Techno-economic Analysis of Novel PV Plant Designs for Extreme Cost Reductions

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***Abstract*—A techno-economic analysis is underway examining the cost and performance of future large-scale photovoltaic (PV) plant components, including bifacial modules, tandem modules, increased plant voltage architectures, and module-level power electronics. Integration of these components into PV plant designs is compared with current PV technologies based on levelized cost of electricity (LCOE). Baseline models are developed and validated against recorded PV plant performance data. Expected cost and performance data of future PV technologies are incorporated into the baseline models. An evolutionary algorithm is utilized to optimize PV plant configuration, technology combination, and LCOE. This paper focuses on the bifacial module analysis.**

Keywords—bifacial modules, photovoltaic, technoeconomic analysis, levelized cost of electricity, utility-scale, evolutionary algorithm, optimization, System Advisor Model.

I. Introduction and Background

Solar PV has experienced a precipitous decline in costs over the past decade, the bulk of which can be attributed to cost reductions and efficiency improvements of PV modules. More efficient modules also reduce the needed amount of land and racking and mounting equipment, bringing down the overall plant cost per Watt-dc. However, with the cost of PV modules falling below $0.30/Wdc globally and efficiencies of crystalline silicon (c-Si) cells approaching theoretical limits, cost reductions and efficiency improvements in traditional c-Si PV modules are anticipated to asymptote.

In an effort to continue PV's decreasing cost trends, research has focused on other individual aspects of plants, including new PV cell and module technologies to further increase efficiency and power output, and increased voltages and module-level power electronics for reduced energy loss. However, more research is needed on how these individual innovations can best come together to provide the lowest cost PV electricity. As with other increasingly constrained and optimized systems, trade-offs need to be made. For PV plants, technology selection decisions balance cost, power output, and reliability to achieve the lowest levelized cost of electricity (LCOE). It is not readily apparent how low of a LCOE can be achieved by any given combination of technologies.

There are two broad areas for opportunity for innovation in PV plant design. The first is improvements in the individual components that make up a PV plant. Table I outlines various pieces of a PV plant and innovations that will impact the cost and performance of a PV plant. The second opportunity for reducing cost through PV plant design is in optimizing the integration of the plant components as a whole.

TABLE I. PV Plant Technologies for Exploration and Associated Design Considerations

PV Plant Technology	Example Plant Design Considerations
Bifacial modules	Added energy from increasing module height vs. increased racking and wiring cost; added energy from increasing ground albedo vs. cost of solution
Tandem modules	Added energy from increasing efficiency vs. increased wiring and balance-of-plant costs
Increased plant voltages above 1500 Vdc	Reduced energy losses vs. increased component costs
Module-level power electronics for large-scale plants	Reduced energy losses and potential for lower cost per inverter vs. increased upfront and maintenance costs

This project seeks to gain a deeper understanding of the cost and performance of the future PV plant components outlined in Table I and how they may be integrated into new PV plant designs that significantly reduce the LCOE of PV. Baseline models for PV plants with three irradiance profiles – Southwest, Southeast, and Midwest – were developed within the National Renewable Energy Laboratory (NREL) System Advisor Model (SAM) and validated against actual PV plant performance data. Cost and performance data of future PV technologies, based upon a comprehensive literature review and responses gathered from industry experts during informational interviews, were incorporated into these baseline models. An evolutionary algorithm was selected and implemented to determine an optimal PV plant configuration and technology combination for each location based on expected performance and cost of these new technology configurations. This paper focuses on the methodology and results of the bifacial module analysis, identifying plant-level configurations that result in the lowest LCOE results and may have the greatest impact on future plant cost and performance.

II. Methodology

A. Baseline Model & Calibration

The first task undertaken was development of baseline models based on three PV plants with varying plant configurations and weather profiles. To accurately calibrate each baseline model, plant data was gathered from three existing utility-scale PV plants in the Southeast, Midwest, and Southwest ranging from 1-MWac to 50-MWac.

For baseline calibration, each plant was modeled within NREL's SAM. Each plant utilizes a variety of array configurations and module types and a mix of fixed-tilt and single-axis tracking (SAT) tracking systems. Therefore, plant arrays were first modeled separately at the inverter level within SAM and simulated using plant-collected irradiance data to compare the modeled energy output with actual plant recorded energy yield on a monthly and annual basis for each plant. To calibrate both the model and plant data, outliers due to identifiable weather anomalies, inverter outages, equipment failures, and data collection complications were filtered from recorded plant data, yielding adjusted monthly totals for each inverter. These adjusted monthly energy totals were then compared to expected monthly output from the models, yielding an average absolute divergence of approximately 5% across all three plants. Fig. 1 illustrates a sample of monthly expected energy and adjusted actual energy over a full year.

Following model calibration and baseline performance analysis, the economic performance of the three baseline PV plants was analyzed using SAM and compared to power purchase agreements for similar plants. System costs and financial assumptions for the baseline economic analysis were developed based on historical data and observed trends for PV project financing and incentives. After calibrating the baseline SAM models, the performance and cost metrics for modules, inverters, and system losses were updated to match current manufacturer specifications and plant configurations to better compare modern PV technologies with the novel PV technologies investigated. These updated models serve as the baseline for the remainder of the study. LCOE values for each plant array are listed in Table II and are used for comparison with the LCOEs of the novel PV technologies (see Results and Discussion).

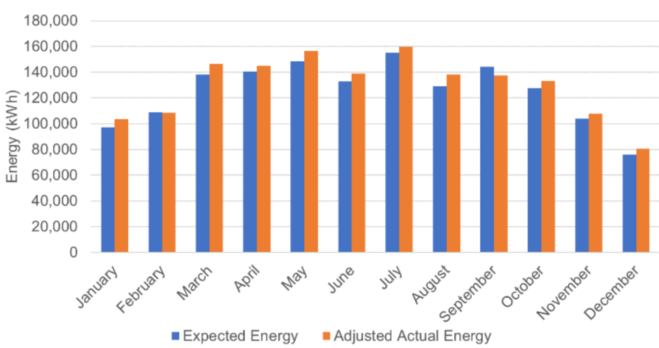

Fig. 1. Comparison of Monthly Expected Energy and Adjusted Actual Energy.

TABLE II. BASELINE LCOE RESULTS

PV Plant		Nominal LCOE ($/MWh)
Southwest Plant	Array 1	35.62
	Array 2	35.62
	Array 3	38.95
Southeast Plant	Array 1	53.05
	Array 2	52.15
	Array 3	51.90
	Array 4	47.50
Midwest Plant		58.02

B. *Literature Review & Informational Interviews*

A comprehensive literature review was conducted to identify background information for the technologies analyzed in this project. Over forty technical reports, articles, and web documents were reviewed to capture the characteristics and the current state of the technologies outlined in Table I. Insights around bifacial modules included the trade-off between increased performance/heat dissipation with increased bifacial module array height versus increased racking costs, with performance saturation estimated at array heights above 2 meters [1][2][3]. Additional literature insights, such as a methodology for modeling low-cost, four-terminal (4T) perovskite-silicon tandem modules, potential benefits of microinverters over string inverters, and challenges associated with increasing plant voltages to greater than 1500 Vdc, were collected [4][5][6].

Informational interviews were also conducted to collect detailed information on the technologies being analyzed in this project. More than a dozen industry experts including researchers, equipment and module manufacturers, and engineering firms were contacted with detailed questionnaires pertaining to characteristics of the technologies outlined in Table I. Bifacial module technical datasheets and tandem module specifications were acquired from PV manufacturers and insights and responses were used to inform the incorporation of the new PV technologies into SAM.

C. *PV Plant Performance Modeling*

Parameters for each of the technologies listed in Table I were incorporated into SAM on an individual basis and are being compared with current PV technologies based on LCOE analysis. To date, bifacial module performance and LCOE analysis/optimization has been completed and is discussed below. Analysis surrounding the remainder of PV technologies included in this study is ongoing.

A custom bifacial module was created within SAM, based on datasheets provided during the informational interview process and incorporated into the SAM models utilizing hourly albedo values within the weather files for bifacial gain calculations. System design specifications, such as modules per string and strings in parallel, were adjusted to accommodate the inclusion of bifacial modules based on module performance characteristics. The remaining plant specifications, such as DC:AC ratio, plant capacity, ground coverage ratio (GCR), and module ground clearance height, were set to match those of the baseline models. These "non-optimized" models were then analyzed for bifacial module optimization sensitivities including varying ground clearance height, GCR, and albedo grooming.

Literature insights discuss the trade-off between increased performance with bifacial module arrays versus increased racking costs for heights above approximately 2 meters [1][2][3]. Typically, as the ground clearance height of bifacial modules increases, reflected light to the backside of each module is also increased, positively affecting energy yield overall. However, the limit of this performance gain can be site-

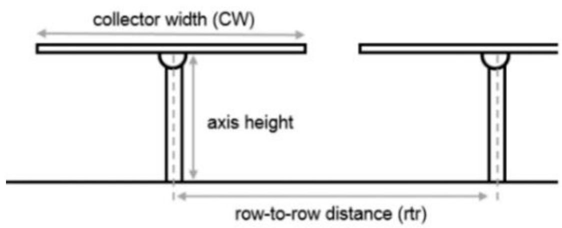

Fig. 2. Ground Coverage Ratio and Ground Clearance Height Diagram [7].

specific, and heavily affected by costs (see section D). To capture the potential performance effects associated with increased ground clearance height, the height was varied between a typical, 1-meter ground clearance height and an extreme case of 5 meters. For a fixed-tilt system, ground clearance height is defined as the distance from the ground to the bottom edge of the array. For SAT systems, the ground clearance height refers to the axis height of the array when tilt is zero (see Fig. 2).

GCR is defined as the ratio between the module area and the PV plant land area, simplified in Fig. 2 as the collector width of an array over the row to row distance. As GCR decreases, row-to-row distance increases and as GCR approaches 1.0, row-to-row distance decreases. This ratio is used to calculate row-to-row shading for an array, as well as to calculate the total land area of the plant, which impacts system costs. To analyze the effects of row spacing on PV plant performance and LCOE, GCR was adjusted compared to baseline plant designs (see Section D).

Albedo can also significantly affect the performance of a bifacial system by impacting the amount of light that is reflected off the ground to the backside of the panels [3][8][9]. For this reason, a groomed albedo sensitivity utilizing white gravel was investigated for performance and LCOE optimization. To implement groomed albedo in SAM, a constant monthly albedo of 0.55 (the average albedo of white pebbles) was applied [10]. Using estimates for additional land preparation costs, the model was optimized to obtain the lowest LCOE based on the interaction between improved albedo, bifacial ground clearance height, and GCR (see Section D).

D. PV Plant Economic Modeling

To determine economic viability of the future PV plant technologies studied, detailed cost breakdowns of the baseline plants were developed, allowing for identification of key cost trade-offs and equipment-level adjustments between the baseline models and the new technology cases. The key cost considerations for the bifacial module case are discussed below. Performance and LCOE analyses for the tandem module, increased voltage architectures, and module-level power electronics cases are ongoing.

Incorporation of the three bifacial module sensitivities discussed in Section C results in several cost and model considerations. For the module ground clearance height sensitivity, items including (but not limited to) steel cost, DC wiring, structural design, and installation for capital costs, as well as module cleaning and other O&M costs, can be affected depending on the plant design, stringing configuration, and PV plant location. As a result, several assumptions must be made to estimate the cost impacts of these factors, if any. Once these assumptions were developed, estimates for cost adders (costs in addition to the baseline costs) were informed by the literature and EPRI experts. The assumptions and cost estimates for the module ground clearance height sensitivity are listed in Table III. Assumptions and cost estimates were similarly developed for the GCR and groomed albedo sensitivities and are listed in Table IV and Table V, respectively.

These cost estimates were incorporated into each SAM sensitivity model for LCOE analysis and optimization. It should be noted that the cost factors in Table III-V are specifically based on the plants studied and are rough estimates. These assumed cost factors can vary and may be significant for other installations, affecting project economics.

TABLE III. BIFACIAL MODULE GROUND CLEARANCE HEIGHT SENSITIVITY COST ASSUMPTIONS

Cost Factor	Assumption(s)	Cost Above Baseline
Steel Cost	Material cost for steel is assumed to be $0.002/W_{DC}$ per linear foot	Combined total: $0.018/W_{DC}$ per linear meter above 1-meter ground clearance height
Wind Ballasting	For every additional linear foot of vertical height, assume 2ft of steel is driven into the ground for ballasting	
Structural Design	Addressed by wind ballasting	
DC Wiring	Negligible; DC wiring may increase, but fewer modules are needed for the bifacial module case, negating cost effects	$0
Installation	Negligible; for ground clearance heights above 7ft (2.1m), a man-lift will likely replace a skid steer	$0
O&M Costs	Module cleaning unaffected; for ground clearance heights above 7ft (2.1m) module maintenance is performed by a skid steer and man lift	$0.171/kW-yr for plants with ground clearance heights above 7 ft

TABLE IV. BIFACIAL MODULE GCR SENSITIVITY COST ASSUMPTIONS

Cost Factor	Assumption(s)	Cost Above Baseline
Land Cost	As GCR increases or decreases, total land area will be affected. This is captured in the land prep costs.	Calculated in SAM: $5000/acre baseline cost
AC Wiring	Negligible; AC wiring length may increase with increased row-to-row distance, but not significantly.	$0
DC Wiring	Negligible; DC wiring between rows may increase, but there are fewer modules per row compared to the baseline, negating any additional DC wiring costs	$0

TABLE V. BIFACIAL MODULE GROOMED ALBEDO COST ASSUMPTIONS

Cost Factor	Assumption(s)	Cost Above Baseline
Land Preparation	White gravel (albedo of ~0.55) will be utilized to groom PV plant land area. A cost of $2.75/ft^3$ is assumed for white gravel at each plant with a gravel coverage depth of 0.5”.	$5,000/acre

E. Optimization Algorithm Selection

To optimize the novel plant designs, the models are exported from the traditional SAM graphical interface to a Python environment, allowing for use by PySAM, a programming interface designed for reading and editing SAM/BAM/VCF/BCF files. Exporting SAM files to the PySAM environment enables the automation of many simulations with varying system parameters. Additionally, this environment makes it possible to implement custom cost equations for the novel technologies that are not yet built into SAM.

The goal when selecting an optimizer for this analysis was to find one that could achieve the minimum LCOE within a reasonable computation time. Because each PySAM model takes approximately 1 minute to execute, it is desirable to select an optimizer that converges efficiently. As a result, the performance of three optimizers – a traditional convergent (or gradient descent) optimizer and two evolutionary algorithms – was compared.

Traditional convergent optimizers perform well when the optimization function produces a smooth solution space. Evolutionary algorithm optimizers are inspired by biological processes, and search for an optimal solution in a distributed manner, using randomized parameters between iterations. These algorithms perform well with optimization functions that are non-convex as the distributed search and random mutations enable evolutionary algorithms to avoid getting stuck in local minimums. Before testing the optimizers, a parametric sweep was conducted on the LCOE versus the ground clearance height and GCR for the Southwest plant (see Fig. 3). At a high-level, the solution space appears smooth, but at a more granular level, the solution space exhibits local minimums.

Two evolutionary algorithms were selected for testing: the particle swarm and the genetic algorithm. Both are well suited for numerical optimization problems. In the particle swarm algorithm, a population of individual particles navigate the parameter space. The speed and direction for each particle is governed by a combination of its locally best-known position and the global best-known position. In the genetic algorithm, there are generations of individuals with a fixed population size, constant across all generations. From one generation to the next, offspring are produced from the parent generation by mating individuals (exchanging parameters), mutating parameters, and selecting among the offspring with the highest fitness (defined as the minimum LCOE in this case). In both algorithms, a population size of 10 is selected. For implementation the python package Distributed Evolutionary

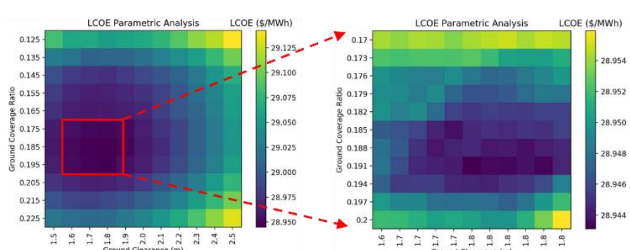

Fig. 3. Parametric Sweep Results Analyzing Bifacial Module Case LCOE Versus Ground Clearance Height and GCR.

Algorithms in Python (DEAP) was used. For the traditional optimizer, the default minimization optimizer in the SciPy python package was used.

A challenge in the application of evolutionary algorithms is the selection of options, called hyperparameters. In each of these, there is a parameter that sets the learning rate. If the learning rate is fast, the algorithm will converge to a solution more quickly; however, there is a risk that it is too fast and may skip over the optimal solution. A slower learning parameter takes longer to converge but has a greater chance of settling on a more optimal solution. The learning parameter for the particle swarm algorithm is the maximum velocity, whereas the learning parameter for the genetic algorithm is the mutation standard deviation. The hyperparameters were evaluated by comparing the algorithm convergence rate with a range of learning parameter values, with results shown in Fig. 4. The faster (larger number) learning parameters tend to converge more quickly than the slower (smaller number) parameters. Ultimately, 0.1 was selected as the learning parameter for the remainder of the analysis to balance accuracy with speed, with the algorithms converging in approximately 40 to 60 simulations with a learning parameter of 0.1.

To evaluate and compare the optimizers' relative performance with each other, the same optimization problem was solved 10 times by each optimizer with randomized starting conditions. Fig. 5 and Fig. 6 show the results of the repeated optimization runs for the particle swarm and genetic algorithm, respectively. In each run, the solution converges in approximately 40 to 80 model simulations.

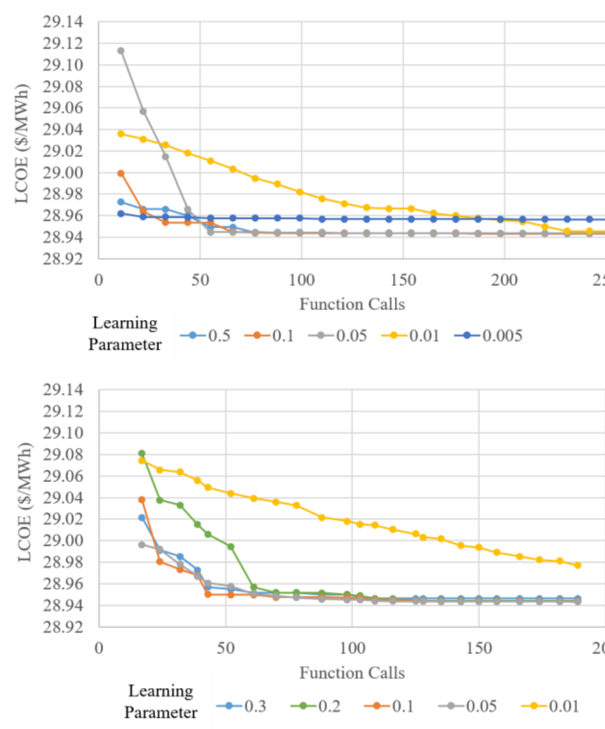

Fig. 4. Particle Swarm Hyperparameter Evaluation (above) and Genetic Algorithm Hyperparameter Evaluation (below).

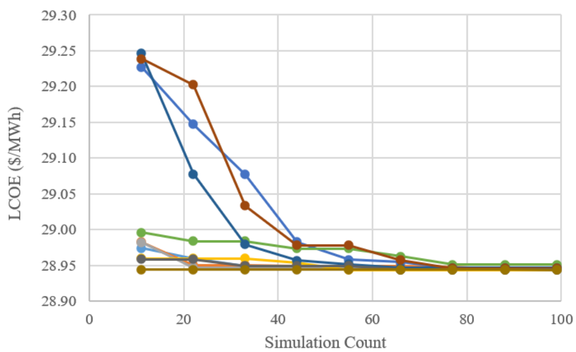

Fig. 5. Particle Swarm Optimization Runs.

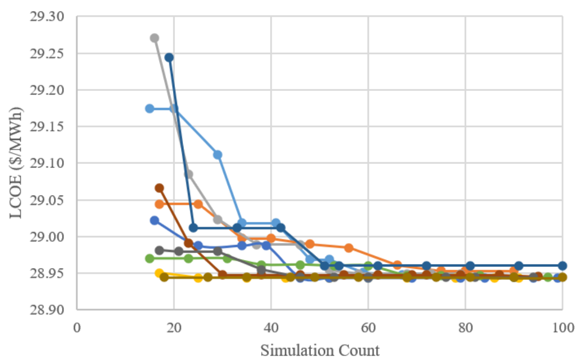

Fig. 6. Genetic Algorithm Optimization Runs.

The average performance of these 10 runs was calculated for each evolutionary algorithm and compared to the average performance of the traditional gradient descent algorithm. It was found that while the evolutionary algorithms took 2 to 4 times longer to converge, they reached more optimal solutions than the traditional gradient descent algorithm. Fig. 7 shows the optimizer performance comparison as a function of simulation count. The optimal LCOE reached at the end of each optimization run is plotted in Fig. 8. This illustrates the greater performance of the evolutionary algorithms. It appears that the gradient descent optimizer finds local minimums and is unable to search the solution space as effectively as the evolutionary algorithms. An exhaustive analysis of traditional optimization algorithms was not performed, so there may exist others that are better suited for this application. In comparing the two evolutionary algorithms, the particle swarm algorithm gives more consistent results than the genetic algorithm. Fig. 9 gives a closer view of the of the optimal LCOE reached at the end of each optimization run for these two algorithms.

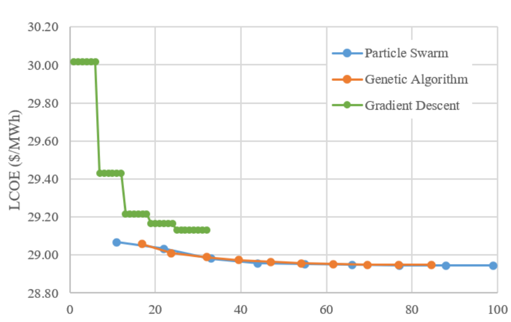

Fig. 7. Optimizer Performance Comparison.

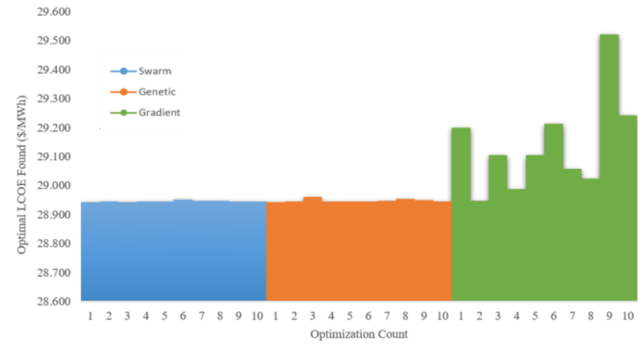

Fig. 8. Optimal LCOE for Each Optimization Run.

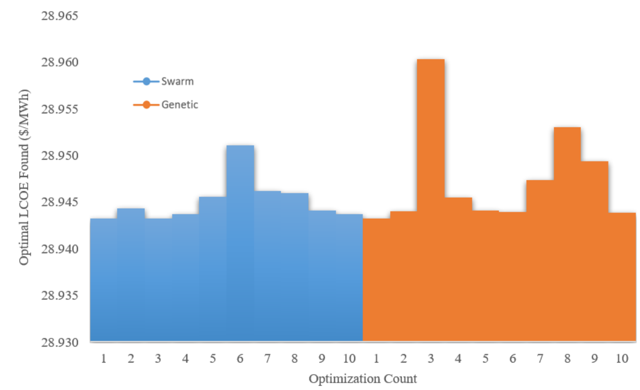

Fig. 9. Optimal LCOE for Each Optimization Run Utilizing Particle Swarm and Genetic Algorithms.

Finally, in examining the parameter values reached from each optimization run, the particle swarm optimizer produced a narrower range. The optimal parameters for each optimization run are pictured in Fig. 10 with the graph spanning the full parameter ranges. In Fig. 11 the graph range is narrowed to highlight the differences between the two evolutionary algorithms, with the highlighted window containing all of the particle swarm optimization runs' optimal parameters. To illustrate the optimizer effectiveness compared to a parametric sweep, this window represents 1/380 of the area of the parameter space (1/31 of the ground coverage ratio and 1/16 of the ground clearance height). To find this solution through a parametric sweep, 380 simulations would be required taking approximately 6.5 hours, whereas the particle swarm optimizer reaches the solution within 100 simulations taking approximately 1 hour and 40 minutes. Based on these tests, the particle swarm optimizer with a learning parameter of 0.1 was selected to optimize the GCR and ground clearance height, looking at both a baseline albedo and groomed albedo, to achieve the lowest possible LCOE configuration for each plant. Results for the bifacial module optimization cases are presented in the next section.

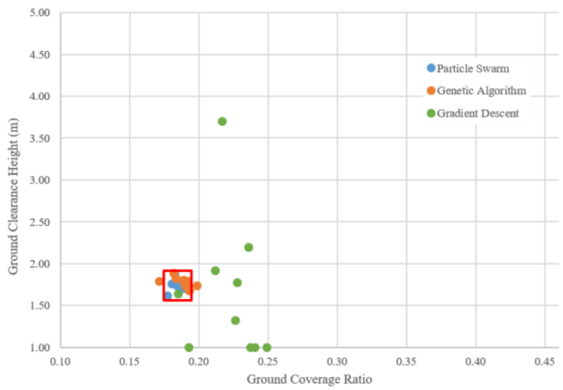

Fig. 10. Optimal Parameters for Each Optimization Run.

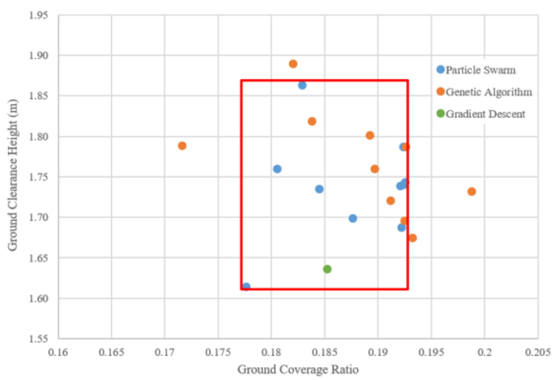

Fig. 11. Optimal Parameters for Each Optimization Run (enlarged).

III. Results and Discussion

Initial performance and LCOE results were obtained for the non-optimized bifacial module cases that kept the original GCR and ground clearance height for the Southwest, Southeast, and Midwest PV locations. These models were then optimized in PySAM utilizing a particle swarm algorithm to determine the optimal GCR and ground clearance height that resulted in the lowest LCOE at each plant array. Preliminary optimized GCR and bifacial module ground clearance height values compared to the baseline are listed in Table VI.

TABLE VI. Preliminary Optimized GCR and Ground Clearance Height Compared to Baseline

PV Plant		**GCR**		**Module Ground Clearance Height (m)**	
		Baseline	**Optimized**	**Baseline**	**Optimized**
Southwest Plant	Array 1	0.463	0.192	1.00	1.82
	Array 2	0.463	0.189	1.00	1.74
	Array 3	0.493	0.185	1.00	1.57
Southeast Plant	Array 1	0.543	0.296	1.00	1.00
	Array 2	0.543	0.313	1.00	1.00
	Array 3	0.543	0.345	1.00	1.00
	Array 4	0.211	0.192	1.00	1.30
Midwest Plant		0.487	0.243	1.00	1.00

For each case, GCR decreases significantly when optimized to reduce row-to-row shading loss. This signifies that, with the estimated land and preparation costs listed in Table IV, it is economically advantageous to increase row-to-row spacing for these three plants under these conditions. However, if land cost assumptions were to increase, optimized GCR may change as a result. For bifacial module ground clearance height, the results show the saturation effect of backside performance gains. For SAT arrays in the Southwest and Southeast plants, average optimal ground clearance height is about 1.7 meters and 1.3 meters, respectively. For all fixed-tilt arrays studied, average optimal ground clearance height is 1 meter. These values are mainly attributed to the differences in tracking technology, combined with locational irradiance and albedo effects, where average annual albedo for the Southwest, Southeast and Midwest plants is about 0.21, 0.14, and 0.26, respectively. As a result, an average bifacial module ground clearance height of 1.7 meters for the Southwest plant is economically viable due to the increased backside energy gain available resulting from tracking and higher annual albedo and irradiance. Contrastingly, the lower albedo and irradiance of the Southeast location does not make it economically viable to increase fixed-tilt ground clearance height over 1 meter. Instead, only the Southeast plant's SAT array's ground clearance height is increased. As an entirely fixed-tilt installation, the Midwest plant optimized ground clearance height remains at 1 meter despite elevated albedo, due to the lower irradiance profile of the Midwest location. These energy differences between bifacial SAT systems and bifacial fixed-tilt systems align with previous conclusions by NREL [11]. However, further optimization below 1-meter ground clearance height for fixed-tilt systems at these plants may be worthwhile to investigate, as optimal LCOE results may change.

Preliminary optimized LCOE results are listed and compared to baseline and non-optimized LCOEs in Table VII. Through GCR and ground clearance height optimization, average LCOE results decreased by 4.3%, 4.6%, and 6.9%, for the Southwest, Southeast, and Midwest plants, respectively, when compared to the *baseline* values. For Array 3 of the Southwest plant, LCOE results for this optimized SAT bifacial array decreased by nearly 10% compared to the baseline, monofacial SAT array. Compared to the *non-optimized* bifacial cases, the optimized bifacial module LCOE decreased by 5.9%, 0.7%, and 3.0%, for the Southwest, Southeast, and Midwest plants, respectively. This LCOE improvement range between plants can be attributed to original plant design and size. For plants where original site design was not optimal for bifacial modules, greater opportunities exist to improve energy optimization and, as a result, LCOE.

Table VIII shows the preliminary optimized annual energy production for the three plants. In all cases, the optimized configurations resulted in increased annual energy output over both the baseline and non-optimized cases, indicating that the cost increases associated with increased ground clearance height and GCR were offset by the increased energy output. These results show how system energy can be improved via GCR and ground clearance height when optimized alongside system costs to achieve the lowest possible LCOE.

TABLE VII. BASELINE, NON-OPTIMIZED, AND PRELIMINARY OPTIMIZED LCOE RESULTS (NOMINAL)

PV Plant		**Nominal LCOE ($/MWh)**		
		Baseline	**Non-Optimized**	**Optimized**
Southwest Plant	Array 1	35.62	37.11	35.18
	Array 2	35.62	37.11	34.91
	Array 3	38.95	37.71	35.19
Southeast Plant	Array 1	53.05	51.14	50.17
	Array 2	52.15	50.32	49.79
	Array 3	51.90	50.76	50.19
	Array 4	47.50	45.14	45.10
Midwest Plant		58.02	55.68	54.03

TABLE VIII. BASELINE, NON-OPTIMIZED, AND PRELIMINARY OPTIMIZED ANNUAL ENERGY PRODUCTION RESULTS

PV Plant		**Annual Energy Production (MWh)**		
		Baseline	**Non-Optimized**	**Optimized**
Southwest Plant	Array 1	89,914	90,674	99,087
	Array 2	25,688	25,932	28,313
	Array 3	30,094	31,370	34,420
Southeast Plant	Array 1	367	383	394
	Array 2	373	389	396
	Array 3	409	425	432
	Array 4	449	471	474
Midwest Plant		4,313	4,517	4,701

As described in Sections C and D, an albedo grooming scenario was incorporated into the models and optimized utilizing the particle swarm evolutionary algorithm to understand how optimal GCR and ground clearance height, and as a result, optimal LCOE, may be impacted by albedo grooming. Preliminary optimized GCR and ground clearance heights, as well as LCOE and annual energy production results from the albedo grooming optimization, are compared to the ungroomed albedo case in Table IX and Table X, respectively. Compared to the ungroomed albedo case, optimal GCR values for the albedo grooming sensitivity increase slightly, resulting in a smaller plant area, while optimal bifacial module ground clearance height decreases. This signifies a point at which decreasing GCR to mitigate row-to-row shading no longer becomes cost effective due to the increased land preparation costs associated with albedo grooming.

TABLE IX. PRELIMINARY OPTIMIZED GCR AND GROUND CLEARANCE HEIGHT RESULTS FOR UNGROOMED AND GROOMED ALBEDO

PV Plant		**Ungroomed Albedo**		**Albedo Grooming Sensitivity**	
		Optimized GCR	**Optimized Ground Clearance Height (m)**	**Optimized GCR**	**Optimized Ground Clearance Height (m)**
Southwest Plant	Array 1	0.192	1.82	0.221	1.77
	Array 2	0.189	1.74	0.214	1.70
	Array 3	0.185	1.57	0.225	1.55
Southeast Plant	Array 1	0.296	1.00	0.374	1.00
	Array 2	0.313	1.00	0.382	1.00
	Array 3	0.345	1.00	0.382	1.00
	Array 4	0.192	1.30	0.238	1.12
Midwest Plant		0.243	1.00	0.308	1.00

TABLE X. PRELIMINARY OPTIMIZED LCOE RESULTS FOR UNGROOMED AND GROOMED ALBEDO

PV Plant		**Ungroomed Albedo**		**Albedo Grooming Sensitivity**	
		Nominal LCOE ($/MWh)	**Annual Energy Production (MWh)**	**Nominal LCOE ($/MWh)**	**Annual Energy Production (MWh)**
Southwest Plant	Array 1	35.18	99,087	35.99	104,266
	Array 2	34.91	28,313	35.72	29,800
	Array 3	35.19	34,420	35.99	35,741
Southeast Plant	Array 1	50.17	394	50.97	420
	Array 2	49.79	396	50.48	423
	Array 3	50.19	432	50.89	456
	Array 4	45.10	474	46.12	495
Midwest Plant		54.03	4,701	54.99	4,949

With an elevated albedo, preliminary annual energy production of the albedo-groomed sensitivity increases by an average of 4.8%, 5.9% and 5.3% for the Southwest, Southeast, and Midwest plants, respectively, compared to the ungroomed albedo cases' optimized energy. However, this increased energy yield is not enough to overcome the additional land preparation cost associated with groomed albedo, resulting in slightly elevated LCOE results for the albedo-groomed sensitivity compared to the optimized, ungroomed albedo LCOE results. These results show the trade-off between different approaches and associated costs to increase plant output. However, they are dependent on the assumptions made for this analysis and further sensitivities could reveal different tipping points depending on cost assumptions.

These preliminary results show the economic viability of strategic coordination between bifacial module technologies and plant design aspects such as GCR, module ground clearance height, and albedo grooming. Although these results are plant-specific, similar optimization of plant performance alongside costs may be able to decrease LCOE for future bifacial PV plants.

IV. CONCLUSION

By identifying potential innovative technologies and designs and their potential impact on cost reduction, this project serves to highlight opportunities in new PV plant design and focus resources on those technologies and designs that are likely to have the greatest impact in reducing cost. Furthermore, this project may serve as an important starting point for the development of a PV plant roadmap. For example, the International Technology Roadmap for PV Modules has been useful for identifying known opportunities for reducing costs and/or increasing efficiency, signaling what research is needed, and forecasting commercialization timelines [12]. A similar roadmap for plants is anticipated to aid decisions made by financiers, performance modeling software vendors, engineering, procurement, and construction (EPC) firms, and owner/operators.

The future PV technologies listed in Table I have been successfully incorporated into the baseline model and a bifacial module case has been evaluated and optimized on a LCOE basis, identifying plant-level configurations that may have the greatest impact on future plant cost and performance. Using the selected optimization algorithm, optimized plant configurations allow for assessment of the effects of coordinated modifications to ground clearance height, GCR, and albedo, based on expected performance and estimated costs associated with these plant changes, showing the value of strategic coordination between bifacial module technologies and plant design aspects. As bifacial module efficiency, size, and costs continue to develop, this work may be utilized as a roadmap to optimize future bifacial plant LCOE based on component-level performance alongside system costs and locational characteristics.

Additional development opportunities for future technology and cost improvements will be identified as the remainder of the technologies identified in Table I are simulated and optimized in future work.

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