Advanced Methods for Incorporating Solar Energy Technologies into Electric Sector Capacity-expansion Models: Literature Review and Analysis

P. Sullivan, K. Eurek, and R. Margolis

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Abbreviations/Acronyms

CGE	Computable general equilibrium
CSP	Concentrating solar power
DHI	Diffuse horizontal irradiance
DLR	German Aerospace Center
DNI	Direct normal irradiance
DOE	U.S. Department of Energy
ELCC	Effective load-carrying capacity
EPA	U.S. Environmental Protection Agency
EPRI	Electric Power Research Institute
EU	European Union
GHI	Global horizontal irradiance
GIS	Geographic information system
G-Rad	Global Monitoring Division Radiation
IAEA	International Atomic Energy Agency
IREC	Interstate Renewable Energy Council
LDC	Load duration curve
LOLP	Loss of load probability
MCP	Mixed complementarity problem
MISO	Midcontinent Independent System Operator
NASA	National Aeronautics and Space Administration
NERC	North American Electric Reliability Corporation
NOAA	National Oceanic and Atmospheric Administration
NREL	National Renewable Energy Laboratory
NSRDB	National Solar Radiation Database
PIK	Potsdam Institute for Climate Impact Research
PNNL	Pacific Northwest National Laboratory
PV	Photovoltaic
QCP	Quadratic complementarity problem
RReDC	Renewable Resource Data Center
SAM	System Advisor Model
SSE	Surface meteorology and Solar Energy
TES	Thermal energy storage
VRRE	Variable resource renewable energy
WECC	Western Electricity Coordinating Council

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1 Introduction

Global and U.S. electricity systems are evolving rapidly. In response, electric utilities, regulators, government agencies, and academic researchers are increasingly using capacity-expansion models to explore the potential mixes of electricity-generating technologies under various future scenarios. Although solar energy provides only a small fraction of U.S. and global energy needs, recent technology cost reductions have driven rapid solar growth, and further solar cost reductions are targeted (Barbose et al. 2013; DOE 2012; IREC 2013).[1] As solar power becomes a more important contributor to the electricity system, capacity-expansion modeling will need to account accurately for the integration of solar technologies. Such analysis will help researchers and policymakers understand the implications of solar expansion.

Capacity-expansion models are used to develop scenarios of electricity system evolution that span large regions—from a single utility service territory to a group of countries—and decades of time. They explore the generating unit investments, transmission planning, and operational changes that might occur in response to shifting demand, unit retirements, and changes to regulation, legislation, and technology. The results illuminate the implications of potential policy and technology developments as well as the factors influencing the evolution of electricity systems over time.

The special characteristics of solar technologies require unique data and modeling capabilities and thus add complexity to capacity-expansion modeling. Whereas conventional thermal generators generally can be dispatched within some operational limits, solar-electricity output is subject to the external factor of solar irradiance. This irradiance is temporally variable and uncertain and geographically heterogeneous. The correspondingly variable and uncertain electricity output affects the operational dynamics of the entire electricity system, for example by changing dispatch profiles and increasing the need for ancillary services. Because the economics and performance of solar are strongly site dependent, solar installations also face unique issues related to transmission access, environmental impact, and public acceptance. Accounting for these characteristics is important for understanding the economics of solar investments and, through capacity-expansion modeling, the potential for solar power within electricity systems.

This report highlights the major challenges of incorporating solar technologies into capacity-expansion models and shows examples of how specific models address those challenges. It is intended to help modelers consider ways to enhance their own models' representations of solar to reflect the state-of-the-art. Following an overview of electric sector capacity-expansion modeling (Section 2), the report covers five important issues related to modeling solar technologies: understanding general methods for modeling non-dispatchable technologies (Section 3), determining which solar technologies to model (Section 4), choosing a spatial resolution (Section 5), incorporating solar resource assessments (Section 6), and accounting for solar generation variability and uncertainty (Section 7). The key points are summarized here.

Each capacity-expansion model is unique and designed with its own priorities, objectives, and level of detail. Although no single model or modeling approach is superior for all circumstances,

[1] For example, the U.S. Department of Energy's SunShot Initiative aims to reduce the price of U.S. solar energy systems by about 75% between 2010 and 2020 (DOE 2012).

each one can provide a valuable perspective. With multiple viewpoints from different models, researchers and analysts can better understand the dynamics of electricity systems, especially with respect to integrating solar technologies.

We survey four general methods for integrating non-dispatchable[2] technologies like solar into capacity-expansion modeling, ranging from simple screening-curve calculations to simultaneous capacity-expansion modeling of dispatchable and non-dispatchable generators. A sophisticated model would capture the complex relationships among unit dispatch, transmission, reliability and market rules, and capacity-investment decisions. Screening curves, which estimate the optimal system mix from the shape of the load-duration curve can provide a first-order approximation of capacity expansion and can be augmented to consider the impact that deployment of non-dispatchable technologies can have on the system mix. Two intermediate methods use extant modeling practices to compare among discrete portfolios of non-dispatchable generators, providing substantial detail and subtlety beyond screening curves but not co-optimizing dispatchable and non-dispatchable investments. Most of the models discussed in this report fall into the fourth category, considering dispatchable and non-dispatchable generators—and often transmission—together. However, these models still differ from one another in their areas of emphasis and in their strategies for accommodating the complexities of integrating non-dispatchable technologies.

Multiple solar technologies exist, and each has particular resource and operational characteristics. That there is such variety in solar generating technologies puts the burden on the model developer to select or combine technologies into a manageable subset. Central photovoltaic (PV) systems and concentrating solar power (CSP) systems without thermal energy storage (TES) are common across models. Fewer include distributed PV and CSP with TES. In the literature we examined, concentrating PV is rarely represented.

Each capacity-expansion model has a particular spatial resolution—from one to hundreds of analytical regions. Tradeoffs between fine and coarse resolution make different choices appropriate for different applications.

Modelers can incorporate solar resource data into their capacity-expansion models; credible data sources and processing tools are available for this purpose. The resource data are often implemented as a supply curve defining the quantity of deployable solar capacity at a given resource quality. The quality is often inversely proportional to the cost of accessibility (that is, regions with the best solar resources are often farthest from electricity demand centers). Therefore, representing solar-related transmission costs is also important. While some models assign a simple transmission cost adder to imply that there are above-average transmission costs to access solar resources, the spatial heterogeneity of the resource means that a model can increase fidelity by constructing “accessibility supply curves” that approximate the distribution of potential sites for solar deployment and include the cost for building transmission to the sites.

[2] ‘Dispatchability’ refers to the ability of a generator to adjust output based on a signal or control from the system operator. Without the aid of dedicated storage, solar technologies lack dispatchability because their output depends on the intensity of sunlight which is variable and uncertain. As such, we classify solar technologies as ‘non-dispatchable.’

To reproduce realistic investment behavior, capacity-expansion models must account for the costs and benefits related to the variable and uncertain operational characteristics of solar technologies, especially the value of solar electricity. To balance accuracy and usability, modelers generally create simplified dispatch periods meant to capture correctly the relationship between solar electricity output, load, and conventional operations—while also allowing the model to account for the solar resource's spatial heterogeneity, explore adequate time horizons, and maintain reasonable computational requirements. Thoughtful selection of chronological or non-chronological simplified dispatch periods and correction factors can provide a balance between accuracy and usability.

Effective capacity-expansion models also consider how solar deployment interplays with the electricity system's resource adequacy and operating reliability. Advanced models account for a solar generator's capacity value (and its erosion with increasing solar penetration) and contribution to resource adequacy as well as the improved capacity value of CSP with hybrid backup or TES. Finally, the variability and uncertainty of the solar resource adds to the system's operating-reliability burden and costs associated with additional need for ancillary services. Some capacity-expansion models ignore these impacts and costs, whereas others incorporate them in various simplified forms. Models typically characterize PV as requiring higher ancillary-service needs than CSP, even CSP without TES. Some of these operational characteristics remain difficult to address with current models and thus represent an area for future research.

Table 1 provides a brief description of each of the capacity-expansion models discussed in this report. While the list is not exhaustive, the included models cover a range of geographic regions and sectoral scope, and they represent several modeling structures. Many of these models are designed primarily for research or long-term policy and technology analysis. We do not include the suite of commercial tools used by utilities and system planners for planning purposes. Mills and Wiser (2012) discuss several of these commercial models within a survey of utility procurement plans. In general, we choose models that are documented with some consideration of solar technologies. Some of these models were developed a decade or more in the past, have not been used widely, or are not actively maintained by their developers today. Still, each includes strategies for integrating solar technologies that provide insights useful for current solar modeling activities.

Table 1. Models Discussed in this Report

Model Name	Primary Reference	Description	Institution
EGEAS (Electric Generation Expansion Analysis System)	Rastler (2011)	Dynamic programming model used for production costing and generation-expansion planning in the United States.	Electric Power Research Institute (EPRI)[3]
ENERGY 2020	SSI and PAC (n.d.)	System dynamics model that explores the energy supply/demand balance across multiple sectors and regions in North America.	Systematic Solutions Inc.
EPPA (Emissions Prediction and Policy Analysis)	Morris (2008)	Computable general equilibrium (CGE) model that explores the interaction of multiple energy and non-energy sectors for multiple regions around the world.	Massachusetts Institute of Technology
GCAM (Global Change Assessment Model)	PNNL (2012)	Partial-equilibrium model designed to examine long-term, large-scale changes in global and regional energy systems.	Pacific Northwest National Laboratory (PNNL)
IPM (Integrated Planning Model)	EPA (2013)	Deterministic linear programming model of the electric-power sector for multiple regions in North America.	ICF International
LIMES-EU	Haller et al. (2012)	Linear programming model of electricity-sector evolution for Europe, the Middle East, and North Africa.	Potsdam Institute for Climate Impact Research (PIK)
MARKAL (Market Allocation Model)	Loulou et al. (2004)	Linear programming model of both the supply and demand sides of the energy system with a flexible regional structure applicable to any spatial extent.	Brookhaven National Laboratory
NEMS (National Energy Modeling System)	EIA (2013)	Economic equilibrium model for the multi-sector energy system of the United States.	U.S. Energy Information Administration
PERSEUS-RES-E	Rosen (2007)	Linear programming model that optimizes the evolution of the electric power sector in Europe.	Universitätsverlag Karlsruhe (Germany)
PLEXOS LT Plan	Energy Exemplar (2013)	Mixed-integer programming model that integrates long-term electric sector planning optimization with detailed operational optimization for regional systems.[4]	Energy Exemplar
ReEDS (Regional Energy Deployment System)	Short et al. (2011)	Deterministic linear program optimization model of the deployment of electric-generation technologies and transmission infrastructure throughout the contiguous United States.	National Renewable Energy Laboratory (NREL)

[3] EGEAS was originally developed for EPRI by the Massachusetts Institute of Technology and the Stone & Webster Engineering Corporation.

[4] PLEXOS LT Plan has been used to model regions including New Zealand (MMA 2007), Australia (Lilley et al. 2009; Malla 2012; Nweke 2012), and Spain (Panagiotakopoulou n.d.).

Model Name	Primary Reference	Description	Institution
ReMIND-R	Luderer et al. (2011)	General equilibrium model that optimizes the welfare of the integrated energy-economy-environment system around the world.	PIK
REMix (Renewable Energy Mix for Sustainable Electricity Supply)	Scholz (2012)	Linear programming model that determines the cost-optimal electricity supply mix for the European Union (EU) and North Africa.	German Aerospace Center (DLR)
RPM (Resource Planning Model)	Mai et al. (2013a)	Mixed-integer linear programming model with high spatial and temporal resolution that can be used for mid- and long-term scenario planning of regional power systems.	NREL
RREEOM (Regional Renewable Electricity Economic Optimization Model)	Budischak et al. (2013)	Optimization model for evaluating high renewable penetration with a reliable least-cost capacity mix for the PJM system in the eastern United States.	University of Delaware
SEDS (Stochastic Energy Deployment System)	Short et al. (2006)	Stochastic simulation model of the U.S. energy markets designed to explore how the U.S. energy economy will evolve in response to the development of new technologies.	NREL
SWITCH-WECC[5] (Solar, Wind, Hydro and Conventional Generators and Transmission)	Johnston et al. (2013)	Mixed-integer linear programming[6] model for least-cost generation, storage, and transmission capacity expansion for the electric-power sector in western North America.	University of California, Berkeley
THEA (The High temporal resolution Electricity-market Analysis-model)	Nicolosi (2012)	Decomposed linear optimization model for investment planning of the electric-power sectors in Texas and Germany with hourly dispatch.	Universität zu Köln, Germany
US-REGEN (United States Regional Economy, Greenhouse Gas, and Energy Model)	EPRI (2013)	CGE model that combines a mixed complementarity problem (MCP) macroeconomic model with a quadratic complementarity problem (QCP) electric sector investment and dispatch model for the United States.	EPRI
WASP-IV (Wien Automatic System Planning – Version 4)	IAEA (2001)	Dynamic-programming model to analyze the economic optimal generation expansion plan for the electric power sector of a user-define spatial extent.	International Atomic Energy Agency (IAEA)[7]

[5] The version of SWITCH referenced here models the area associated with Western Electricity Coordinating Council (WECC) service territory. There also exists a version of SWITCH specifically for California (Fripp 2012).
[6] The traditional mixed-integer linear programming formulation for SWITCH-WECC can be relaxed and run as a linear program as demonstrated by Mileva (forthcoming) and Nelson (2013).
[7] WASP-IV was originally developed for IAEA by the Tennessee Valley Authority and Oak Ridge National Laboratory.

2 Overview of Electric Sector Capacity-expansion Modeling

Capacity-expansion models, the subjects of this paper, are mathematical models that make generation (and often transmission) investment decisions based on system operation needs.[8] Given a set of rules and objectives, the model will construct an electricity system from scratch or update one through time to meet evolving needs. Capacity-expansion models use three primary methods to determine which type of new capacity will be built: optimization, simulation, and equilibration. Optimization models typically select the least-cost method of meeting load while satisfying reliability and other requirements. Simulation models make investment decisions through a series of formulas: if an investment option is expected to garner sufficient revenue to support its capital and operating requirements, it is built; alternatively, a quantity of required capacity is subdivided across eligible technologies according to their relative costs (a market-share algorithm). For example, SEDS (Short et al. 2006) uses logit functions to simulate the market share for competing technologies. Equilibrium models find a set of prices such that supply and demand across the set of relevant parameters (electricity, fuels) equilibrate. As an equilibrium model, EPPA (Morris 2008) includes CSP and PV technologies as imperfect substitutes for conventional generators to represent a set of aspects particular to variable renewables, including integration challenges. These three model types each have distinct advantages and disadvantages, but that discussion is outside the scope of this report; for more on model classification, see Mai et al. (2013b) and Van Beeck (1999).

Numerous studies have reviewed capacity-expansion planning in the electric sector, including methodologies and challenges. Phupha et al. (2012) discuss the major issues in developing an expansion plan, including forecasting demand, identifying technology options, evaluating technology economics, and addressing reliability. Van Beeck (1999) classifies different types of energy models according to their methodology (e.g., equilibrium, optimization, simulation), mathematical approach (e.g., linear programming, integer programming, dynamic programming), and scope (e.g., geographic, temporal, sectoral). Palmintier (2013) outlines models specific to the electric sector—both detailed operations and capacity-expansion—and organizes them by timeframe (milliseconds to years), modeling detail (system level to component level), and scope (type of questions to answer).

Early versions of older electric sector models (e.g., EGEAS, MARKAL, NEMS, and WASP) focus primarily on modeling the deployment of large, dispatchable thermal generating units fueled by coal, natural gas, and uranium. With the changing electric sector landscape, modeling teams have been either modifying existing models to better represent variable resource renewable energy (VRRE) technologies or constructing new models designed to consider VRREs (e.g., ReEDS and SWITCH-WECC). Recent efforts also have begun exploring the challenges of integrating wind and solar technologies into the grid at high levels of market penetration: DOE (2008), DOE (2012), GE Energy (2010), Mills et al. (2009), NERC (2009), NREL (2012), and Zavadil et al. (2004).

[8] In addition to generation and transmission investments, these models can also consider investments in electricity storage, energy efficiency, and demand response.

Moving forward, there is a need for improved modeling of renewable impacts on the grid, including large-scale, high-resolution models that simultaneously consider capacity expansion and dispatch to inform long-term planning with wind and solar (Möst and Fichtner 2010; Nelson et al. 2012). Also not well explored are the effects of temporal resolution on high–renewable energy scenarios, the characterization of the variable and uncertain nature of VRREs within traditional capacity-expansion models, and the sensitivity of renewable capacity expansion to exogenous inputs, e.g., technology cost and performance characteristics (Kammen et al. 2011; Neuhoff et al. 2008; Nicolosi 2012). McCalley (2012) identifies a need for better long-term electric sector planning tools that consider co-optimization of transmission and generation, long time horizons, chronological dispatch with greater resolution, demand-side options, geographic impacts on renewables, effects of cycling, ramping needs for VRREs, multiple-objective optimization, and improved handling of uncertainty.

Next-generation models will have an increased focus on evaluating uncertainty. Brun (2011) discusses general areas of uncertainty in capacity-expansion modeling, including macroeconomic data, technological innovations, technology financing, climate dynamics, technical generator characteristics, regulations, and public opinion. Models address uncertainty using methods such as Monte Carlo simulation, scenario development and stochastic programming. As a simulation model, SEDS (Short et al. 2006) samples uncertain input parameters such as future technology costs, fuel prices, economic growth, and policies from probability distributions to produce probabilistic forecasts of electricity-supply infrastructure deployment. Milligan et al. (2012) discuss stochastic methods for planning and operating power systems with large amounts of wind and solar power. Drury et al. (2014) explore three types of uncertainties for residential customers investing in rooftop PV and the relative impacts of uncertainty mitigation. These uncertainties include interannual solar variability, PV technical performance and maintenance costs, and market risks.

With that overview as background, the next section discusses general methods for modeling non-dispatchable electricity-generating technologies.

3 General Methods for Modeling Non-dispatchable Technologies

Electric utilities, regulators, governments, academic researchers, and others are interested in understanding how new and growing generation technologies might interact with the traditional structure of the electricity system. Wind and solar power in particular, being non-dispatchable,[9] are likely to require changes in how conventional technologies are valued and operated (NERC 2009). This section discusses four methods researchers use to explore VRRE integration into electricity systems:

1. Screening curves with merit-order dispatch
2. Renewable and conventional technology portfolio analysis using detailed operational modeling
3. Renewable technology portfolio analysis using conventional technology capacity-expansion modeling
4. Renewable and conventional technology capacity-expansion modeling.

The first method is the simplest, an analytical estimation of how VRRE deployment is likely to change the operation levels of the conventional fleet, and what that is likely to mean for VRRE investment attractiveness. Methods 2 and 3 use two categories of electricity system models that are not necessarily strong on VRRE modeling to provide some insight into VRRE impacts. The fourth method uses the category of full-featured capacity-expansion models on which this paper focuses.

3.1 Screening Curves with Merit-order Dispatch

A screening curve estimates the optimal generating mix for serving a load assuming the lowest-cost units sufficient to meet demand are always selected for dispatch (merit-order). Given a load duration curve (LDC), a screening-curve algorithm can estimate how often each class of unit will run, based on marginal operating cost, and will select appropriate units for investment by optimizing capital and operating costs compared to expectation of hours operated (Figure 1). Screening curves do not consider plant startup costs, ramping constraints, or minimum turndown—or system considerations like transmission and ancillary services—and so only approximate actual unit commitment. Nevertheless, this first-order approximation can be useful for capacity-expansion planning.

[9] Both wind and solar power technologies depend on resource that is variable and uncertain. As such, we classify both as 'non-dispatchable.'

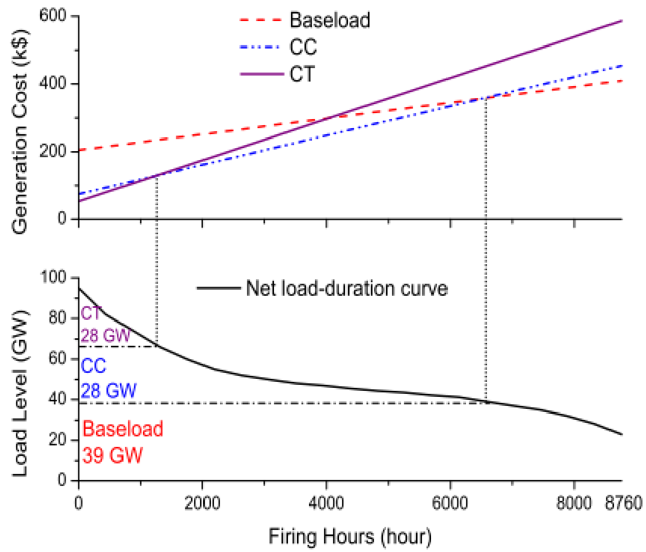

Figure 1. Illustration of the screening curve method

Source: Zhang (2013)

While designed for systems comprising conventional generators, screening-curve methodologies can be revised to evaluate the effect of VRREs on the operation of the conventional fleet. Because wind and solar power have no fuel needs, they can be assumed to operate at near-zero marginal cost and therefore to be dispatched first in a merit-order dispatch stack. The VRREs thus can be treated as load modifiers, reducing the net demand variably across hours—based on the characteristics of the variable resources. The screening-curve calculator can then report the optimal shares of conventional generator types for dispatching to that adjusted (residual) LDC, compared to the fleet for the original LDC. Figure 2 gives an example of an adjusted LDC. Lamont (2008) notes that the load-modifier approach neither accounts for the optimal VRRE deployment (i.e., VRREs are added to the system without considering their economic competitiveness in relation to other generation technologies) nor offers explicit insight into the marginal value of VRREs. Despite these shortcomings, comparing the screening-curve results with and without the VRREs can estimate the impact VRRE deployment might have on the electricity system such as fuel savings, emissions reductions, and a shift in generation mix toward more intermediate and peak-load capacity.

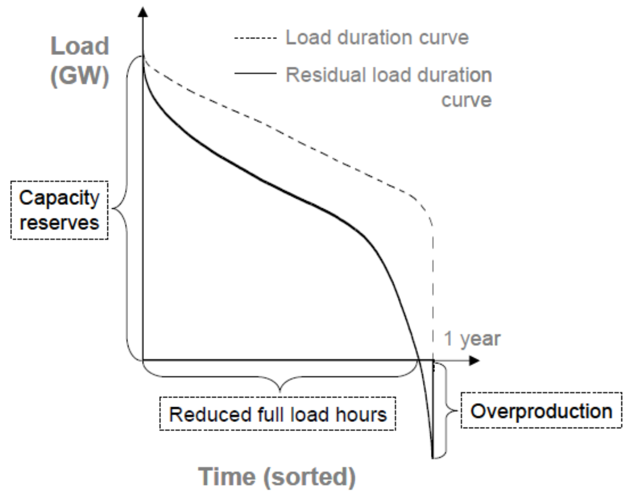

Figure 2. Illustration of a residual load duration curve

Source: Ueckerdt et al. (2011)

Screening-curve estimates of optimal system mix can provide value, especially if augmented by consideration of reliability needs; compared to more complex methods, screening curves have much lower data and computing requirements. The screening-curve method could be useful, for example, to identify obvious technology choices or develop a large pool of candidate technology mixes over a range of input assumptions quickly. Screening-curve and LDC analysis was a key component, alongside dynamic programming in WASP-IV, of developing a system-expansion plan for Pakistan's power system (Shinwari et al. 2012). EGEAS includes capacity-expansion planning tools ranging from simple screening curves to complex non-linear optimization and dynamic-programming models. A MISO energy-storage study used the dynamic-programming capabilities of EGEAS for the detailed model analysis but also applied screening curves to illuminate the decision making of the dynamic-programming tool by visualizing the marginal-cost curves for different technologies (Rastler 2011).

3.2 Renewable and Conventional Technology Portfolio Analysis Using Detailed Operational Modeling

A step up in complexity and fidelity from screening curves is to use a chronological production-cost or unit-commitment model on a proposed system or ensemble of systems that include both renewable and conventional generators and transmission. GridView (ABB 2008), HiGRID (Eichman et al. 2013), PLEXOS,[10] PROMOD (Ventyx 2012), and RREEOM (Budischak et al. 2013)[11] are all detailed operational models that can evaluate a suite of predefined portfolios for operational details. Models like these can be used by electric utilities and other entities engaged in the integrated resource planning process for detailed investigation of how a particular investment likely will be used within a complex system.

[10] PLEXOS here is the production-cost model. This is different than PLEXOS LT-Plan, which uses the production-cost capabilities in a capacity-expansion tool. See PLEXOS for power systems at http://www.energyexemplar.com.
[11] Most detailed operational models evaluate system operations for 1 year. As an exception, RREEOM compares the minimum-cost portfolios for a 4-year simulation of 1.7 billion combinations of renewable energy/storage technology portfolios such that renewable energy completely serves load for a threshold number of hours.

Operating a production-cost model in place of a screening curve incorporates the operational details (startup cost, ramp rates, transmission considerations) that are overlooked in the screening-curve approximations. Studies evaluating the gap between screening curves and operational models have shown that screening curves do miss some subtleties of operation, especially relating to costs and prices, even if bulk-generation numbers are similar to those produced through detailed models (Staffell and Green 2012). Depending on the characteristics of interest, it may be worthwhile to take advantage of the flexibility, ease of use, and speed of screening curves to evaluate a large ensemble of system configurations. Analysis including revenue or operational details would benefit from detailed operational modeling. Like screening curves, this method only compares among predefined portfolios; it does not select or suggest optimal system configurations. For that, a capacity-expansion model is needed.

3.3 Renewable Technology Portfolio Analysis Using Conventional Technology Capacity-expansion Modeling

Capacity-expansion models extend the capabilities of the previous two methods in that the model itself constructs an internally consistent electricity system that meets demand and reliability requirements in a planned way, rather than relying on the user to enter predefined generating portfolios. If the model uses an optimization algorithm, it devises a solution based on some optimality objective such as cost minimization or profit maximization.[12] Capacity-expansion models also usually make investments over time to meet changing demands, which provide scenarios of system evolution compared to the snapshot results from the first two methods. If a capacity-expansion model does not have the capabilities to explicitly model VRREs, a set of candidate renewable portfolios can be prescribed and a balance-of-system built around each. If an optimization model is used, the result will be a discrete set of VRRE-driven conventional investment decisions, each optimal for the given VRRE portfolio. The resulting systems, costs, and operational behaviors can be compared across systems to evaluate the relative costs and impacts of each of the candidate portfolios. THEA (Nicolosi 2012) uses a residual-load approach (load minus generation from VRRE) to incorporating prescribed VRRE profiles, and then it uses capacity-expansion modeling to optimize conventional generation around that residual-load system.

3.3.1 Combining Capacity-expansion Modeling with Detailed Operational Modeling

Capacity-expansion models generally have simplified operation compared to the full production-cost models described in Section 3.2 because of concerns about high computational requirements. Capacity-expansion models typically have reduced-resolution dispatch, for instance, with aggregate units and time blocks or only a subset of hours. In exchange for the reduced operational detail, capacity-expansion models gain long-term planning capabilities. A recent combination technique pairs capacity-expansion models (including those with prescribed VRRE portfolios described in this section as well as those with optimized VRRE portfolios described in Section 3.4) with production-cost models, producing investment scenarios in the former and dispatching them in the latter for increased operational information and validation (DOE 2012; Lew et al. 2013; NREL 2012). Figure 3 shows an example of a dispatch stack

[12] Models can use a variety of optimality objectives, but cost minimization is used commonly.

produced from the GridView production cost model to validate a generation portfolio produced from ReEDS in a high solar penetration analysis (DOE 2012). Similarly, Ueckerdt et al. (2011) model capacity expansion using ReMIND-R and validate dispatchability using MICOES.[13] Nelson et al. (2012) use SWITCH-WECC to determine an investment portfolio and validate using a detailed operational model with two years of historical hourly data in weekly batches. As an extension, Mileva et al. (2013) use this validation routine for SWITCH-WECC to identify hours of capacity shortfalls, which are then added into the capacity-expansion optimization. Poullikkas et al. (2011) optimize the capacity mix using WASP-IV and determine the optimal dispatch with IPP.[14]

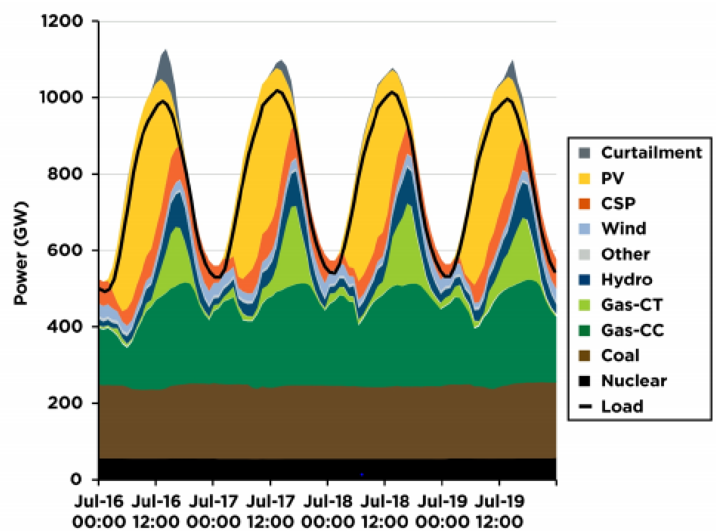

Figure 3. GridView-simulated national mean dispatch stack during 4 days in summer for a high solar penetration scenario

Source: DOE (2012)

3.4 Renewable and Conventional Technology Capacity-expansion Modeling

The methods discussed so far compare user-defined electricity systems or VRRE portfolios, but for many analysis questions the goal is an evenly balanced evaluation of all generation-investment options. That explains the rise of capacity-expansion models with a robust representation of VRREs, a category that encompasses most of the models discussed in this report. Much of the rest of this report discusses what constitutes a robust representation, including resource-assessment needs, transmission analysis, spatial resolution, and operational detail that enable consideration of the impact of a generator's variability and reliability on system operation.

Simultaneous consideration of conventional and renewable generators transfers the analytical burden from analyst to model and enables systematic evaluation of how the complicating aspects of VRREs affect their value to the system. For solar power, these characteristics include:

[13] For a description of MICOES, see Harthan et al. (2011).
[14] For a description of IPP, see Poullikkas (2009).

- Solar generator technology (characteristics and performance)
- Solar resource accessibility (connecting solar to the transmission and distribution network)
- Solar output profile and smoothing through resource diversification
- Coincidence of residual peak load and solar plant output profiles
- Value of solar energy at the time it is available
- Ability of a solar system to replace conventional generation sources (capacity value)
- Operating reserve requirements induced by variable generation
- Inability to use solar energy (curtailments) due to oversupply of power (e.g., minimum stabilization levels for thermal generators).

Capturing all these factors in full detail is likely to result in a highly complex model with steep computational and data requirements. An effective, full-featured capacity-expansion model therefore requires a balance between model usability and absolute fidelity. The remainder of this report discusses a subset of modeling decisions an analytical team must make when incorporating solar technologies into a model as well as existing techniques used in models to capture the characteristics listed above.

4 Determining Which Solar Technologies to Model

Each solar technology has unique resource and performance characteristics that affect its interaction with the electricity system. Capturing the full gamut of technology options in any single model would be unreasonable, so one role of the model developer is to capture a representative sample of the technologies available to enable the model to tackle its intended questions effectively. The two major categories of solar technologies are CSP and PV:

- **CSP** systems focus direct sunlight onto fluid at a focal point.[15] The fluid typically generates steam, which runs a turbine. There are multiple CSP technologies that differ in cost and performance characteristics and in their ability to store thermal energy for later use. CSP fields augmented with either TES or natural gas backup can allow the system to operate more like a traditional generator than a VRRE technology.
- **PV** systems are solid-state devices that convert sunlight (both direct and diffuse[16]) straight to electricity. As with CSP technologies, there is diversity in PV options that affects cost and performance, so a modeler must choose which specific configurations to represent. PV modules take multiple forms and can be manufactured from a range of semiconductor materials, although silicon is the most popular. PV modules are deployed in both small and large arrays, on buildings or on the ground. Large arrays can be mounted on mechanical tracking systems that rotate the modules throughout the day to follow the sun's trajectory and improve performance.

Other technologies that are not yet commercially available could also be incorporated into models. For example, integrated PV and compressed air energy storage systems could enable the PV to act as a dispatchable generator with cycling, regulation, and non-spinning reserve capabilities (Fthenakis et al. 2009).

Most models reviewed here represent PV and CSP without TES, because these technologies can be treated simply as load modifiers. Capturing the operational details of CSP with TES is more difficult, because the storage makes the generator dispatchable, which requires the addition of operational detail and increases computational burden. Although several models examined here consider this technology (e.g., GCAM, ReEDS, REMix, and SWITCH-WECC), a much smaller subset of models allows dynamic time shifting of CSP input energy via TES. ReEDS, REMix, and SWITCH-WECC allow CSP with TES to dispatch within energy limits imposed by the solar multiple, hours of storage, and the time profile of the insolation.[17]

Models might choose to ignore certain solar technologies. For example, nascent technologies like concentrating PV that have not yet gained a significant foothold in the market are often excluded. Among the models considered, only SWITCH-WECC represents concentrating PV (Kammen et al. 2011). Moreover, if the spatial extent of interest does not have sufficient solar resource, then

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[15] Direct sunlight is referred to as direct normal irradiance or DNI. In the United States, the best direct sunlight exists in the Southwest.

[16] Diffuse sunlight is referred to as diffuse horizontal irradiance or DHI.

[17] Insolation is the amount of solar radiation striking a unit of surface area. In this report it is used interchangeably with the term "solar resource."

solar technologies are not likely to be economically viable. For instance, ReEDS does not model CSP in Canada, because the CSP resource (direct normal irradiance or DNI) in Canada is not generally considered to be economically viable (Martinez et al. 2013). Finally, central planning models typically do not endogenously consider residential rooftop PV systems in their investment decisions, because the central-planning decision criteria do not sufficiently capture residential rooftop market dynamics. However, a small subset of models mentioned here directly represents distributed rooftop PV. For example, SEDS (DeForest et al. 2011) includes a module for the buildings sector that endogenously models the supply-demand balance of energy resources (e.g., passive solar, rooftop PV) and end uses (e.g., heating, lighting) in commercial and residential buildings. SWITCH-WECC (Johnston et al. 2013) endogenously models rooftop PV deployment at 216 sites, limiting the total deployed capacity based on an assessment of available roof area and rooftop spacing ratios. Residential PV can also be added exogenously. For example, NREL accounts for distributed PV in ReEDS by entering the output from its SolarDS model (Denholm et al. 2009) into ReEDS. This approach has limited feedback between the dynamics of residential PV adoption behavior (SolarDS) and utility-scale decisions and electricity price (ReEDS). In contrast, endogenously modeling rooftop PV (central-planner style) co-considers rooftop PV adoption and investment decisions for the rest of the system, although this approach may not effectively capture individual consumer behavior.

5 Choosing a Spatial Resolution

Spatial resolution in models can vary from a single region to hundreds of regions depending on the study area, level of detail desired, and model intent. Model size and complexity are generally limited by data and computational practicality; larger, more detailed models have larger upfront data and programming requirements and also generally take longer to execute. As such, scope and detail are the common tradeoffs in model design. Global and economy-wide models (e.g., GCAM and ReMIND-R) generally have far fewer regions than electricity system models, because the additional model scope needed for geographical and sectoral expansiveness occupies some of the data and computational space that could have gone to geospatial detail. These models usually emphasize the larger relationships among large regions and across sectors rather than focusing on the details of any one region and sector. Models focusing solely on the electric-power sector (e.g., IPM, ReEDS and SWITCH-WECC), on the other hand, can represent more regions because the reduced model scope affords added complexity elsewhere.

Energy-system models can gain benefits in model fidelity by increasing geospatial resolution, because increased resolution can reveal resource, transmission, and market structures that spatially coarse models overlook. Especially for certain model types, additional resolution also means an increased number of decisions, which can diversify outcomes, not only through technologies finding favorable niches in small regions, but also simply because more decision events with subtle differences (load levels, fuel prices, transmission connections) tend to spread results, reducing "knife-edge" or "winner-take-all" behavior (Short 2007).

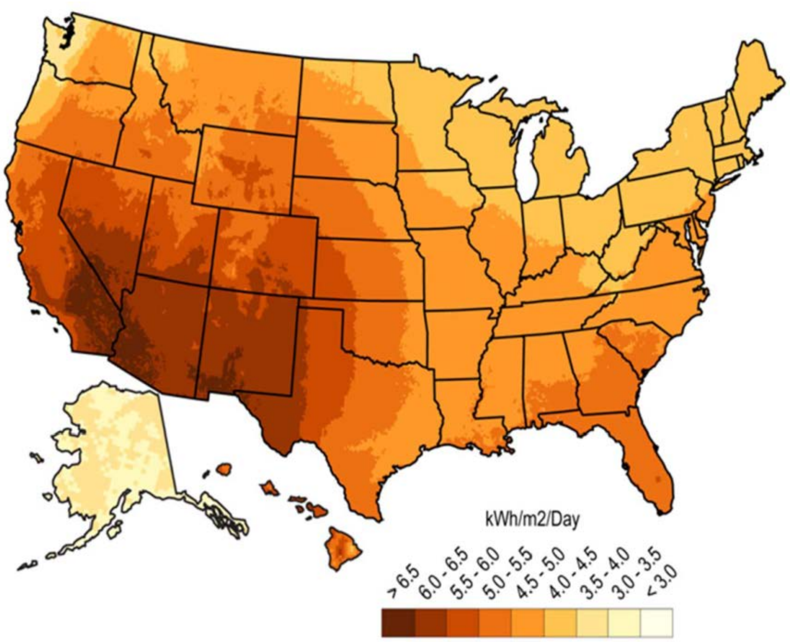


Figure 4. Map of the mean solar resource available to a PV system facing south and tilted at an angle equal to the latitude of the system

Source: Drury et al. (2012)

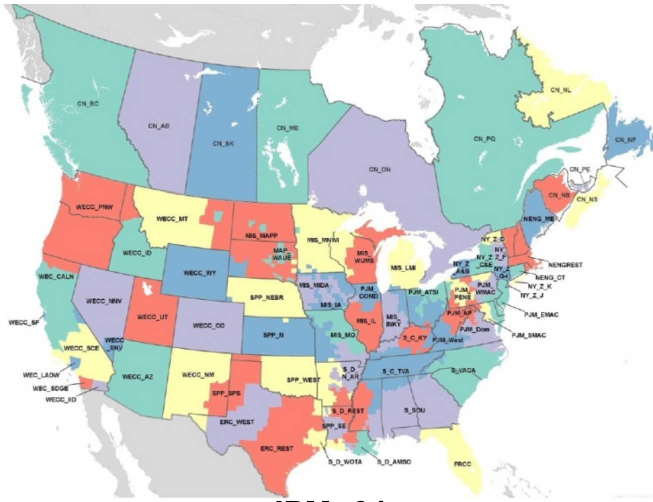
Considering renewable resources like solar power, the fact that resource quality and characteristics vary significantly by location means that greater spatial resolution can improve the fidelity of solar investment placement and plant performance. Figure 4 is a map of PV resource quality in the United States showing the dramatic regional differences in insolation across the country. Accounting for regional differences in resource quality can help solar technologies compete effectively in high-resource areas. Solar output profiles also vary from site to site, so models with large regions can miss the benefits accrued by spatially diversifying solar resources to smooth the solar output profiles (Tarroja et al. 2013). Models can—and often do—include constructs (e.g., resource supply curves) to provide sub-regional information about solar resource characteristics. Examples of models with regional supply curves are presented in Section 6.

Geographic resolution is not the only possible repository for added detail: some models downplay regionality, instead prioritizing temporal detail, modeling of individual generator operations, or other characteristics. Single-region models may be sufficient for modeling a small or isolated system such as an island, small country, or service territory, or they may be desirable if the analytical focus values simplicity or short run times. Short et al. (2006) constructed SEDS with a single region covering the United States because of the complexity associated with developing and assigning probability distributions to model parameters, the desire for quick run-times, and the focus of the model on which system characteristics are most likely to lead to national market-penetration swings. SEDS is predicated on the hypothesis that market-penetration swings occur at a national level, with national rather than local factors providing the major penetration drivers.

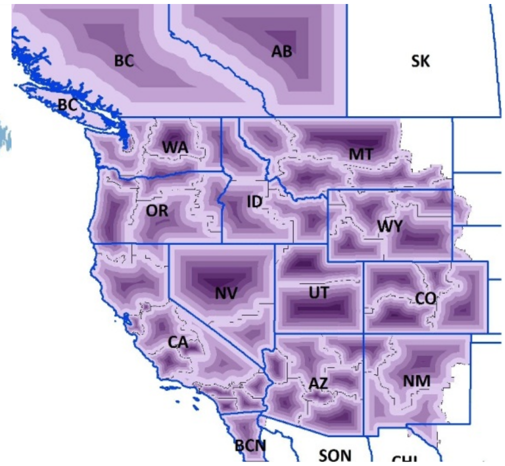
Table 2 summarizes the spatial extent and resolution for selected models. Many of the models encompass the continental United States, and Figure 5 shows regional maps for several of those models to allow comparison. Even among aggregated models, certain regional divisions, for instance carving out the sunny Southwest from neighboring regions, can improve differentiation of solar resource by establishing a region with an excellent resource. Further subdivision within a large resource regime—as in IPM, ReEDS and SWITCH-WECC—can allow a model to distinguish solar resource further as being near major cities or remote or distinguish among subtleties in seasonal performance, daily solar cycles, and so forth. Maps for most of the models not shown in Figure 5 are available in the cited publications.

Table 2. Spatial Extent and Resolution of Selected Models

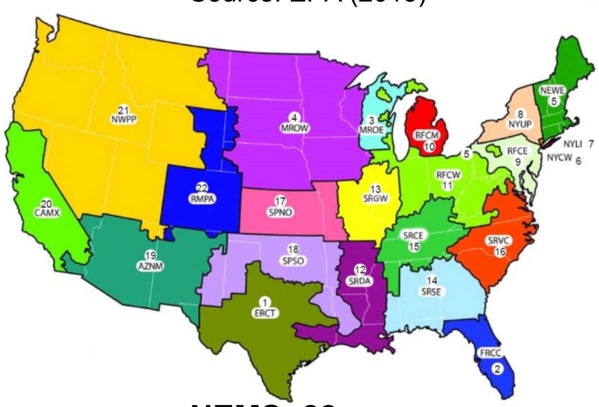
	Model	Spatial Extent	No. of Regions
U.S. Regional Models	RREEOM Budischak et al. (2013)	PJM (Eastern United States)	1
	RPM Mai et al. (2013a)	Rocky Mountain Power Pool	31
EU (+) Models	THEA Nicolosi (2012)	Germany – interconnected systems with 11 EU zones	11
	LIMES-EU Haller et al. (2012)	EU, Middle East, and North Africa	20
	PERSEUS-RES-E Rosen (2007)	EU-15 and 6 neighboring EU countries	21
	REMix Scholz (2012)	EU and North Africa	36
U.S. Models (some including parts of Canada)	SEDS Short et al. (2006)	Lower 48 United States	1
	NEMS EIA (2013)	Lower 48 United States	22
	US-REGEN EPRI (2013)	Lower 48 United States	15
	SWITCH-WECC Johnston et al. (2013)	Western Interconnect (#U.S. + #Canada + #Baja California Norte)	47 + 2 + 1
	ENERGY 2020 SSI and ICF (2012)	Lower 48 United States and Canada (#U.S. + #Canada)	50 + 10
	ReEDS Short et al. (2011) Martinez et al. (2013)	Lower 48 United States and Canada (#U.S. + #Canada)	PV regions: 134 + 18 CSP regions: 356 + 45
	IPM EPA (2013)	Lower 48 United States and Canada (#U.S. + #Canada)	54 + 10
	GCAM Smith et al. (2011) PNNL (2012)	United States	12
Global Models		Global	14
	ReMIND-R Luderer et al. (2011)	Global	11



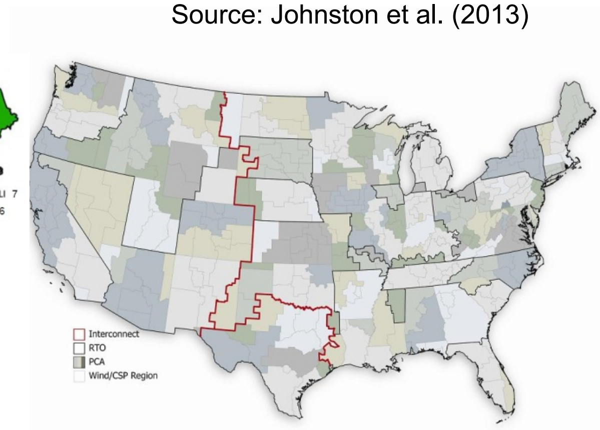
IPM: 64
Source: EPA (2013)



SWITCH-WECC: 50
Source: Johnston et al. (2013)

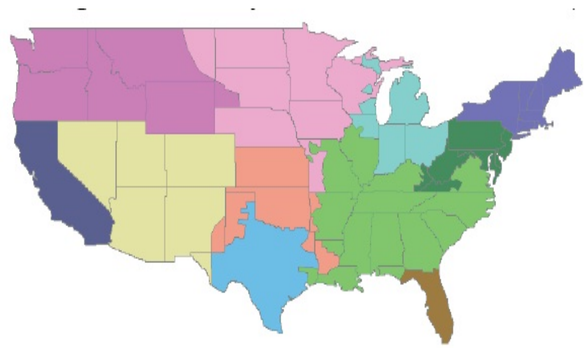


NEMS: 22
Source: EIA (2013)



ReEDS: 134 PV, 356 CSP
Source: Short et al. (2011)

US-REGEN: 15
Source: EPRI (2013)



GCAM-USA: 12
Source: Smith et al. (2011)

Figure 5. Regional maps of selected electricity system models with United States (or similar) coverage

6 Incorporating Solar Resource Assessments

The deployment of solar technologies is limited by the availability of solar resource (insolation), which is defined using a solar resource assessment. This assessment is a geospatial analysis that uses solar resource data to estimate the quantity and quality of solar resource that can be used to generate electricity over some spatial extent. The following subsections describe solar resource data and solar resource assessments.

6.1 Solar Radiation Data

A solar resource assessment begins with quantifying ground-incident solar radiation in a given area. Solar radiation can reach the earth's surface either directly from the sun (direct normal irradiance) or indirectly after being scattered by the atmosphere or cloud interference (diffuse horizontal irradiance). The sum of the direct and indirect radiation gives the total solar radiation reaching the earth's surface (global horizontal irradiance or GHI). The amount of ground-incident radiation that actually reaches a solar array[18] is a function of the type of solar system (fixed-axis PV, tracking PV, CSP) and the orientation of the solar array relative to the sun's position in the sky. PV systems can use both direct and diffuse radiation as well as ground-reflected[19] radiation in the case of tilted arrays. Tracking PV arrays and mirrored solar arrays (CSP) mainly rely on the DNI component (3TIER 2013; SECO 2008; Yates and Hibbert 2010).

Estimates of direct and diffuse solar radiation are derived either from actual measurements or from radiation models. Because ground-based solar radiation measurements are expensive to collect (e.g., due to hardware, operation, and maintenance) and inconsistent across sites (e.g., due to variable instrument quality and incomplete data), comprehensive, consistent datasets are largely sourced from radiation models (Wilcox et al. 2008). Both models and ground measurements are used to develop datasets. Commercial solar datasets such as Meteonorm[20] and 3TIER provide detailed global coverage. Meteonorm is a comprehensive source of synthetic global meteorological data based on 8,300 meteorological stations and satellite data. The 3TIER global solar dataset provides satellite-derived estimates of hourly radiation over 15 years (3TIER 2013). Publically available solar datasets are typically not as detailed or as comprehensive as commercial products, but the information is free. For example, the National Oceanic and Atmospheric Administration (NOAA) Global Monitoring Division Radiation (G-Rad) Observation Networks[21] includes measured solar radiation for more than two dozen sites worldwide, with half of the sites in the United States. The Satel-Light dataset[22] includes solar radiation for western and central Europe on multiple times scales. The National Aeronautical and Space Administration's (NASA's) Surface meteorology and Solar Energy (SSE) dataset[23] provides global coverage of modeled solar radiation. The NREL Renewable Resource Data Center (RReDC)[24] is a clearinghouse for multiple sources of measured solar radiation for multiple regions in the United States as well as India and Saudi Arabia. The RReDC also

[18] Here, solar array refers to either a configuration of PV panels or CSP heliostats.
[19] The ground-reflected radiation is usually negligible compared to direct or diffuse radiation.
[20] Meteonorm: http://meteonorm.com/products/meteonorm/.
[21] NOAA G-Rad: http://www.esrl.noaa.gov/gmd/grad/.
[22] Satel-Light: http://www.satel-light.com/.
[23] NASA SSE: https://eosweb.larc.nasa.gov/project/sse/sse_table.
[24] RReDC: http://www.nrel.gov/rredc/solar_data.html.

includes a modeled dataset[25] named the National Solar Radiation Data Base (NSRDB), which includes simulated hourly radiation for nearly 1,450 meteorological ground stations and 10-km gridded solar radiation sourced from a satellite-based model for the United States (Perez et al. 2002).

6.2 Assessing the Potential for Solar Power

Raw solar resource represents an upper bound on resource potential: the expected insolation levels over the study region. To produce a data assessment useful for an electricity model, that raw insolation data needs to be processed, taking into account geographic restrictions and engineering and economic considerations. To reflect these aspects of quantifying resource potential, producers of resource assessments have organized a hierarchy defining levels of assessment types. The resource assessment levels described by De Vries et al. (2007) are the following:

- **Geographic potential** is the theoretical extractable energy flux in areas suitable for development. Suitable areas are determined using topographical and land-use constraints. Capacity-expansion models using geographic-potential supply curves need a method for converting the theoretical extractable energy into an estimate of electricity production.
- **Technical potential** accounts for considerations of the deployed technology, including conversion losses and deployment density (or packing factor), [26] that reduce the amount from the geographic potential. The conversion losses can be estimated with a conversion efficiency, statistical method, or production-simulation model. Deployment density sets the amount of production capacity that can be arrayed in a given area. In exchange for harvesting a larger fraction of insolation, tracking PV systems occupy more area than a comparable capacity of fixed-tilt PV. Technical potential is a likely input for an electricity system capacity-expansion model with internal mechanisms for comparing the economics of solar resource options with other non-solar resource options.
- **Economic potential** is the technical potential that can be produced at costs competitive with alternative energy sources. An assessment of economic potential should incorporate factors influencing cost competitiveness non-uniformly across regions: expected performance, accessibility of the resource to transmission infrastructure and load, and environmental or public concerns that might influence cost.
- **Implementation potential** is the speed at which the potential for solar resource to produce electricity is realized (if at all). The implementation depends on production costs of solar resources and non-solar resources, policies, and societal preferences.

Most capacity-expansion models are designed to make economic decisions internally. Models that use solar resource assessments usually start from supply curves best characterized as hybrid technical/economic potential: the assessment quantifies and orders attractiveness of potential sites but does not draw the cost-competitiveness line. That line, and therefore the economic and implementation potential, are determined within the model.

[25] Less than 1% of the dataset is sourced from measured data.
[26] Denholm and Margolis (2008a) give suggestions for PV system packing factors.

That supply curves order sites by attractiveness does not necessarily imply that performance is fully monetized in the supply curves. A supply-curve step can offer quantity available (megawatts of capacity or megawatt-hours of energy generated) with expected performance, at a set cost (dollars per megawatt or per megawatt-hour). The model can then factor both cost and performance into its decision making.

Expected performance can be classified in upstream terms of insolation or downstream terms like capacity factor[27] or expected annual output. Converting from site insolation to an output metric can be done roughly by applying a conversion-efficiency figure or more completely by using a statistical analysis or by processing a site irradiance time series into expected power output using a production-simulation model. A statistical analysis could, for example, quantify the expected power output of a solar system by considering the current-voltage diagram for a PV system vis-à-vis a distribution of expected solar radiation during a particular period. A production-simulation model projects the estimates of ground-incident solar radiation onto a solar array and uses detailed engineering calculations for simulating the electrical output of a particular solar system based on the design specifications. Yates and Hibbert (2010) compare a suite of solar production-simulation models used in North America, including PVWatts, System Advisor Model (SAM), PV-DesignPro, PV*SOL, and PVsyst.[28] Both PVWatts and SAM are publically available and free of charge. Yates and Hibbert state that PVWatts has been the PV industry standard in the United States for estimating solar production in part due to its simplicity. SAM has more flexibility in model options and provides detailed financial calculations as well as ancillary tools for design optimization, parametric analysis, sensitivity analysis, and statistical analysis. PV-DesignPro, PV*SOL, and PVsyst are all commercial models that require user buy-in for the full model license. PV-DesignPro is similar to SAM but provides highly detailed information to the user during each step of the modeling process. PV*SOL models multiple arrays and inverters in a single simulation, which similar models do not. PVsyst's flexible input structure allows users to define system characteristics accurately.

Information about site-specific costs (e.g., for connecting a site to transmission or load) or costs relating to permitting and environmental concerns are candidates for inclusion in the cost dimension of the constructed supply curve. Some environmental concerns might remove a possible site from the potential itself (as part of the geographic potential assessment), but sites requiring additional scrutiny or special remediation—rather than those where development is simply off the table—can be dealt with via added cost in a techno/economic supply curve.

Many of the models surveyed include transmission connection cost in their resource assumptions but at varying levels of detail. Costs can be captured using a simple cost adder per kilowatt-hour, applying a cost per line size and estimated distance, or constructing a supply curve from detailed geospatial analysis that links individual sites to transmission infrastructure features. Using the

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[27] Capacity factor is the fraction representing the ratio of power generated during a specific period to the power that could have been generated had the plant operated at full power throughout the period.

[28] PVWatts: http://pvwatts.nrel.gov/
SAM: https://sam.nrel.gov/
PV-DesignPro: http://www.mauisolarsoftware.com/
PV*SOL: http://www.solardesign.co.uk/pv.php
PVSyst: http://www.pvsyst.com/en/

most basic approach, EPPA applies a simple cost adder of $0.01/kWh to account for additional transmission requirements to access solar resources (Morris 2008). Both RPM and SWITCH-WECC use a flat cost per distance (e.g., dollar per megawatt-mile) of transmission required to connect solar resource to the existing grid (Mai et al. 2013a; Johnston et al. 2013). Several models— GCAM, NEMS, ReEDS and SEDS—use analyses based on a geographic information system (GIS) to apply additional solar resource transmission detail (Zhang et al. 2010; EIA 2013; Short et al. 2011; Short et al. 2006).

Overall, the process of developing a resource potential supply curve with a GIS analysis involves a significant effort, but a resource assessment does not necessarily have to be done by the model team or be specific to one model. Especially if the assessment's spatial-reporting resolution can be adjusted easily to different models' regional structures, a high-quality resource assessment or set of supply curves can be useful to multiple models. For example, PNNL adopts rooftop PV supply curves developed by NREL in Denholm and Margolis (2008b) for use in GCAM (Smith et al. 2010). Other recent solar resource assessments include those produced by Lopez et al. (2012), for the United States, and Trieb et al. (2009), for global CSP potential.

7 Accounting for Solar Generation Variability and Uncertainty

When considering the economic viability of VRRE technologies such as PV and CSP, one should consider both the cost and value of the services provided by the technology. For solar technologies, this cost-value proposition includes, among other things, the value of produced energy (including the likelihood the plant will produce power at valuable times and the lost value of production curtailed when supply exceeds demand), the ability to displace the need for alternate generation sources (capacity value), and any additional operational costs induced in other generating units. Thus, a capacity-expansion model seeking to reproduce realistic investment behavior must account for such operational factors and their corresponding costs and benefits. Because capacity-expansion models are primarily designed to reproduce reasonable investment behavior, they seek not operational fidelity but sufficient information about operation to inform investment behavior properly. Solar generation is variable and uncertain. Variability means that plant output fluctuates over time, based on predictable and unpredictable external factors. Uncertainty means that some portion of the output variability is unpredictable. The total variability can be mitigated with an increased number of/more dispersed PV systems. Figure 6 illustrates this mitigation effect by comparing the higher total variability for one PV system versus 100 systems. In addition, PV and CSP without TES are not dispatchable technologies: an operator has limited ability to adjust output based on system needs (especially to generate more power; reducing output is significantly easier).

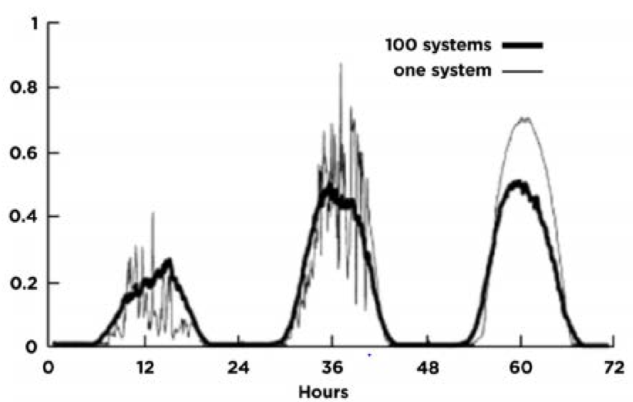


Figure 6. Solar variability: 100 small PV systems throughout Germany, June 1995

Source: Wiemken et al. (2001)

Because of these characteristics, electricity models generally treat VRRE technologies differently from conventional, thermal technologies. The models we discuss do not always incorporate all the characteristics, and they account for the characteristics in different ways. In the world of simplified operation required for capacity-expansion models, the variety of techniques produces a marketplace of ideas from which modelers can learn. The following subsections address ways in which capacity-expansion models account for the impact of solar energy's variable and uncertain generation on dispatch, curtailments, and electric-system reliability.

7.1 Dispatch (Value of Energy at Time Delivered)

Computational constraints limit the level of system-operation detail in long-term capacity-expansion models compared with unit-commitment or production-cost models. To balance accuracy and usability, modelers generally reduce the temporal resolution of the model from the hourly or sub-hourly ideal and create simplified dispatch periods, either by selecting a representative subset of hours to model or by aggregating hours into time blocks. Surveying across models shows the variety of methods for reducing time resolution, some that maintain chronology (sequential time series) and some that do not:

- Representative subsets of *chronological* hours, e.g.,
    - Select a representative peak and non-peak period
    - Select a weekend and weekday
    - Select typical days in each month or season
- Time blocks of *non-chronological* aggregate hours, e.g.,
    - Organize consolidated hours by when they occur (time-slices, e.g., summer afternoons)
    - Organize consolidated hours by their load characteristics (load-duration-curve segments, e.g., base load, intermediate, and peak)
    - Focus on extreme hours (e.g., combinations of high/low demand with high/low VRRE output).

Table 3 summarizes the simplified dispatch period representations for selected models. The number of annual dispatch periods ranges from as few as three (SEDS) to more than 400 (RPM). Having only three dispatch periods does not necessarily mean a model is less useful than one with more than 400; rather, each model is designed with the temporal resolution best suited for the model's scope. Certain models are inter-temporal optimizations and consider multiple investment periods simultaneously. These models might choose to have fewer dispatch periods for each investment period compared with models that sequentially optimize investment periods. Some models consider chronological hours, which allow for more detailed thermal-generation modeling (e.g., ramping, minimum up/down times). Figure 7 illustrates the dispatch periods for three particular models that use either non-chronological or chorological dispatch periods.

Nweke et al. (2012) discuss the benefits of chronological optimization in relation to PLEXOS,[29] noting that the demand profile is a significant input. Chronological modeling can capture more effects of VRRE on the dispatch of thermal units (e.g., unit commitment, startups, and ramping) than non-chronological modeling can. However, the more detailed modeling of dispatch constraints also introduces longer computational times.

A primary purpose of having multiple dispatch periods (either representative subsets of chronological hours or time blocks of non-chronological aggregated hours) is to capture the greater value of providing energy in times of higher load and the lower value when load is low.

[29] This is the detailed operational model and not the capacity-expansion model PLEXOS LT Plan.

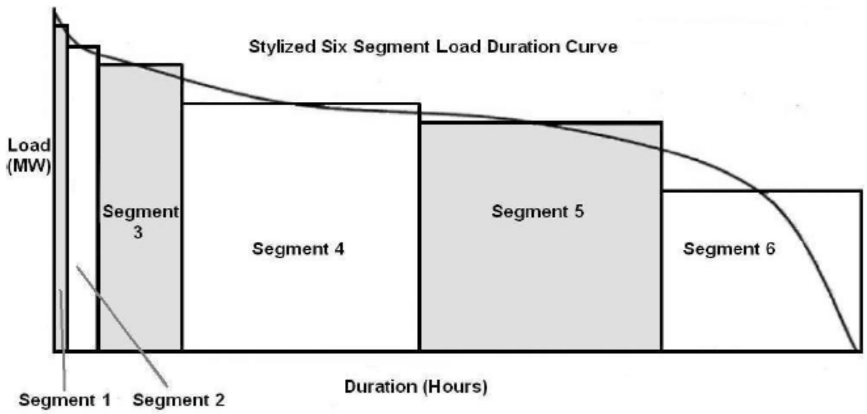
Because solar power is generally correlated with load—higher during the day, lower at night, and greater in the summer, when many regions in the United States experience their peak loads—having good temporal differentiation allows models to see that solar power is more valuable than a simple cost-of-energy metric would indicate and to incorporate that apparent value into their investment decisions.

To capture the relationship between solar power output and load correctly, models need high temporal resolution or a correction factor that distills the solar-load correlation. For example, NEMS (EIA 2013) and ReEDS (Short et al. 2011) both use seasonal and diurnal time-slices (9 in NEMS, 17 in ReEDS) and use time-slice capacity factors to approximate the relationship between VRRE and load. Similarly, GCAM (Zhang et al. 2010) uses 10 time blocks for a simple dispatch algorithm to assess the relationship between solar output and load. The time-block results are aggregated to the annual scale for use in a long-term analysis of balancing energy supplies and end-use demands across multiple sectors. US-REGEN (EPRI 2013) uses a clustering algorithm to select time blocks with similar load-wind-solar as well as extreme moments (e.g., the set of high load hours with low output from wind and solar). Certain models such as MARKAL, PLEXOS LT Plan and RPM have the benefit of allowing for user-defined temporal resolution (Loulou et al. 2004; Energy Exemplar 2013; Mai et al. 2013a).

Some capacity-expansion models consider a full 8,760-hour dispatch (i.e., every hour of every day in a year), but doing so tends to limit detail in other areas like spatial coverage, transmission, or time horizon (e.g., THEA). REMix uses chronological hourly profiles in its 10-region version, but it requires temporal reductions (e.g., every 2 hours of every 5 days) to explore 36 regions (Scholz 2012). Similarly, PLEXOS LT Plan uses hourly modeling for a short-term planning horizon and has the capability to employ either reduced sampled chronology or load-duration-curve time blocks for longer horizons to maintain computational tractability (Energy Exemplar 2013). Palmintier and Webster (2011) combine long-term planning and real-time dispatch (hourly), but their model disregards transmission and balances supply and demand for only one node. Contemporary hardware and algorithms simply do not enable the model complexity that hourly resolution would entail in a model with the technological and geographical detail and time horizons desired for relevant analysis. Fortunately, clever choice of subsets or aggregation of hours can provide good operational fidelity with manageable complexity.

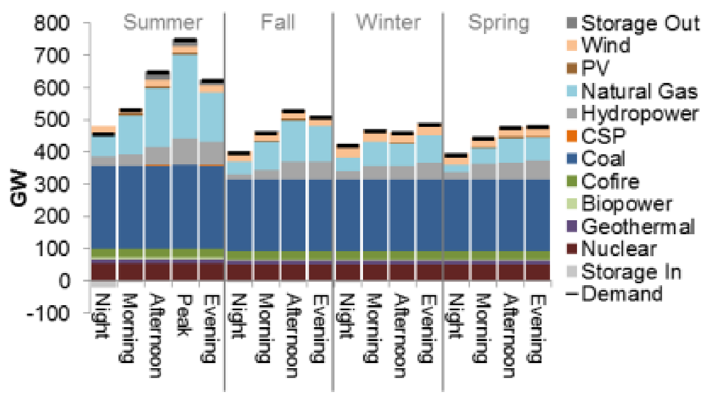
Models that operate representative subsets of chronological hours rather than time blocks of aggregate non-chronological hours can benefit from selecting appropriate subsets and well-paired solar output data to avoid over-specifying the system. The fewer hours represented, the greater the risk of two undesirable conditions: for the system overall, a mismatch between performance of modeled hours and actual time; and, for solar specifically, arbitrarily high or low values assigned to particular solar resources when output over those hours is well or poorly correlated with load. Modelers use a variety of techniques to select subsets that minimize such concerns. LIMES-EU uses an algorithm to select 12 characteristic days that are representative of temporal and spatial fluctuations (Haller et al. 2012). RPM selects a week for each season that is most representative of "typical" seasonal electricity demand, i.e., the week with the lowest root mean square error deviation from the demand in each hour of the average week of the season (Mai et al. 2013a).

Solar system operation within the modeled time resolution is a strong determinant of how the system is valued within the model. For example, models that use time blocks of non-chronological aggregate hours (whether time-slices or load-duration-curve segments) generally assume that dispatch (output, prices, etc.) is uniform within a dispatch period. Therefore, if seasonal and diurnal solar output differences are represented with high fidelity by time block—e.g., differentiation between midday and overnight—solar is likely to be valued more accurately than if not. To be clear, load-duration-curve segments often do differentiate between day and night because that segmentation falls out naturally from the traditional late-afternoon-peaking load profile.



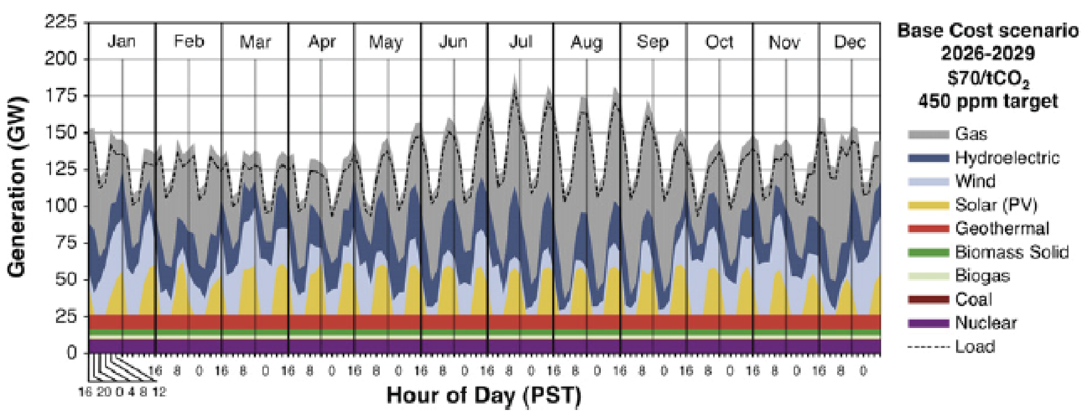
IPM: 6 dispatch periods per year; non-chronological LDC

Source: EPA (2013)



ReEDS: 17 dispatch periods per year; non-chronological time-slices

Source: Mai et al. (2012)



SWITCH-WECC: 144 dispatch periods per year; chronological hours

Source: Nelson et al. (2012)

Figure 7. Visualization of dispatch periods for selected electricity system models

Table 3. Description of Simplified Dispatch Periods for Selected Models

Model	Inter-temporal or Sequential	Detailed Breakdown of Dispatch Periods (dp.) per Year (yr.), Season (s.), Month (m.), Day (d.)	Dispatch Periods (dp.) per Year (yr.)	Chronological
SEDS Short et al. (2006)	Sequential 5-year steps through 2050	3 dp./yr. (peak, intermediate, base load)	3 dp./yr.	No
IPM EPA (2013)	Sequential Seven model years from 2016 – 2050[30]	2 s./yr. (summer, winter) x 3 dp./s. (peak, intermediate, base load)	6 dp./yr.	No
NEMS EIA (2013)	Sequential 1-year steps through 2040	3 s./yr. (summer, winter, fall/spring) x 3 dp./s. (peak, intermediate, base)	9 dp./yr.	No
GCAM PNNL (2012)	Sequential 15-year steps through 2095	10 dp./yr. (summer-5, winter-3, spring/fall-2)	10 dp./yr.	No
ReEDS Short et al. (2011)	Sequential 2-year steps from 2010–2050	4 s./yr. x 1 d./s. x 4 dp./d. (morning, afternoon, evening, night) + 1 super peak dp.	17 dp./yr.	No
Energy2020 SSI and ICF (2012)	Sequential 1-year steps with a variable model horizon	4 s./yr. x 6 dp./s. (high peak, low peak, high, intermediate, low, intermediate, high base load, low base load)	24 dp./yr.	No
PERSEUS-RES-E Möst and Fichtner (2010)	Sequential 5-year steps through 2030	4 s./yr. x 2 d./s. (2 weekend days, 1 weekday) x 3 dp./d. (weekend) OR x 6 dp./d. (weekday)	48 dp./yr.	Yes
US-REGEN EPRI (2013)	Inter-temporal 5-year steps from 2010–2050	46 dp./yr.	46 dp./yr.	No
LIMES-EU Haller et al. (2012)	Sequential 5-year steps from 2010–2050	4 s./yr. x 3 d./s. x 4 dp./d. + 1 peak dp.	49 dp./yr.	Yes
SWITCH-WECC Johnston et al. (2013)	Inter-temporal 10-year steps from 2010–2050	12 m./yr. x 2 d./m. (peak, median) x 6 dp./d.	144 dp./yr.	Yes
RPM Mai et al. (2013a)	Sequential 5-year steps from 2010–2030	4 s./yr. x 4 d./s. (1 weekend, 3 weekdays) x 24 dp./d. + 1 peak day (24 dp.)	408 dp./yr.	Yes

[30] The seven model run years in IPM include 2016, 2018, 2020, 2025, 2030, 2040 and 2050.

7.2 Curtailment

Estimating curtailments in capacity-expansion models is important to valuing potential solar investment properly, but it is a complex, multifaceted problem involving expectations for load, solar output, and thermal-unit commitments. A primary difference between solar generation and conventional, thermal generation is that solar output is primarily constrained by external (insolation) conditions, rather than being available as the system or plant operator desires. Unlike a fossil unit that can choose to operate as load allows, shifting fuel from low demand times to high, a solar facility (except for CSP with TES) does not have the luxury of shifting insolation to more-valuable hours.

System operators encounter periods when the minimum output of committed units exceeds load and will often shut down or reduce the output of a renewable generating facility before shutting down a fossil unit, because the renewable generators often have much lower startup costs and quicker shutdown/startup. This curtailment is a deadweight loss to the solar operator, because any unexploited insolation cannot be recovered. A solar facility with high curtailments takes in less revenue, meaning that expected curtailment levels are an important component of investment decisions.

Expected curtailment levels are a function of the relationship between plant output and load but are also affected by the rest of the generating fleet: other renewable generators and the must-run level of committed thermal units. In particular, while solar curtailments are generally low at low levels of solar penetration—because loads are high through the middle of the day when solar output is maximized—analyses have shown that curtailment levels can increase dramatically with increasing solar penetration (Denholm and Margolis 2007a; Denholm and Margolis 2007b; DOE 2012; NREL 2012); even if solar could provide much of the midday energy, thermal units have to remain online to be available to meet evening loads. A corollary to curtailments increasing with solar fraction is that increased baseload capacity, e.g., a new nuclear plant, will also tend to increase VRRE curtailments. In light of curtailments being a system-wide consequence, while the curtailed unit is singled out for reduced operation, the curtailment should be considered a system-wide cost (foregone potential energy) rather than a penalty upon that generator.

Models have been approaching the curtailment problem in two ways. In models with sufficient temporal resolution to model unit commitment and cycling directly, like PLEXOS LT Plan (MMA 2007),[31] the model will often return a negative price—representing the willingness of thermal unit operators to pay to stay online rather than incur the cost of shutting down and starting up again later—in curtailment hours to signal renewable generators to turn down. THEA (Nicolosi 2012) uses a technology premium as a proxy for market-driven curtailment to define the price level (negative) at which to curtail energy. As with value of energy, it is important to have sufficient temporal extent as well as resolution to obtain a representative sample of hours. Time-block models must approach curtailments indirectly, assigning curtailment levels by time block based on system conditions. ReEDS operates a statistical algorithm to estimate the fraction of hours within each time-slice in which renewable generation is expected to be curtailed, both for existing units and for potential new investments (Short et al. 2011).

[31] Specifically, this discussion relates to the short-term chronological dispatch module of PLEXOS LT Plan.

7.3 Electric System Reliability

In addition to considering the energy provided by solar generators, an effective capacity-expansion model considers how solar deployment interplays with the electricity system's goals of resource adequacy and operating reliability. The North American Electric Reliability Corporation defines these characteristics as follows (NERC 2008):

- "Adequacy is the ability of the electric system to supply the aggregate electric power and energy requirements of the electricity consumers at all times, taking into account scheduled and reasonably expected unscheduled outages of system components."
- "Operating reliability is the ability of the electric system to withstand sudden disturbances such as electric short circuits or unanticipated loss of system components."

The following subsections explore how various capacity-expansion models account for resource adequacy and operating reliability.

7.3.1 Resource Adequacy: Effective Load-carrying Capacity

Resource adequacy is a requirement to be able to supply enough raw power to serve all expected loads. Adequacy metrics are often statistical estimates of the generating capacity that must be procured to meet loads given the uncertainty in timing and magnitude of peak-load events and incorporating the risk of outages to generators and transmission lines. Brun (2011) cites 1 day in 10 years (1-in-10) as a common loss of load probability (LOLP) target for adequacy. Effective load-carrying capacity (ELCC)—the amount of load that can be added to the system without changing the system's LOLP—gauges how much a generator contributes toward adequacy. ELCC is often called "capacity value" or "capacity credit."

Even though solar generators are not fully dispatchable and reliable like thermal generators, they do have substantial capacity value, especially at low penetration fractions. The average capacity value tends to erode with expansion of solar generation capacity, because increasing solar generation eventually causes the residual (load less VRRE) peak load to shift to an hour when no or less solar resource is available (Sigrin et al. 2014). Including capacity value—for instance, by accounting for the reduced need for additional peaking units—as a component of a prospective investment's net value can measurably improve the economics of solar investments, although that value stream erodes as deployment increases and the capacity value declines.

Although a few models disregard solar's capacity value—such as PERSEUS-RES-E, which does so on the basis that solar will have a small future impact in the German electric power system over the modeled time horizon[32] (Rosen 2007)—most models reviewed here attempt to account for it. Other models, like ENERGY 2020 (SSI and ICF 2012), assume a fixed capacity value for VRRE even though a fixed-value estimate can misrepresent solar's contribution to adequacy. One common formulation is a requirement that VRRE be accompanied by backup capacity to fill the gap between the VRRE's capacity value and its nameplate capacity. These formulations, as with GCAM (Smith et al. 2011), allow erosion of capacity value with increasing VRRE penetration: a low level of required backup with little solar increases to higher levels—even 100% backup—at high solar penetration. There is risk in such a backup-capacity formulation of

[32] PERSEUS-RES-E uses a statistical analysis of wind feed-in to estimate capacity value for wind power.

over-penalizing the renewable generator by requiring backup capacity even if the system already meets resource adequacy.

To include both capacity value and adequacy needs in the model, many optimizations include a constraint to meet adequacy requirements and allow solar generators to contribute some capacity value metric toward that constraint. REMix (Scholz 2012) and SWITCH-WECC (Nelson et al. 2012) assign a capacity value equal to the capacity factor in that hour or time block. RPM (Mai et al. 2013a) uses a simplified net-load approach that estimates the capacity value as the ability of solar to reduce the peak load. Other models use exogenous estimates of capacity value. PLEXOS LT Plan (MMA 2007) uses peak contribution factor estimates from Transpower[33] multiplied by capacity to determine a generator's contribution to reserves during peak periods.

Finally, some models use endogenous calculations for determining capacity value. ReEDS (Short et al. 2011) dynamically estimates the capacity value of solar using a z-statistic approximation for ELCC (Dragoon and Dvortsov 2006) based on solar deployment level, resource diversification, transmission, and correlation with load and other renewable generators.

CSP can be modeled with or without TES (Section 4), with strong implications for capacity value. GCAM and ReEDS (Zhang et al. 2010; Short et al. 2011) assume CSP with hybrid auxiliary backup (GCAM) and CSP with TES (both models) can be relied on for power when necessary and therefore contribute full capacity toward adequacy requirements. ReEDS models CSP without TES as akin to PV: with a z-statistic approximation for ELCC.

7.3.2 Operating Reliability: Ancillary Service Requirements

The need for ancillary services to maintain operational reliability imposes a cost on electric-power systems by holding some otherwise-economic-to-dispatch capacity in reserve to respond to system needs. The variability and uncertainty of VRRE increases the variation in residual load and adds to the operating-reliability burden of the system. Various studies (Ela et al. 2010; Hummon et al. 2013) have characterized how solar and wind generators affect the operation of other units and the need for ancillary services, for instance by increasing the size and frequency of 1-hour ramping events. These operational costs induced by VRRE can be significant, so whether and how capacity-expansion models account for them can affect the attractiveness of potential renewable generator investments.

These additional reliability burdens can vary across solar technologies. By their nature, PV systems are highly sensitive to changes in insolation (due to cloud cover), although dedicated storage systems for PV plants can cushion the effects of variability and uncertainty. CSP, even without TES, has a smoother response to changes in insolation than PV due to thermal inertia, so models often consider it to have reduced ancillary-service needs. ReEDS (Short et al. 2011), for instance, assumes that CSP generators do not require additional operating reserves. In reality, CSP systems may not be quite this robust unless they include TES or a dedicated auxiliary backup system (e.g., a natural gas turbine). For some models, the existence of storage is justification for ignoring the effects of solar variability and uncertainty on ancillary service

[33] Transpower owns and operates the National Grid, the high-voltage transmission network connecting areas of generation with towns and cities across New Zealand (https://www.transpower.co.nz/about-us).

requirements, including costs. GCAM (Zhang et al. 2010) assumes away the effects of variability and uncertainty for CSP with TES and CSP hybrid plants with auxiliary backup. RREEOM (Budischak et al. 2013) ignores reserves requirements, intra-hour resource variability, and ramping by assuming these will be covered by quick-response storage in a scenario where nearly all of the electricity demand is supplied by a portfolio of wind, solar, and electrochemical storage.

There are different classes of operating-reserve products, such as regulation reserves and load-following reserves (Ela et al. 2010). Figure 8 illustrates regulation and load-following reserves. There are also different classes of operating-reserve contributors—such as automatic generation control, spinning, and non-spinning reserves—that can supply these products. Large-scale, long-term planning models are unlikely to include a large number of these services, choosing instead to simplify to one or two operating-reserve products and generalizing the contributors that can provide them. ReEDS (Short et al. 2011) requires operating reserves based on two standard deviations (95% confidence interval) of the distribution of hour-to-hour changes in output, a structure adopted from the Minnesota Wind Integration Study (Zavadil et al. 2004). In most models that include operating-reserve products, as in real systems, conventional generators and electricity-storage systems are allowed to withhold generation in favor of providing spinning or non-spinning reserves.

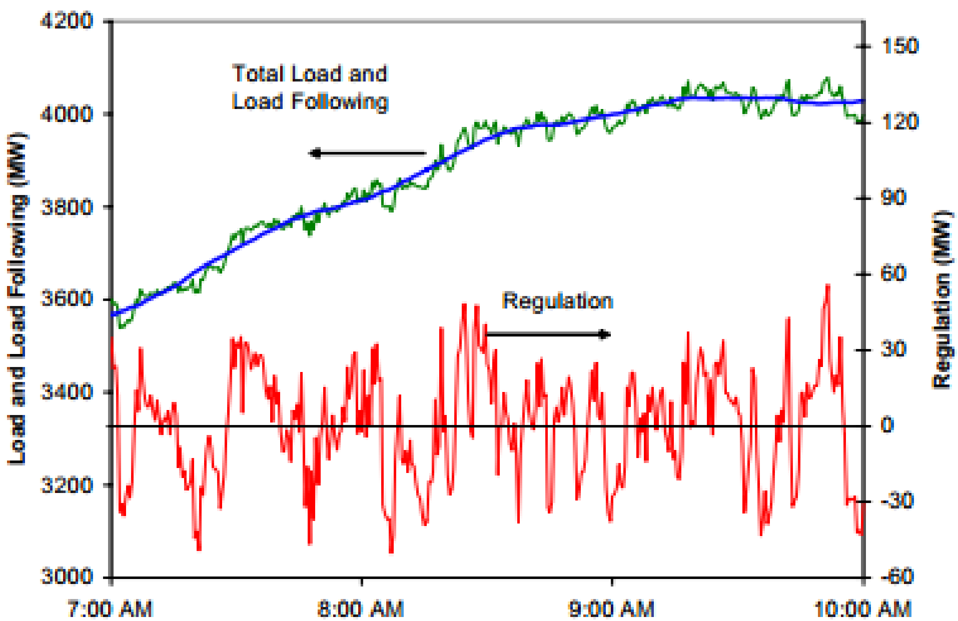


Figure 8. System load following and regulation.

Source: Kirby (2004)

The European convention for operating reserves is to distinguish primary, secondary, and tertiary reserves, which correspond to progressively longer response timescales. Primary reserves respond immediately to changes in system frequency and stabilize it. Secondary reserves return the frequency to its nominal value during contingency and ramping events. Tertiary reserves are manually activated during a contingency event to replace supply units that fail or to reroute power during a transmission outage. They operate on a timescale above 5 minutes and allow both spinning and non-spinning (quick-startup) resources. Both THEA (Nicolosi 2012) and PERSEUS-RES-E (Rosen 2007) include positive and negative tertiary reserve products: baseline tertiary reserve requirements for contingencies and demand fluctuations, with additional reserves required to balance renewable forecast error. PERSEUS-RES-E also applies an efficiency penalty to conventional units whose operation is changed to accommodate VRRE, increasing generation cost and/or emissions due to increased startups, shutdowns, and ramping.

8 Conclusions

The process of designing and developing a capacity-expansion model for making long-term electricity system projections includes many tradeoffs. Electricity systems are famously complex: comprising hundreds or thousands of generation and transmission components, requiring precise balancing of generation and load across wide areas in real time, and involving dozens of entities making continual decisions about planning, operation, regulation, and markets. Compressing such a complex system into a model that can be populated with real-world data and solved in a reasonable interval requires a host of approximations and simplifications.

This report highlights a set of the decisions modelers must make to represent solar generating technologies in capacity-expansion models, and it discusses current practices among a set of electricity models used for research or long-term policy and technology analysis. Compared to a dispatchable thermal generation technology like a natural gas plant, solar technologies embody several subtleties that should be included to represent the behavior of their real-world analogues. In particular, solar generation varies substantially—and sometimes unpredictably—over time (from inter-annual to seasonal to sub-hourly variations) and across space. The variability and uncertainty produce numerous important consequences for electric-system operation and capacity investments, which capacity-expansion models must capture as solar becomes a larger contributor to electric systems.

No single method of incorporating solar technology characteristics is best for all models, as each model has its own structures, circumstances, and priorities that color its decisions. This report, therefore, shows examples of how specific models address the various challenges and compromises associated with incorporating solar technologies. The multiple viewpoints from different models create a landscape of solutions from which to understand these issues better.

Taken together, the growing body of advanced models and accompanying literature—enabled by improved data, algorithms, and computing power—has been enhancing the representation of solar technologies as these technologies have become more widespread.

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