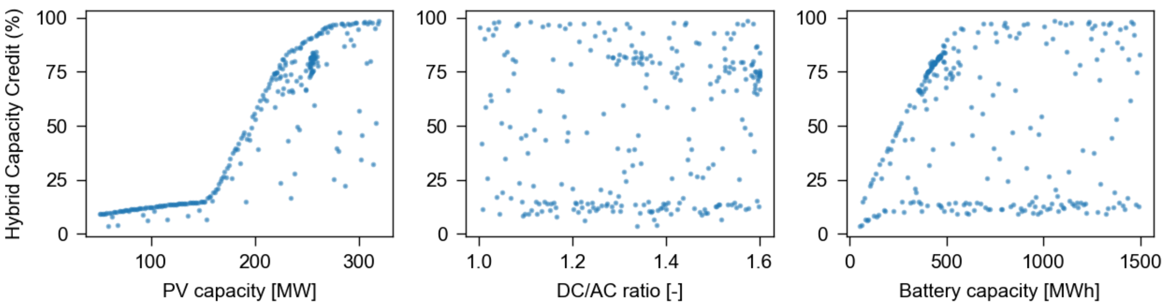

Figure 4. Capacity credit of the PV-BESS configuration for all the samples explored as a function of PV capacity, DC-to-AC ratio, and BESS capacity.

From Table 2, the CSP-TES-PV-BESS configuration minimizes the BESS capacity within the hybrid system. We expect our model to remove the BESS completely, if it could, because the CSP-TES-PV configuration results in a higher benefit-to-cost ratio than the CSP-TES-PV-BESS configuration, shown in Table 3. The CSP-TES-PV-BESS configuration resulted in the highest annual generation, highest installed cost, and lowest LCOE (real) across all the configurations. Note that the LCOE value is reported for reference, but our analysis does not minimize LCOE; therefore, for all the configurations there exist solutions with lower LCOE values than those provided in Table 3. A CSP-TES-PV-BESS configuration would be most interesting for an island grid scenario in which the system must meet 100% of the load with high reliability.

In this scenario, the TES would be used for bulk energy generation while the BESS would be used as a “buffer” between PV and the TES-driven power cycle. This analysis would require sub-hourly fidelity to understand BESS sizing requirements to meet a reliability metric which is currently not available through HOPP.

4. Conclusions

This work briefly presents the Hybrid Optimization and Performance Platform (HOPP) that enables analysis of CSP systems hybridized with PV and/or BESS, and provides a case study which demonstrates the ability of HOPP to optimize hybrid system design sizing variables to maximize the system benefit-to-cost ratio in the context of an example future scenario. This approach provides an open-source methodology for modeling CSP with TES hybridized with PV as well as hybrid PV-BESS systems, enabling a direct comparison of the technology configurations. This modeling framework is based on hourly time fidelity, which can provide insight about how bulk energy generation can be shifted to high-value and/or high-load hours; however, the model is currently unable to capture fine time-fidelity behavior that could be valuable in balancing generation. Specifically, in a CSP-TES-PV-BESS configuration, the BESS could provide frequency response and a “buffer” between transitions of CSP and PV generation, which could be valuable if the system were powering a remote load without a grid interconnect.

Underlying and related material

The HOPP modeling framework is publicly available on GitHub at https://github.com/NREL/HOPP. The repository contains example scripts for simulating a single plant design, conducting a parametric study (i.e., sampling), executing a design optimization study, and executing a design optimization with initial parallel sampling. These examples can be found at: https://github.com/NREL/HOPP/tree/master/examples/CSP_PV_Battery_Analysis.

Author contributions

William T. Hamilton: Conceptualization, Methodology, Software, Writing – Original Draft, Writing - Review & Editing, Visualization; **Janna Martinek:** Software, Data Curation, Writing - Review & Editing, Visualization; **John Cox:** Software, Visualization; **Alexandra Newman:** Software, Supervision, Writing - Review & Editing.

Competing interests

The authors declare no competing interests.

Funding

This work was authored in part by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-EE00034455. Funding provided by the U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Solar Energy Technologies Office. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes. Additionally, this work was in part funded by The World Bank Group in collaboration with Solar Dynamics LLC under Contract No. 7201329.

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