Modelling for PV plant optimization

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ABSTRACT

Because most of the costs of developing a PV power plant are paid before any energy is generated, optimizing the energy production from the plant is critical during plant design. Lost energy and increased operations costs due to non-optimal site characterization, technology choice, plant design, installation and other factors result in lower energy production and a higher levelized cost of energy (LCOE). Many design decisions are based on results from PV performance models. Current PV performance models can represent only some of the differences between sites, technologies, designs and operations choices. This paper provides a description of what is currently known about some of the performance tradeoffs faced by PV plant designers and operators. It presents a vision for improving PV performance models so that in the near future a full optimization can be carried out to improve the performance and lower the costs of PV plants. This will hasten the adoption of clean energy production from the sun.

Introduction

While the cost of PV components and systems are rapidly falling, the upfront costs of PV (before any energy is generated) are still high. This is especially true when compared with conventional, fossil-fuel-based generation, where capital costs are lower but a significant portion of the total cost is for fuel over the lifespan of the plant. In contrast, with PV systems the fuel is 'free' and the costs are associated with initial installation and operations and maintenance. As a result, there is a high incentive to accurately predict and optimize the performance of the PV plant. This paper focuses on the issues that need to be considered in order to ensure that a PV plant will perform to its maximum potential. This is a relatively new field and there are plenty of opportunities for improvements.

The levelized cost of energy (LCOE) ($/kWh) is a useful measure to optimize because it factors in all aspects of a project's value, including costs and revenue as well as the time value of money. A simple representation of the LCOE is

$$\mathrm{LCOE} = \frac{\sum_{n=1}^{N} \dfrac{C_n}{(1+d)^n}}{\sum_{n=1}^{N} \dfrac{Q_n}{(1+d)^n}} \qquad (1)$$

where the numerator represents the total cost (C) in today's currency of the system over its lifetime (N years), and the denominator is the total amount of energy produced (Q), which is corrected for degradation and discounted for time. Future costs and revenue from energy production are discounted each year (n) by the discount rate (d) (or weighted average cost of capital), which takes into account the time value of money and the perceived risk of the project. A more detailed description and discussion of the LCOE can be found elsewhere [1].

> "To optimize PV system performance and the LCOE, it is necessary to evaluate and compare costs and benefits related to technology and design decisions."

If the value of the energy is higher than the LCOE, the project will earn a profit over its lifetime. The LCOE can increase if operating costs are higher than expected and/or if energy production is less than predicted. Optimizing (minimizing) the LCOE is complicated by the fact that costs and energy production are correlated in ways that are just beginning to be understood. For example, careful monitoring of the health of a PV system may increase system output by reducing downtime when components fail. However, this will only lower the LCOE if the additional cost of monitoring is less than the revenue gained from greater energy production as a result of higher availability. Conversely, simply lowering the cost of the system by using less-expensive components will not reduce the LCOE if the lower quality components compromise reliability and increase operations and maintenance costs during the life of the system. In order to optimize PV system performance and the LCOE, it is necessary to evaluate and compare costs and benefits related to technology and design decisions.

PV plant design considerations

Proper design is critical for building and operating a top-performing PV plant. At each step of the process, choices must be made that will have a significant impact on the performance (both expected and real) of the plant. In many cases, the choice that must be made may be whether or not to perform a certain type of pre-assessment, rather than being purely engineering or technology based. The following steps in the development of a PV plant will be explored:

- Site characterization
- Technology choices
- Array configuration
- Electrical system configuration

An example comparison will then be given of three PV systems, each using a different design and/or module technology. This comparison highlights some important balance-of-system (BOS) implications of common design tradeoffs. This is followed by a discussion of plant operations issues and, finally, a discussion of opportunities for improving PV performance models to support performance optimization studies.

Site characterization

Assessment of the local solar resource potential is an important aspect of the selection of a PV site: inadequate prior assessment is a common source of underperformance. Long-term, high-quality irradiance datasets are available at only a handful of locations. Satellite data can be processed to estimate irradiance in most locations, but even this data can be biased by several per cent [2]. PV developers frequently set up a dedicated weather station at a site for a few months to a year and then compare direct measurements with other historical datasets, including satellite estimates. Developers often assume that bias errors can be identified and reduced as a result of the comparison (e.g. see Thuman et al. [3]).

The quality of the irradiance data for such a field campaign is critical: use of inaccurate sensors, failure to clean and maintain sensors, or lack of sensor calibration can introduce significant errors in irradiance measurements. It is also important to realize that certain irradiance sensors only respond to a specific spectral range, which may not match the absorption spectrum of the planned PV modules. For example, the use of a silicon photodiode pyranometer to characterize the irradiance resource for a CdTe PV system may introduce a bias error.

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The proximity of the nearest available, long-term irradiance dataset to the selected site is important to consider as well, since annual insolation can vary significantly over even short distances (microclimates). Gueymard and Wilcox [4] presented a study of irradiance variability in space and time for the USA, using a 0.1° (~10km × 10km) gridded dataset; they concluded that spatial variability was highest (covariance of annual average insolation >5%) along the coastlines and mountainous areas, and lowest in flat areas. Local studies in San Francisco have shown an even larger spatial variation in annual insolation across the city (>12%) [5]. For sites lacking such detailed studies, interviewing local residents, real estate agents, farmers and so on can be quite effective in identifying if there are local patterns in insolation.

Finally, uncertainty in irradiance and insolation data can be significant and should be considered. Uncertainty in irradiance (e.g. see Myers [6]) is different from the uncertainty in annual insolation, especially when the uncertainty that matters most is the mean annual insolation over the lifespan of the PV plant. Random errors that affect irradiance measurements will average out over time and have little effect on annual insolation. However, bias errors in the irradiance measurement – which can result from sun angle, temperature and spectral effects – can compound and result in a bias error in annual insolation.

Interannual variability of insolation is important to quantify because it largely determines the variation in energy production (and revenue) from year to year. Interannual variability quantifies the possible differences in insolation from year to year caused by climate cycles (e.g. ENSO/El Niño/La Niña, etc.). Gueymard and Wilcox [4] also examined interannual variability across the USA and found direct normal irradiance (DNI) to be 2–3 times more variable than global horizontal irradiance (GHI). They also found that interannual variability appears to be positively correlated with cloudiness, with lower variability in sunnier locations. They found that the variation in the annual insolation was typically (95% of the time) less than 2% in the best PV locations in the southwest USA. In contrast, in more diffuse climates, such as central New York State, the interannual variability was much higher (>10%). Thus it might be expected that the annual PV output from a PV plant in a diffuse climate would vary year to year more than in a sunny climate.

Figure 1. Two-axis tracker used at Sandia National Laboratories in Albuquerque, New Mexico, to measure module performance parameters.

Figure 2. Analysis of *I-V* curves under a variety of conditions is used to estimate PV module performance parameters for a number of available models.

Technology choices

PV developers are faced with a plethora of technology choices when designing a system. Understanding the differences between the available technologies is critical to optimizing system performance. Most developers today choose module technology by weighting differences in module performance, quality, reliability, cost and confidence in the manufacturer's ability to honour its warranty.

Module performance characteristics have a large effect on design considerations. Higher efficiency modules require less area and fewer BOS components (racks, wires, combiners, etc.), and may run cooler than less efficient modules. Differences in module design and materials can affect operating temperature and resulting efficiency. These aspects should be considered when comparing module costs. In addition, the spectral response of different cell types (c-Si, CdTe, CIGS, etc.) to actual site conditions can result in a spectral shift (actual performance relative to performance at the G173 spectrum). Nelson et al. [7] have shown that CdTe performance is sensitive to the spectral changes due to the variation of precipitable water in the atmosphere, which fluctuates seasonally at many sites. Available PV performance modelling applications do not include calculations that take account of this effect and may therefore introduce a seasonal bias error when estimating performance for CdTe systems.

Power Generation

Figure 3. Long-term PV system test bed at Sandia National Laboratories, Albuquerque, New Mexico. Module and inverter performance is continuously monitored, and components are re-characterized annually.

Another factor that can be important is the degree of consistency between modules. Differences in module performance characteristics can lead to mismatch and reduced performance when connected in series and operated at a single voltage typically controlled by the inverter. Module warranties usually include a tolerance on the power rating (e.g. 215W±5%, which means a module delivers between 204 and 226W at STC). At Sandia National Laboratories in Albuquerque, New Mexico, outdoor performance is characterized by accurately measuring *I-V* curves from modules mounted on a two-axis tracker (Fig. 1).

These data are used to determine the parameters for PV performance models (Fig. 2), including the Sandia Photovoltaic Array Performance Model [8]. PV systems for long-term performance tests are also fielded at a number of different climate locations to measure system performance degradation rates, identify failure modes and track differences in performance in different weather conditions. Fig. 3 shows one of these long-term test beds at Sandia.

Array configuration

Optimizing an array configuration involves choosing between fixed tilt and tracking, which has implications for row-to-row spacing, ground coverage area and total site area. Module orientation on racks can also affect performance, especially when row-to-row shading is an issue. Single-axis tracking can boost annual energy production by as much as 25% and dual-axis tracking by as much as 45% compared with a fixed-tilt system, but increased land is required to see these gains [9]. Additionally, tracking includes a mechanical system, which needs periodic maintenance and repair. Modern tracking controllers provide 'back tracking', which minimizes row-to-row shading at the beginning and end of the day. Such systems can require more stringent site preparation to ensure that the rows are level, since differences in row-to-row elevation can introduce row-to-row shading during certain times of the year. Some single-axis trackers add a tilt to the rotation axis (e.g. Sun Power's T20); this design results in a 6–7% increase in the plane-of-array irradiance (compared with horizontal-axis tracking) and is less sensitive to levelling issues, reducing the amount of site preparation that needs to be done [10]. However, tilted-axis tracking requires more land area than horizontal configurations because of the need to space the arrays further apart to minimize row-to-row shading.

Electrical system configuration

The electrical configuration of a PV array affects the system performance in a number of ways. Current electrical codes in the USA (NEC) limit the maximum DC voltage to less than 600V. However, increasing the DC voltage can improve performance for several reasons. At higher voltages, currents are lower, resulting in smaller resistive losses in the DC wiring and/or enabling the use of wire with less copper and thus lower in cost. Higher voltage systems can utilize strings with more modules, reducing the number of combiner boxes and the wiring between strings. To explore these benefits, utility systems in the USA (which are not constrained by NEC) are installing systems designed for 1000V. Some systems in Europe are experimenting with voltages as high as 1500V. However, using higher system voltages also has its drawbacks, such as potential-induced degradation (PID) of certain types of module in humid environments [11,12]. Research into the costs and benefits of increasing DC voltages for PV systems is ongoing.

Designing for optimum performance requires that the electrical configuration take account of any shade that will be cast on the array. Module orientation (portrait vs. landscape) and string wiring design can be very important if any shading will occur. A small band of shade along the short edge of a typical PV module affects string performance far less than a shade band hitting the long edge, because the typical wiring pattern and the use of bypass diodes between the substrings of PV cells inside a module mean that shade along the short edge affects each substring equally and results in less mismatch between substrings. Similarly, shade affecting one string that is connected in parallel with other stings will have a different effect than the same shade area affecting parts of each of the parallel strings [13].

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New inverters and power electronic devices, including DC–DC converters, are making the electrical design of PV systems more complicated, but also offer additional avenues for optimizing system performance. Centralized inverters are usually able to convert DC to AC more efficiently, but, as arrays grow larger, DC current must be harvested from greater distances, resulting in longer wire lengths and greater DC losses. Switching to smaller 'string' inverters can reduce these wiring losses. In addition, because power output reporting is usually included as part of the inverter, smaller inverters may increase the fidelity of the monitoring system, providing granular information about power production from smaller parts of the system and allowing outages to be identified and located earlier. Such advantages must be weighed against differences in efficiency and costs.

BOS implications of technology choice

Sandia National Laboratories recently conducted a design study of three typical 2MW PV systems to illustrate and document design, cost and performance differences between different PV technologies [14]. The study focused on three system types:

- **System A**: mc-Si modules (230W STC); fixed latitude tilt
- **System B**: CdTe modules (75W STC); fixed latitude tilt
- **System C**: mc-Si modules (230W STC); horizontal single-axis tracking

A solar developer was commissioned to provide the system designs, with each system using eight 250kW inverters. Systems A and C were designed with the same modules and shared the same string configurations. Annual system performance was then estimated for a location in Salt Lake City, Utah, using PVSyst [15]. LCOE was estimated using the System Advisor Model [16]. The following summarizes some of the design differences between these systems.

System B required 3.1 times the number of modules and 1.4 times the land area needed by System A. The open-circuit voltage for System B's CdTe modules was 2.4 times greater than for the mc-Si modules used in Systems A and C, resulting in fewer modules per string. This, combined with the greater number of modules, resulted in System B requiring 8.6 times the number of strings needed for the mc-Si system. Because of the larger number of strings, System B required 1680 combiners and 48 recombiners, while Systems A and C only needed 48 combiners and no recombiners. System B also required more wire and trenching work than the other systems.

Total installed costs, predicted annual performance and LCOE are summarized in Table 1. Because of the larger area and greater number of components to install, System B had higher installation costs. However, despite significant differences between these system designs, the LCOE values are very similar.

The real performance differences show up when the predicted output for the systems is compared over time: Fig. 4 shows predicted monthly system output. Note that System C produced significantly more energy during the summer but only slightly less energy during the winter than Systems A and B. This is a general characteristic of most horizontal single-axis tracked systems.

Fig. 5 shows the average hourly output for each month and demonstrates that System C can deliver more energy at the beginning and end of the day during the summer because of the tracking of the modules; during the winter, however, the output in the middle of the day is significantly lower than the fixed-tilt systems. The CdTe system (System B) shows slightly improved performance during the summer owing to the lower temperature coefficient on the maximum power of CdTe modules compared with mc-Si. These plots illustrate that different designs can significantly affect the timing and magnitude of power generation, which in turn can affect how these systems impact the electrical systems to which they have to be connected.

	System A	System B	System C
Technology	mc-Si fixed	CdTe fixed	mc-Si tracked
Installed cost estimate [$/Wp]	2.88	2.99	3.24
Plane-of-array irradiance [kW/m^2-yr]	1980	1980	2340
Annual output [MWh/yr]	3295	3407	3784
Levelized cost of energy [¢/kWh]			
IPP financing	11.71	11.76	11.98
Cash financing	8.0	7.7	7.9

Table 1. Energy production and cost estimates for three example 2MW PV systems in Salt Lake City, Utah.

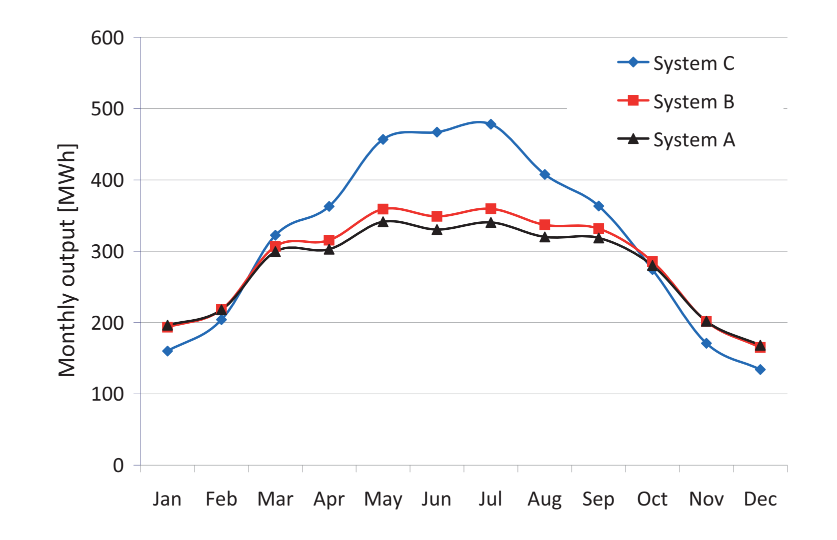

Figure 4. Estimated monthly system output (from Quiroz and Cameron [14]).

Operations

After an optimized PV plant has been designed and built and then connected to the grid, there is no guarantee that it will perform as predicted. Large PV plants comprise hundreds of thousands, sometimes millions, of components. The system is exposed to the environment, which can include dirt, plants, animals, snow, hail, wind and rain. Catastrophic losses (e.g. glass breakage due to hail) are usually covered by an insurance policy, but other issues such as cleaning the array,

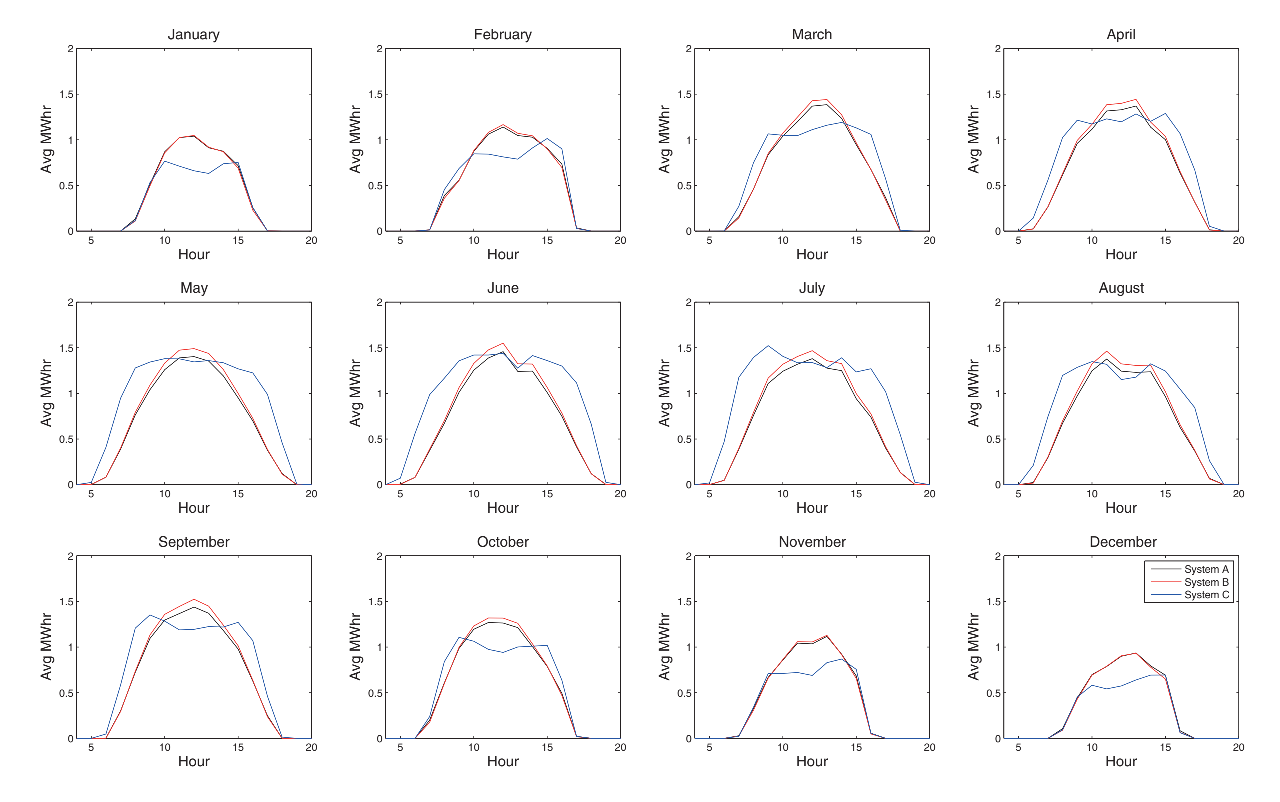

Figure 5. Estimated average hourly output by month for systems in Salt Lake City, Utah (from Quiroz and Cameron [14]).

grass/brush cutting around the array, and damage caused by vegetation control equipment, by wind or rain, or by animals are usually the responsibility of the owner/operator or covered in an operations and maintenance (O&M) contract.

Soiling on the array is one of the most significant causes of lower than expected energy production [17,18]. Since there are no standards for measuring soiling rates as part of site characterization activities, each developer uses its own methods (e.g. see García et al. [19] and Caron and Littmann [20]). Seasonal variations can be significant, requiring a minimum of a one-year study to adequately characterize a site. Soiling rates are also highly dependent on module tilt angle [21–23]. For much of the world, commercial rooftop systems with modules oriented at a typical 10–20° tilt may be more dramatically affected than utility-scale plants where the modules are mounted at latitude tilt. There is evidence that certain soil constituents may affect PV performance far more than the absolute amount of soil on the module surface, thus complicating measurement techniques [24,25]. Cleaning modules is expensive and may even be impractical or impossible because of water availability or environmental regulations. The soiling level is dependent upon rainfall frequency and intensity, so an assessment of precipitation patterns and forecasts can help to optimize cleaning schedules. Research into soil-resistant coatings for module surfaces also offers promise for reducing energy loss from soiling [26].

Accelerated soiling studies are a new field with promise to reduce the time required to determine the severity of loss due to specific soil types and morphology, as well as assisting in determining appropriate mitigation methods [27,28].

Large PV arrays are frequently located in dry regions. However, covering these areas with impervious modules can cause precipitation to be focused on the lower edge of the array, creating a microenvironment favourable to rapid growth of vegetation. This can lead to an increase in the frequency of vegetation management when compared with the estimates made before the PV plant was built.

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Finally, in the event of module breakage or excessive degradation, it is important to realize that spare parts matching the original components may not be available after installation, since technology changes rapidly. The inclusion of spares in the initial design may be important to keep the system running at full capacity. Without spares, performance can suffer beyond a simple reduction in nameplate capacity, and strings must be reconfigured to remove failed modules.

Modelling expected performance

Evaluating the sensitivity of choosing between different sites, technologies, designs and operations strategies requires a sophisticated set of models and data. Existing PV performance modelling applications [29] are designed to estimate annual energy yields and can only distinguish between a few differences in designs (e.g. fixed vs. tracking, some module technology characteristics, etc.), and are not able to evaluate others (e.g. interannual and spatial variability, spectral and electrical mismatch, distributed vs. centralized power conversion, reliability of components, O&M strategies, etc.). These other factors are frequently included in the evaluation, but with simplified assumptions or derating factors. Users rarely have a robust technical basis for estimating the magnitudes of these factors and therefore model estimates are considered to have large uncertainty bounds. Some modelling applications do offer valuable features that allow uncertain parameters to be sampled from distributions, with the aim of minimizing or maximizing a reported output. An example of this feature is included as part of the National Renewable Energy Laboratory's System Advisor Model (SAM), which incorporates 'sensitivity' and 'optimization' functionality [16].

To respond to this situation, Sandia National Laboratories and the US Department of Energy have recently started the PV Performance Modeling Collaborative (PVPMC) [30] to collect and organize the latest information about PV performance modelling algorithms and methods, as well as to provide open-source analytic tools and functions that can be used to validate and expand existing modelling algorithms and methods. On the PVPMC website [31], stakeholders can research various modelling algorithms, download documents and gain access to a PV modelling toolbox for Matlab called the PV_LIB Toolbox. This toolbox contains numerous documented open-source functions; it offers a great resource for model developers and users for learning about and validating the modelling steps used for estimating PV system yields.

The PVPMC has organized the process of PV performance modelling into a set of standard steps (Fig. 6):

1. **Irradiance and weather**. This step involves choosing a source for defining the irradiance and weather conditions expected for the site. Common sources include typical meteorological years (TMY), satellite-derived data and on-site ground measurements. There are numerous possible approaches for choosing weather inputs for performance modelling studies.
2. **Incident irradiance**. This step aims to translate irradiance measured at standard orientations (horizontal, plane of array and normal to the sun) to beam and diffuse components on the plane of the array. Many algorithms are available for performing these translations but there is little consensus on which one is the most accurate for any given site and system.
3. **Shading, soiling and reflection losses**. If the array is partially shaded or the modules are soiled, the amount of the incident irradiance available for conversion to electrical energy is reduced. There are various algorithms for calculating the shading and its effect on the system, but only a few methods exist for predicting the amount of soiling on the array with time. Usually this step is treated with a constant or time-varying derating factor.
4. **Cell temperature**. The PV cell temperature is influenced by a number of factors, including module materials and construction, mounting and racking configurations, and the incident irradiance (modified by shading and soiling), wind speed and ambient temperature, among other variables. Many methods have been proposed for estimating cell temperature from these variables.
5. **Module *I-V* output**. In this step the *I-V* curve of the module is predicted under the conditions described previously: irradiance (including spectrum) and cell temperature. There are various types of model that have been applied (single diode, semi-empirical, etc.).
6. **DC and mismatch losses**. This step involves estimating the losses in the DC circuit(s) due to wire resistance

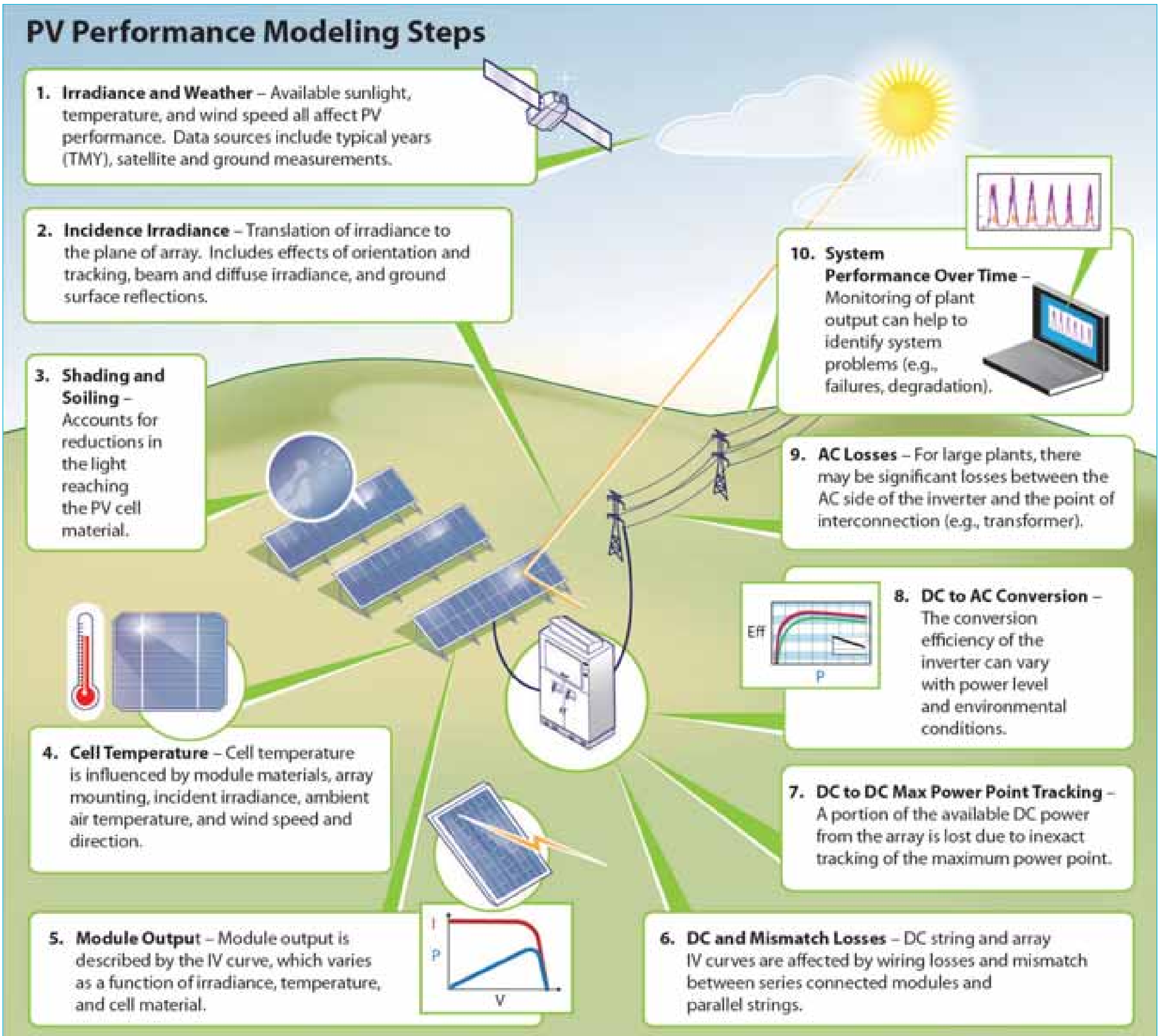

Figure 6. Standard steps in modelling PV plant performance (from the PV Performance Modeling Collaborative [31]).

and mismatch between series-connected modules and parallel strings. Few performance modelling applications include this step explicitly, except by means of a scalar derating factor. Treating this part of the performance modelling problem is especially important in order for PV performance models to accurately represent performance of distributed-array technologies designed to reduce such mismatch losses (DC–DC converters, string-level inverters, microinverters, etc.).

7. **DC to DC maximum power point tracking**. Most, if not all, modelling applications assume that the array's DC voltage can be held at the maximum power point (MPP) for the array at all times. Differences between maximum power point tracking (MPPT) algorithms mean that the ability of different inverters to hold the MPP varies. Furthermore, PV systems may sometimes operate away from the maximum power point by design (e.g. 'curtailment' or operation at non-unity power factor).
8. **DC to AC conversion**. This step accounts for the conversion efficiency of the inverter. This efficiency can vary with environmental parameters such as temperature and with electrical conditions such as DC power level.
9. **AC losses**. Once the power has been converted to AC it must be transmitted to a point of interconnection (revenue meter). Any losses along this transmission path (wire losses, transformer losses, etc.) are represented in this step. Few existing models represent this process in any detail [32].
10. **System performance over time**. Monitoring of plant output can help to identify system problems (e.g. degradation and component failures). There are a number of metrics used to track and evaluate system performance (performance ratio, performance index, etc.).

In many cases, existing PV performance models skip one or more of these steps by making assumptions or by including a loss or derating factor. As PV system design options become ever more complicated with new components (e.g. DC–DC converters), many of these previously overlooked and simplified steps will see more attention.

> "Work on standardizing the modelling process has begun as part of the PV Performance Modeling Collaborative."

Conclusions

The wide variety of PV system technologies, system designs, site conditions and operations strategies means that complex models of PV system performance are needed in order to represent the performance of PV plants. Existing performance models only include a subset of the features and processes that affect system performance, and differences between these models mean that direct comparisons are difficult to make. The result is a lack of consensus on which model to use and how to document performance analyses so that the PV community has confidence in the performance predictions. Work on standardizing the modelling process has begun as part of the PV Performance Modeling Collaborative and provides a framework for adding model improvements, developing best practices and allowing different models to be compared in a consistent way. As PV performance models improve, the promise of full system optimization will eventually be fulfilled.

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