Design Optimization in Constrained Applications

By Paul Grana

Courtesy Aerocompact

A constraint does not simply determine the size of a system. Different constraints applied to the same system will lead to dramatically different design choices.

Solar designers all want to make sure they are building an optimized design, or at least "the right" design. But not everyone thinks rigorously about what optimization means. The most basic version of an optimization exercise involves a variable that you change and an objective that you try to maximize: "If I change X, does Y improve?" A slightly deeper understanding of solar optimization acknowledges the importance of inputs such as module cost, electricity value and array location.

Constraints are part of every system design. In fact, they are so commonplace that designers often factor them in without explicitly calling them out. However, few engineers realize that the constraint drives design choices. The naïve concept of a constraint is that designers first determine the optimal array—given the location, costs and so forth—and then look at constraints to understand how much of that system they can build. In practice, the constraints drive the optimal design, and if the constraints change, so does the design.

Here I provide context for how to think about constraints holistically. I then explain the most common constraints. Finally, I show that even with the same set of inputs, such as system costs and utility rates, changing the fundamental constraint can lead to a dramatic change in the optimal system design.

APPROACHING CONSTRAINTS HOLISTICALLY

Constraints might seem like an annoyance to avoid or minimize, but they are intrinsic to real-world activities. If that seems counterintuitive, keep in mind that a system without constraints would be infinitely large!

Often a constraint is so self-evident that you do not think about it explicitly. For example, when building a system on a commercial rooftop, a designer will typically begin the engineering process with the whole roof in mind. The tenant almost always has the energy demand and the budget to justify building out the whole roof; therefore, it is only a question of how to best populate the available area. In this scenario, the designer takes for granted that the roof area, not the budget, will be the dominant constraint of the array. Similarly, for many residential applications, particularly as net metering is on the decline, a designer might instinctively orient the design process around the homeowner's energy demand, making this the factor that drives many other decisions about the system. These are both examples of constraint thinking at work.

Assess the hierarchy of constraints. As the optimization framework in Figure 1 illustrates, a fairly universal set of attributes commonly constrain a system: the budget, the available roof or land area, and the energy demand. In different applications, these various constraints become more or less relevant. Typically one primary constraint drives a system design. You might think that a system is both space constrained and budget constrained, but in practice, one of those constraints imposes limits first. For example, the budget might constrain the system to be smaller than the rooftop would allow. In that case, the financial budget is the actual bottleneck, even though there is technically also a space constraint. While one constraint might be the primary constraint for an array, all the constraints will exist at some level. No project has infinite land. No financier has an infinite budget. And no off-taker has an infinite demand for energy.

Identify the bottlenecks. An analogy can be helpful here: Any factory machine process has a *bottleneck,* a step in the process that sets the rate of production for the entire line. When you solve one bottleneck—say, by improving the machine's speed or adding a second machine to share the load—the result is not that you get rid of all bottlenecks, but rather that the bottleneck shifts to the next-slowest step in the process. Since there will always be a bottleneck somewhere in the system, the goal of the optimization process is not to eliminate bottlenecks but rather to manage them.

Similarly, solar designers always have constraints. The goal is to understand and harness them in designing and delivering the system. One of the key lessons is that you should never

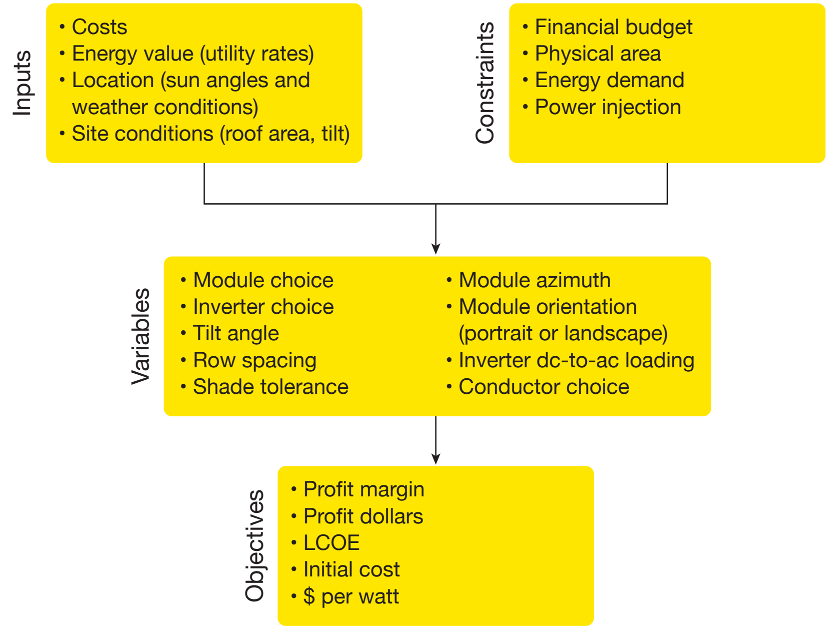

Figure 1 Whether solar project designers realize it or not, design constraints often drive system optimization activities.


Courtesy Solar Design Associates

Area constrained Solar Design Associates used a dual-tilt mounting system at Clark University's Alumni and Student Engagement Center to maximize ground-cover ratio, total system capacity and energy yield per unit of area.

starve the bottleneck (the constraint) of resources. In other words, the slowest machine in a manufacturing operation should never spend a moment waiting, since that machine will determine the maximum throughput of the factory. We can apply the same approach to constraints in solar design.

Focus optimization efforts on constraints. Identifying the bottleneck of the design process—the rate-limiting factor—allows designers to focus their efforts on optimizing the array based on that primary constraint. In a space-constrained array, the designer seeks to maximize the energy yield per unit area. Where ac power is capped based on the interconnection capacity, the designer seeks to maximize financial benefits against that maximum power rating. You can begin to intuit why different design constraints, in the hands of a skilled system engineer, lead to different design outcomes.

UNDERSTANDING THE MAJOR CONSTRAINTS

A number of common constraints apply when designing solar arrays, including physical area, budget, energy demand and power injection back to the grid.

Area. An area constraint is most common in commercial arrays, as those systems often have ample energy demand and a sufficient financial budget relative to their roof space. This constraint can also come up in residential arrays, especially if you restrict designs to south-facing roofs only, as well as in ground-mount designs.

The ultimate objective for this design constraint is to maximize energy yield per unit of area, which generally results in an economically optimal array. Specifically, this means maximizing the module fill within the available area, meaning that you want to maximize power density (kWp per unit of area) rather than specific yield (kWh per kWp). Since power density typically increases faster than specific yield decreases, maximizing this value tends to maximize energy density (kWh per unit of area). In a world of relatively inexpensive hardware, this approach produces a clear economic win.

The variables that move the needle on power density are the tilt and spacing of the modules. Specifically, optimizing area-constrained applications tends to result in systems with lower tilt angles and tighter spacing between modules, especially with low-cost modules. This is why the industry has seen a huge push toward commercial mounting systems with 5° tilt angles or dual-tilt orientations.

Budget. A budget constraint can happen in systems of all sizes. Assuming the project is a cash deal where the off-taker is the purchaser, available cash can be a determining factor in the size and design of an array. This constraint also applies if an incentive is capped in total dollars or based on system capacity. For example, a local jurisdiction might offer a dollar-per-watt incentive up to a certain system size. For optimization purposes, this acts as a budget constraint because the marginal economics of a system larger than what is incentivized become much less appealing.

Financing options such as power purchase agreements and loans are popular across the industry because they mitigate budget constraints. As long as the economic returns are adequate, many customers are able to access up-front financing. Property assessed clean energy (PACE) financing is a possible exception, as PACE funds are often capped at 20% of the property value in commercial applications, which sometimes acts as a budgetary constraint for large commercial rooftops.

With a constrained cost, the financial return (revenue minus costs) for a system tracks closely with the total revenue. The costs are tied to the system's dc nameplate value because the module costs, racking costs, electrical costs and installation labor are all directly related to the dc capacity rating. As a result, the objective that tends to matter most is maximizing the array's specific yield: the revenue is tied to the energy (kWh) generated, while the costs, and therefore the capacity (kWp), are fixed.

The design goals are similar in a capacity-constrained market. If a developer can only obtain a certain quantity of modules per quarter, that developer will want to deploy them in a way that derives as much financial value as possible. This optimization exercise would mimic that for a budget-constrained application.

Energy demand. This constraint is most common in residential arrays, where the homeowner uses only so much energy. It becomes particularly acute with net metering, since the designer must not only design to an annual energy budget, but also align the energy production by month or even hour of the day. This type of optimization exercise is all about system capacity. When there is only so much demand for energy, the size of the array is critical, especially since overproduction can waste energy.

Two metrics matter here: energy usage and specific yield. First, the engineer must understand the usage demands, typically based on the off-taker's energy bills. This can be complex based on when the customer's bills are trued up, whether it is monthly, annually or every 15 minutes (for demand charges). Next, the designer focuses on delivering that energy most efficiently by maximizing specific yield. In residential applications, designers tend to have fewer tools at their disposal, as the roof area is often relatively constrained and the roof itself determines the tilt angle.

In residential applications with energy-demand constraints, designers generally base their decisions on which roof surfaces to use and how close to get to shading obstructions. In commercial or ground-mount applications, optimizing a system with energy-demand constraints often leads to wider row spacing and a higher tilt angle, as these options improve system yield and profitability.

Power injection to the grid. A power constraint is most common in utility-scale arrays, which inject the energy produced directly into the grid. In those situations, the grid operator often dictates the maximum instantaneous power the grid can handle at any time. As a result, there is a very clear power limit on what an array can produce, which the designer can achieve by simply matching the inverters' rated output power to the grid's requirements.

Power-injection constraints can also arise when regulatory procedures change significantly based on system capacity. A jurisdiction might have an expedited permit or interconnection process for arrays up to 200 kWac, whereas larger systems are subject to a more demanding set of requirements. These policies can artificially limit system capacity. If the permitting process gets significantly more stringent above 200 kWac, you might decide to constrict the ac output power to 200 kW—even if the roof area would otherwise support a 250 kWac system—just to keep the permitting process simple and/or inexpensive.

In this scenario, inverter ac power capacity is considered a fixed variable and dc system capacity becomes the key design variable. Since dc capacity determines system revenue and therefore profit, this variable drives financial performance. The designer incrementally increases the dc nameplate power while looking to maximize financial metrics. The marginal revenue of each group of modules drops successively, since the clipping losses get larger as the dc-to-ac ratio increases. However, the designer can continue increasing array capacity as long as the marginal revenue covers the marginal cost of adding modules, racking and wiring. Inverter power limiting is no longer a loss factor to minimize, but instead is a necessary tradeoff to increase revenue and maximize the financial performance of the array. This optimization exercise tends to push the dc system capacity to 1.4–1.7 times that of the ac inverter capacity, depending on the array location.

Constraint-Based Design Optimization

Array characteristics	Reference system	Design constraint: Area	Design constraint: Budget	Design constraint: Power injection
Tilt angle (°)	20	5	30	20
Row spacing (ft.)	2.4	0.5	8	2.4
Area (acres)	2.85	2.85	4.5	3.92
Array capacity (kWdc)	1,000	1,391	975	1,377
Inverter capacity (kWac)	810	1,125	810	810
DC loading	1.23	1.24	1.20	1.70
Performance metrics				
Specific yield (kWh/kWp)	1,532	1,474	1,581	1,390
Energy production (MWh/year)	1,531	2,050	1,542	1,931
Revenue (NPV)	$2,205,000	$2,952,000	$2,220,000	$2,780,000
Cost of system	$1,440,000	$1,900,000	$1,440,000	$1,799,000
NPV of system	$765,000	$1,052,000	$780,000	$981,000
Profit	53.1%	55.4%	54.2%	54.5%
NPV improvement vs. reference	—	38%	2%	28%

Table 1 This table illustrates how the optimal system design varies based on different design constraints. While each of the constraint-based designs improves the net present value (NPV) relative to the reference design, there are significant differences among them.

CALCULATING THE OPTIMAL DESIGN

To illustrate the importance of constraints on system design, I will start from a reference design with fixed cost and revenue assumptions and show how different design constraints lead to different optimal system configurations. For the purposes of this exercise, I am using the project's net present value (NPV) as the optimization objective. The details of the reference design are as follows:

System capacity: 1 MWdc
Array area: 2.85 acres
Array tilt angle: 20°
Array azimuth: 180°
Interrow spacing: 2.4 feet
Location: San Francisco

In the scenarios that follow, I fix one of three major design constraints at a time—area, budget or ac capacity—while leaving the other two variables unconstrained. As shown in Table 1 (p. 25), this exercise results in three distinctly different designs.

Area-constrained scenario. Here I fix the array area based on that of the reference design while adjusting other variables to maximize NPV. The most profitable system design results from packing the modules closely together and reducing the tilt angle. These two variables go hand in hand: by dropping the tilt of the modules, you can reduce the row spacing without incurring a significant amount of interrow shading.

Optimizing the area-constrained array results in a 5° tilt angle and a row spacing of 0.5 feet. Note that the lower tilt in this design reduces the specific yield by 4% compared to the reference design, from 1,532 to 1,474 kWh/kWp. However, the reduced spacing increases the system capacity by 40%. Therefore, the overall energy production grows by 35%. The area-constrained design is even slightly more profitable. While the 4% lower productivity would typically translate to a lower profit margin, the larger array is able to amortize the fixed costs over a larger base. As a result, the ROI of the system is slightly better than that of the reference design.

Budget-constrained scenario. Here I fix the budget while giving the system free rein in terms of array area. In this case, the design goal is to maximize specific yield. As detailed in Table 1, raising the tilt angle to 30° and spreading the interrow spacing out to 8 feet increases the specific yield by 3%, from 1,532 to 1,581 kWh/kWp.

Of course, expanding the array area does not come without costs. Since our budget is fixed, I have accounted for this by decreasing the array capacity to account for the costs associated with the additional land requirements (modeled at $500 per acre per year) as well as the longer wire runs. In spite of the fact that the array area nearly doubles over that of the reference case, optimizing for specific yield in the budget-constrained scenario still results in 2% improvement in NPV.

Power-constrained scenario. Lastly, I constrain the system based on capacity, assuming that the maximum allowable power injection to the grid is 810 kWac, but do not constrain area or budget. In this case, dc system capacity has a significant impact on the overall system economics, since a larger dc system has greater revenue potential. Maximizing NPV in this scenario results in a dc system capacity of 1.38 kWp, which is a 1.7:1 dc-to-ac ratio.

This design approach results in a significant amount of inverter power limiting, with clipping losses of approximately 9.1%. Yet a dc loading of 1.7 optimizes the profit of the array by maximizing revenue with an eye toward controlling costs. While locations with higher insolation result in a lower dc-to-ac ratio, the optimal inverter loading will still be considerably higher than that of the reference design.

Cross-applying the results. Based on these scenarios, we see that applying three different design constraints to one location, with one set of cost assumptions, leads to three very different optimal designs. It may seem like a counterintuitive or even flawed premise that a single set of cost and revenue assumptions can lead to different optimal designs just based on the primary design constraint, but we can test this premise by cross-applying the optimal designs.

To illustrate, let us swap the area-constrained array with the budget-constrained array and evaluate how the designs perform when applied to a different set of design constraints. On the one hand, the area-constrained design results in tilt of 5° and spacing of 0.5 feet, effectively maximizing power

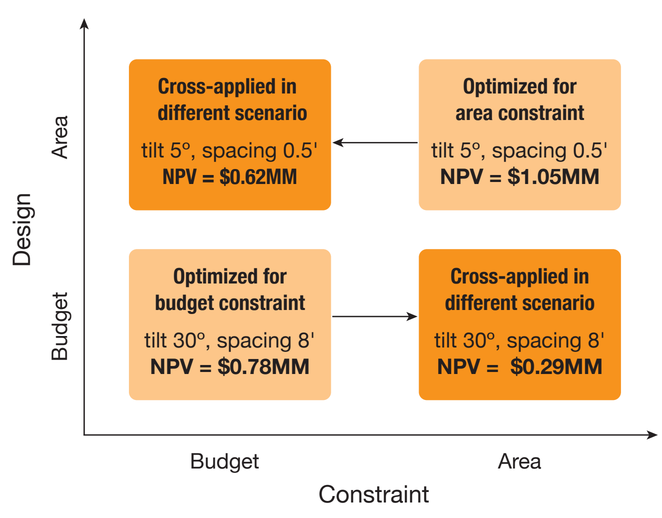

Figure 2 This figure illustrates how NPV drops when you apply one set of constraint-based design assumptions in a scenario with a different set of constraints.

density to increase revenue. On the other hand, the budget-constrained design results in a 30° tilt and an 8-foot-wide row spacing, effectively maximizing the specific yield of the array. Though the increase in profit is greatest in the area-constrained scenario, the budget-constrained design still generates more profit than the reference design.

Figure 2 shows what happens if we swap the design choices between these two applications, which causes the economics of both arrays to fall greatly. Applying the area-constrained design (low tilt and tight spacing) to the budget-constrained scenario results in an array with the same capacity as the reference design but a lower energy yield; as a result, the system NPV drops 40% to $620,000. Meanwhile, applying the budget-constrained design (high tilt and wide spacing) to the area-constrained scenario results in a 50% smaller array capacity; as a result, the NPV drops to under $300,000.

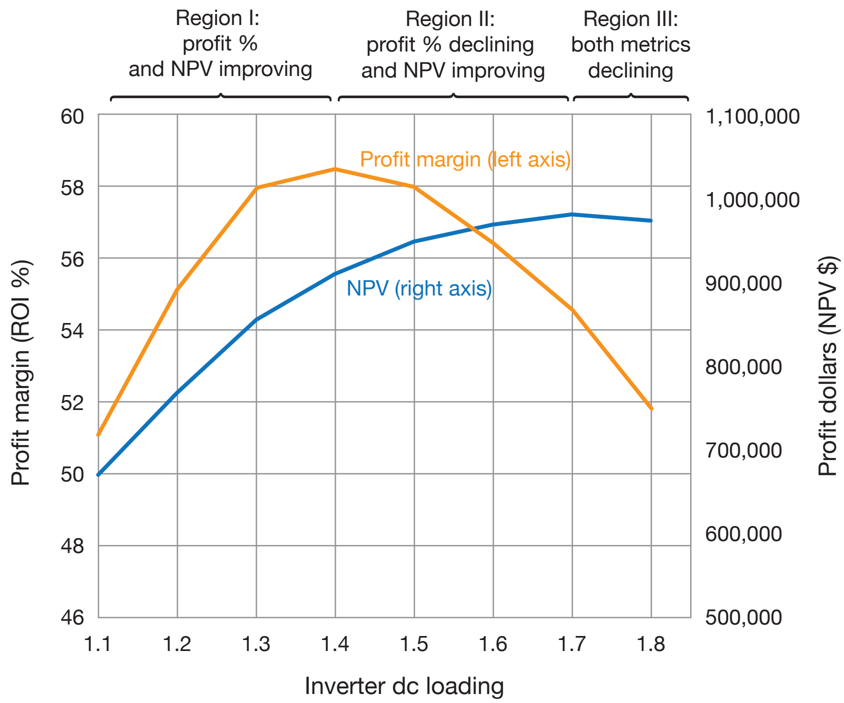

Figure 3 This figure illustrates how the optimal system design can vary according to your chosen optimization objective—in this case, profit margin versus NPV.

OPTIMIZATION OBJECTIVES

The selection of the design objective is important to any optimization process. In the previous examples, I maximized profit dollars by optimizing for NPV. Other common optimization objectives include profit margin, levelized cost of energy (LCOE) and initial cost. While these all seem like good objectives, choosing one over another can lead to a different design outcome.

To illustrate, let us consider the difference between optimizing for profit dollars and for profit margin in the power-constrained scenario above. As shown in Figure 3, optimizing for NPV results in a dc-to-ac ratio of 1.7:1, whereas optimizing for profit margin results in a dc-to-ac ratio of 1.4:1. Based on these results, we see that increasing the dc-to-ac ratio above that of the reference design (1.23) initially improves both profit margin and profit dollar. This is because increasing the dc loading initially improves both specific yield and profitability. Above a dc loading value of 1.4, however, profit margin starts to decline and profit dollars accrue more slowly. This is because the specific yield and revenue associated with each new group of modules starts to fall due to inverter power limiting. Because of these losses, it ceases to be profitable to add modules above a dc loading of 1.7.

The fact that different optimization objectives could lead to different designs is not self-evident. After all, when arrays underperform, all performance metrics generally suffer. For example, module or inverter failures or unexpected shading all reduce the array's profitability and raise the system's LCOE. This suggests that optimizing PV system designs based on one performance metric will optimize others as well. Figure 3 illustrates that this is not necessarily the case. In this example, the decision about whether to optimize based on profit margin or NPV will swing system capacity by more than 20%, from a dc loading of 1.4 to 1.7, respectively.

Which of these objectives will serve you better? It depends. If money is constrained, then you want to spend each dollar as effectively as possible, in which case profit margin is a better objective to go for. If money is not so tight, you might prefer to spend a bit more and receive more profit dollars.

If we take a step back, we can see that the design objectives for PV power systems are far less complex than those in other industries. Consider the many objectives that engineers must consider when designing a car: fuel efficiency, torque, acceleration, styling, driver visibility, weight, turn radius, length, cost, storage area, range, crash safety rating, reliability and so forth. For better or worse, electricity is a commodity. By definition, therefore, generating the lowest-cost electricity is generally the singular focus of PV system design activities. This is true even when you are making more-nuanced design decisions, such as optimizing for reliability or to streamline O&M activities. The solar industry's primary optimization objective is to reduce LCOE, regardless of whether designers are optimizing based on initial or future costs.

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