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Methodology for examining potential technology breakthroughs for mitigating CO_2 and application to centralized solar photovoltaics

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Abstract Aggressive reductions in US greenhouse gas emissions will require radical changes in how society generates and uses energy. Technological breakthroughs will be necessary if we are to make this transition cost effectively. With limited resources, understanding the breakthrough potential of various alternative technology options will be critical. One common approach for comparing technology options is via their relative levelized cost of electricity. This measure does not account for many of the complexities of the landscape in which the technologies compete, however. As an alternative, we describe the use of an energy system model within a nested parametric sensitivity analysis. The approach is applied to examine the breakthrough potential of a specific class of technology, centralized solar photovoltaics (CSPV). We define a "breakthrough" as being a tangible reduction in the *system-wide* cost of meeting a CO_2 mitigation target. As "tangible" is a subjective term, we characterize the relationship between technology cost reductions and system-wide cost reductions for several mitigation targets. The results illustrate the importance of considering contextual factors in evaluating and comparing technologies. For example, the critical role that fuel switching and vehicle electrification play in mitigation scenarios is shown to affect the competition between CSPV and baseload technologies for market share. This breakthrough analysis approach can be applied to other technologies and is expected to be useful in assessing and comparing breakthrough opportunities across the energy system, including both energy production and use.

Keywords Breakthrough technology · CO_2 mitigation · Energy system · Solar power · Photovoltaic · Nested sensitivity analysis

Introduction and objectives

The Intergovernmental Panel on Climate Change (IPCC) estimates that anthropogenic greenhouse gas (GHG) emissions must be reduced by 50 to 80 % from 2000 levels to prevent the global mean temperature from increasing more than 2.4 °C (IPCC 2007). As the primary source of man-made GHG emissions is the combustion of fossil fuels, achieving these GHG reductions will require a revolution in how energy is produced and used (IEA 2009). Energy efficiency, conservation, and the production of low-carbon energy likely will all be important components of a solution.

One path toward GHG mitigation involves transitioning the residential, commercial, industrial, and transportation sectors from direct use of fossil fuels to electricity, while at the same time reducing the CO_2 intensity of electricity production (IEA 2010). This transition may involve large-scale adoption of low- and zero-carbon renewables such as wind, solar and biomass, and also may involve the capture and sequestration of CO_2 emissions from fossil fuel and biomass combustion. Relative to the scale of deployment needed, these technologies are in their infancy, with costs that typically exceed traditional fossil fuel technologies and installed capacities that are orders of magnitude below what is needed to meet GHG reduction goals. Reliability concerns are constraining the adoption of renewables,

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as well. The intermittency of wind and solar resources, for example, may limit their long-term market potential unless large-scale and cost-effective stationary energy storage can be introduced (NREL 2010).

Fortunately, as a society, we have shown a great ability to innovate. Technology breakthroughs have led to putting humans on the moon and to downsizing electronics so that the smart phones in our pockets are more powerful than the supercomputers of several decades ago. Similar breakthroughs in low- and zero-carbon energy technologies will be needed to meet GHG mitigation goals identified as being necessary by the IPCC. This need raises important questions, such as "What constitutes a breakthrough?" and "Where would breakthroughs be achieved most readily and most cost effectively?"

The objective of this article is to demonstrate a modeling approach for evaluating the potential of energy technology developments to yield a breakthrough in achieving GHG mitigation goals. The approach, which makes use of the MARKet ALlocation (MARKAL) energy system model (Fishbone and Abilock 1981; Loulou et al. 2004; Rafaj et al. 2005) within nested parametric sensitivity analysis, allows technologies to be examined quantitatively in a dynamic energy system context. This approach allows consideration of complex factors that influence competition among energy technology alternatives, such as turnover of existing stock, daily and seasonal electricity demand profiles, impacts of supply and demand on fuel prices, and the sometimes synergistic and sometimes conflicting influences of various environmental, energy and climate policies. Results can provide insights into ripe opportunities for breakthroughs and the relative "bang-for-buck" in various parts of the energy system (e.g., energy production, storage, transmission, or use). The context in which a potential breakthrough technology is competitive can also be identified, including combinations of technology cost, fuel prices and CO_2 mitigation targets.

An important aspect of this approach is the interpretation of the word "breakthrough." To a manufacturer, a breakthrough may be an advancement that leads to a high degree of market penetration. From a system-wide perspective, however, high market penetration does not necessarily yield overall benefits. For example, cost reductions in a low-carbon technology may yield minimal system benefits if the technology is merely winning market share from another low-carbon technology. A "breakthrough" may be more appropriately interpreted as an advancement that leads to a system-wide benefit, such as a major reduction in the cost of meeting mitigation targets. This latter interpretation of a breakthrough is used here.

In this article, the breakthrough analysis approach is applied to a centralized solar photovoltaics (CSPV) technology. The market penetrations of CSPV and competing technologies are examined for various combinations of CSPV costs and CO_2 reduction targets. The relationship between CSPV cost and reductions in system-wide CO_2 mitigation costs is then characterized. CSPV was chosen for this analysis because its operation does not result in competition for fuels with other technologies or sectors. CSPV thus provides a more straight-forward demonstration of the breakthrough analysis approach than would an analysis of natural gas fuel cells, for example. The methodology could readily be applied to such a technology, however, and in future work we plan to examine technologies across the energy system and with wide-ranging operational characteristics and input fuels. This article lays the groundwork for those applications.

Background

To convey the benefits of using an energy system model for breakthrough technology evaluation, it is important first to discuss a more commonly-used alternative: the calculation and comparison of the levelized cost of electricity (LCOE) of competing technologies. LCOE typically represents the total cost of a technology, including capital, operation and maintenance, fuel, and other costs, amortized over each unit of electricity expected to be produced over the technology's anticipated lifetime. This value is often represented in units of dollars per kilowatt-hour ($/kWh). Table 1 lists estimates of levelized costs in 2016 for a variety of electricity production technologies. These data were obtained from the assumptions used in the US Department of Energy's 2010 Annual Energy Outlook (US DOE 2010b).

For a prospective technology to be the least-cost option compared to the technologies in Table 1, *all else being equal*, it would need to achieve a levelized cost of less than $0.079/kWh. In the real world, however, all else is *not* equal, and there are niches that lead to the penetration of technologies that do not have the lowest cost or that have low cost in some geographic regions but not others. For example, wind power costs are impacted by meteorological conditions, land valuation and accessibility. While there is considerable heterogeneity in these factors, only a single LCOE value is listed for onshore wind in Table 1. Thus, while LCOE calculations are useful in providing a high-level comparison, this approach does not consider many important factors that influence competitiveness, such as:

- when the technology will be technically and commercially viable;
- whether factors such as limited raw materials or equipment, engineering expertise, or the ability to obtain suitable land will constrain the rapid introduction and expansion of the technology;

Table 1 Levelized cost estimates in 2016 for various electricity production technologies, as reported in the 2010 Annual Energy Outlook (US DOE 2010b)

Technology	Levelized cost ($/kWh)
Conventional coal	0.100
Advanced coal	0.111
Advanced coal with CCS	0.129
Natural gas combined-cycle turbine	0.083
Natural gas advanced combined-cycle turbine	0.079
Natural gas advanced combined-cycle turbine with CCS	0.113
Natural gas combustion turbine	0.139
Natural gas advanced combustion turbine	0.124
Advanced nuclear	0.119
Wind	0.149
Offshore wind	0.191
Solar photovoltaic	0.396
Solar thermal	0.257
Geothermal	0.116
Biomass	0.111
Hydro	0.120

CCS carbon capture and sequestration

- whether the electricity produced suffers from spikes, dips, or harmonics that could negatively impact use or damage electrical equipment;
- the extent to which electricity production potential from the technology varies in space and time and whether these variations are predictable;
- whether electricity production is dispatchable on demand and the related role that the technology can play in meeting demand along different portions of the load duration curve (e.g., baseload, shoulder or peaking);
- the technology's useful lifetime and whether lifetime can be extended via retrofit or repowering;
- the rate and timing of turnover of existing capital;
- up-front investment costs and the availability of low-cost financing or other incentives;
- the amount of lead time necessary to build new capacity, including permitting, equipment manufacturing, and construction;
- the technology's expected capacity factor, including its downtime for maintenance;
- whether the technology emits GHGs and other pollutants, and the emission rates for each;
- other real and perceived environmental and health risks; and
- the land or water footprint associated with the technology.

In addition to these *technological* factors, *contextual* factors can influence competition. For example, the playing field on which a prospective breakthrough competes may be transformed by a GHG policy that places a price on carbon. Figure 1 depicts how the levelized costs for a selected set of the technologies in Table 1 change when various CO_2 prices are considered. These calculations were made using technological and cost assumptions from the Annual Energy Outlook 2010 (AEO) for the year 2016 and assuming carbon capture and sequestration (CCS) capture rates of 95 % for advanced coal and 90 % for natural gas combined cycle (US DOE 2010a).

The impact of a policy-induced price on CO_2 may be much more complicated than indicated in Fig. 1, however. Cap-and-trade policies, for example, typically result in CO_2 prices that increase over time as the most cost-effective measures are adopted first. Under such a policy, there is no *one* CO_2 price that can be used to evaluate and compare technology costs.

Other contextual factors influence competition, including current and future policies directed at air quality, water quality, and energy security; fuel prices and fuel price volatility; the quantity and temporal distribution of projected energy service demands; the possible risk of technology lock-in; developments in synergistic technologies such as batteries for stationary storage; and the role of public opinion and preference on the adoption of new and potentially different technologies. There is considerable uncertainty about how these factors will influence competition, particularly within analyses that stretch many years or even many decades into the future.

These factors that influence technology competition are not static, as implied by the simple relationships between LCOE and CO_2 price shown in Fig. 1. Rather, the

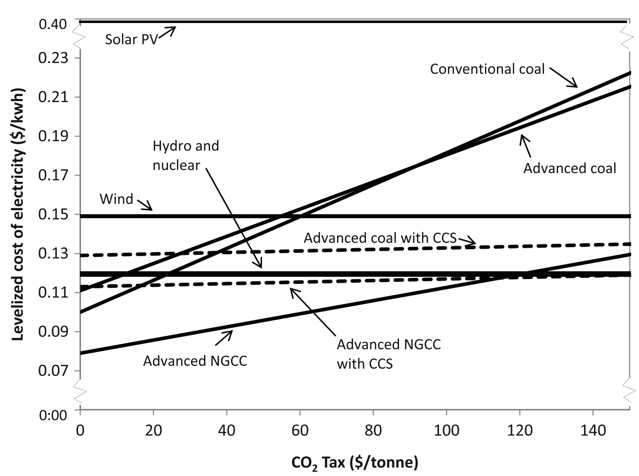

Fig. 1 Levelized costs of electricity production technologies, including the cost of emitting CO_2. NGCC represents natural gas combined-cycle turbines

relationships are dynamic, as different technologies will have different cost advantages under changing conditions. For example, the LCOE values shown in the figure assume constant utilization of the technologies over the range of CO_2 prices. In practice, an operator may opt to decrease utilization of a high CO_2-emitting technology when factoring in the cost of emissions. This response would increase the technology's LCOE as the LCOE calculation amortizes costs over each unit of electricity produced over its lifetime. Furthermore, entry barriers for new technologies, sunk investments, and the other factors noted above will change the relative attractiveness in ways that are not apparent when considering only LCOE in a static context.

It is not possible to consider all of these technological and contextual factors within simple extensions to the spreadsheet model used to generate Fig. 1. However, some of these factors can be considered using a comprehensive energy system or energy-economic model. Many such models exist, ranging greatly in their solution approach as well as in their temporal, spatial, sectoral, and technological coverage and resolution (Johnson and Keith 2004; Huntington and Weyant 2004).

An important class of applications of energy-economic models is the identification of efficient portfolios of technologies for achieving climate change mitigation targets (IEA 2010; Clarke et al. 2006; Clarke et al. 2007; EPRI 2009; Fawcett et al. 2009; US EPA 2009a). In many of these applications, a CO_2 reduction target is specified, and the model is used to select a low-cost technology pathway for achieving the target. Alternatively, a price can be placed on CO_2, and the technology and emissions response evaluated. The CO_2 price then can be iteratively revised until the desired CO_2 reductions are achieved. Sensitivity analysis is sometimes used to evaluate how assumptions about technologies or other aspects of future scenarios impact the selection of cost-effective technological pathways.

Energy-economic models have also been used to examine the prospects of specific technologies. For example, the National Renewable Energy Laboratory has used the Renewable Energy Deployment System (ReEDS) model to evaluate the ability of wind power to achieve a 20 % market share in the US by 2030 (US DOE 2008). Similarly, Karplus et al. (2009) have explored the prospects for plug-in hybrid vehicles in the US using the Emissions Prediction and Policy Analysis (EPPA) model, and Borjesson and Ahlgren (2010) have used MARKAL to investigate biomass gasification.

Increasingly, modeling exercises are including consideration of uncertainty when examining technology options. For example, Yeh et al. (2006) used the MARKAL model within parametric sensitivity analysis and Monte Carlo simulations to identify conditions under which hydrogen fuel cell vehicles penetrate the US passenger vehicle market. Similarly, Greene et al. (2010) used Monte Carlo simulations with a spreadsheet model to identify essential technologies for achieving mitigation targets.

In this article, we present the application of a nested parametric sensitivity analysis approach with the MARKAL model. This approach involves discretizing key technology and contextual input parameters into several values, then testing all combinations of these values within the model. An advantage of nested sensitivity analysis is that it does not require parametric sensitivities to be examined from a particular baseline, but instead allows for selection of a baseline from the set of modeled combinations. Further, the approach allows responses to changes in *multiple* inputs to be examined simultaneously. Thus, the results allow us to deduce the combinations of conditions that may drive a particular result.

Energy system modeling with MARKAL

At the heart of our application is MARKAL. MARKAL is a mixed-integer linear programming framework that characterizes the mathematically optimal evolution of the modeled energy system over a multi-decadal time period. MARKAL accomplishes this task by selecting the technologies and fuels over time that minimize the net present value (NPV) of meeting current and projected demands for energy, while at the same time accounting for a wide array of factors that may constrain the evolution of the system.

The MARKAL framework represents the various components of an energy system, including energy resource supplies; technologies for converting these supplies to fuels or electricity; technologies for using these fuels or electricity to meet energy service demands (e.g., space heating/cooling, lighting, process heat, vehicle miles traveled) in the residential, commercial, industrial, and transportation sectors; technology- or fuel-specific pollutant emission factors; and various constraints on energy use and emissions.

The MARKAL objective function has been summarized by LouLou et al. (2004) via the following equation:

$$\mathrm{NPV} = \sum_{r=1}^{R} \sum_{t=1}^{t=\mathrm{NPER}} (1+d)^{\mathrm{NYRS}*(1-t)} * \mathrm{ANNCOST}(r,t) \\ *(1+(1+d)^{-1}+(1+d)^{-2}+\ldots+(1+d)^{1-\mathrm{NYRS}})$$

where NPV is the net present value of the total cost for all regions, ANNCOST (r,t) is the annual cost in region r for period t, d is the general discount rate, NPER is the number of periods in the planning horizon, NYRS is the number of years in each period t, and R is the number of regions.

ANNCOST represents the sum of fuel costs, the capital and operations and maintenance costs of each region's energy system technologies, and taxes related to fuels and emissions. See Ref. LouLou et al. (2004) for more information about the model formulation and a detailed description of the ANNCOST function.

To apply MARKAL, a database is developed that characterizes these components and their linkages (i.e., the energy flows) for a specific energy system. The data are used to populate the mathematical model, and an optimization solver then is used to identify the least-cost solution. MARKAL also can be used to explore the response of the least-cost solution to changes in various assumptions or constraints. For example, a GHG policy can be applied, and the impact on least-cost technology choices, fuel use, and emissions calculated.

MARKAL databases have been constructed for a wide range of applications. For example, MARKAL has been used at a local scale to optimize energy choices for Manhattan, NY (Bhatt et al. 2010). At the regional scale, MARKAL is being used by the Northeast States Consortium for Air Use Management (NESCAUM) to investigate GHG, air quality and energy policies (Goldstein et al. 2008). The US Department of Energy (DOE) and Brookhaven National Laboratory are using MARKAL to examine the cost-effectiveness of DOE's technology development programs (Friley 2007). The US Environmental Protection Agency is using MARKAL to investigate climate and emissions impacts on long-term air quality (US EPA 2009b; Loughlin et al. 2011). At the international level, MARKAL has been applied in over 37 countries, and the International Energy Agency uses a version of MARKAL to generate its Energy Technology Perspectives reports (IEA 2010).

To support its MARKAL modeling efforts, US EPA has developed two MARKAL databases. One is a single-region representation of the US energy system that covers the time horizon of 2005 through 2055. MARKAL runtime using this database is only several minutes on a typical desktop computer (e.g., 2 GHz dual-core processor, 2 GB RAM), allowing the model to be used readily within a "what-if", exploratory modeling context, as well as in sensitivity and uncertainty analyses that may involve dozens to thousands of MARKAL runs. The US EPA has also developed a 9-region version of the database. The 9-region database covers the same time horizon, but represents the country at the US Census Division resolution. This added spatial resolution results in runtimes of 20–45 min. Both databases are available to the public (US EPA 2011a, b).

The US EPA MARKAL databases and technology assessment

The detail within EPA's MARKAL databases allows many of the complexities of technology competition to be considered. Modeled technology attributes include:

- initial capacity for existing technologies or first year of commercial availability for new technologies;
- capital cost;
- fixed and variable operations and maintenance costs;
- input fuel or other energy resources;
- efficiency of converting the input to electricity or other forms of useful energy;
- maximum capacity utilization;
- operational lifetime;
- applicability for meeting base, shoulder and peaking loads;
- constraints limiting absolute growth or rate of growth;
- emission rates of CO_2 and other pollutants; and
- a technology-specific discount rate.

In addition, multi-sector coverage of the database captures competition among sectors for both electricity and fuels, with fuel prices being calculated endogenously as a function of supply and demand. This feature is important because a policy or action that leads to additional use of a fuel in a sector can impact the use of the fuel in others sectors as well.

The representation of a simple load duration curve within the 1- and 9-region databases is also important. This representation allows the model to account for the suitability of a technology for meeting seasonal base, shoulder, and peak loads. The economics of meeting peak load are affected by fuel prices and utilization patterns, and may result in a special niche for breakthroughs. Inclusion of emission factors within the database allows taxes or constraints on air pollutant emissions to be modeled. By covering a time horizon from 2005 through 2055, the databases allow issues related to the turnover of capital stock and addition of new capacity over time to be explored more readily than with steady-state models or those with shorter modeling horizons.

The 9-region MARKAL database allows differences in resource supplies and technology performance from one region to another. For example, the high regional resources of wind in the central plains and solar power in the southwest can be considered. Further, transportation costs associated with moving fuels from one region to another can be included. Regionalization also facilitates inclusion of region-specific policies. For example, the EPA's Cross-State Air Pollution Regulation limits NO_x and SO_2 emissions for states in the eastern US (US EPA 2011a, b). MARKAL can approximate the impacts of this rule on regional technology choices. All of these factors are considered simultaneously as MARKAL seeks to identify optimal solutions.

Methodology and application

Technology assessment with MARKAL is inherently an exploratory modeling exercise, and its application thus involves iterative analysis and refinement. Providing a generalized structure to this process can be useful. Nested sensitivity analysis involves selecting two or more inputs to a model. These inputs are then discretized across their expected ranges, and combinations of input values are evaluated within the model. If a small number of inputs, such as two to four, are being evaluated, tables and simple figures may be sufficient for analyzing the results for combinations of input values that yield specific outcomes. Analyses with a higher number of dimensions may benefit from statistical analysis and the application of data-mining algorithms.

In the application presented here, we explore only two dimensions: cost reductions for a technology and the stringency of a CO_2 mitigation target. Thus, we are exploring one parameter specific to the technology and another that influences the context in which the technology competes. The analysis could be expanded to include additional inputs. For example, including alternative projections of natural gas supplies, oil prices, and growth in energy service demands would allow additional contextual uncertainties to be explored.

In our application, we examine breakthrough potential of a CSPV technology. Our nested sensitivity analysis approach includes the following steps:

Step 1. Investigating sensitivity to cost reductions. CSPV cost is decreased incrementally, allowing examination of the relationship between technology cost and market penetration under baseline contextual conditions (e.g., without a CO_2 mitigation target).

Step 2. Investigating sensitivity to CO_2 mitigation targets. Under baseline technology cost assumptions, increasingly stringent CO_2 reduction targets are applied to the energy system, and the impact of these limits on the market penetration of CSPV and competing technologies is examined.

Step 3. Investigating combined impacts of cost and mitigation target. Combinations of decreases in CSPV cost and increasingly stringent CO_2 reduction targets are evaluated.

Following Step 3, the resulting set of MARKAL solutions is then analyzed to evaluate the interplay among technology cost, stringency of CO_2 reduction target, competition with other technologies, and impacts on mitigation costs.

Baseline CSPV technology assumptions within the MARKAL database primarily are derived from the 2010 Annual Energy Outlook (US DOE 2010a). These assumptions include capital cost, variable and fixed operation and maintenance costs, efficiency and expected lifetime. Regional availability factors representing capacity utilization potential by time of day and season were calculated using the RETScreen PV.3 model (NRC 2005). MARKAL does not explicitly account for variability at a more fine temporal resolution, nor does it explicitly account for reliability constraints that may arise when using high levels of renewables.

The LCOE of CSPV is calculated endogenously within MARKAL and thus is not an input lever that can be adjusted. Instead, we adjust LCOE in an approximate manner in Steps 1 and 3 by adjusting the capital and operational costs of the technology. For example, a 50 % reduction in these costs is assumed (as a first order approximation) to result in a 50 % reduction in LCOE. These estimates of LCOE are useful in interpreting the results in the context of the competing technologies shown in Fig. 1.

Application of each of the three steps is described below.

Step 1. Investigating sensitivity to cost

Seven different assumptions about the trajectory of CSPV levelized costs over time were considered. These simple trajectories, shown in Fig. 2, varied considerably in their optimism about the potential for relatively rapid (e.g., over a 15-year period) cost reductions.

At the high end, CSPV costs remain at their initial values, equivalent to approximately \$0.40/kWh. At the low end, CSPV costs are reduced by 80 % between 2010 and 2025, resulting in an ultimate equivalent LCOE of \$0.079/kWh. This LCOE is lower than that of any technology in Table 1, being only slightly less than natural gas combined cycle turbines. If decisions were made based on LCOE alone and there were no additional constraints on capacity expansion, CSPV at this price would represent all new electricity production capacity and likely would displace much of the existing capacity.

A recent report by the Melbourne Energy Institute helps put these trajectories in context (MEI 2011). Seven PV cost

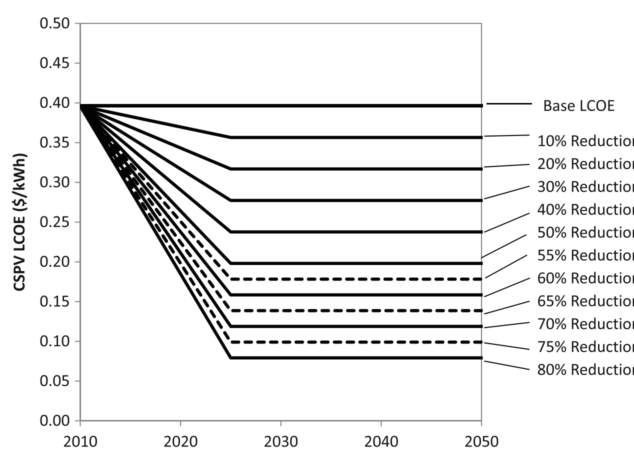

Fig. 2 Levelized cost trajectories for CSPV that were explored in Step 1

projections were examined, with estimated reductions from 2015 to 2030 ranging from 28 to 65 %. Thus, the trajectories in Fig. 2 encompass these percentage improvements, although the decreases are implemented 5 years earlier. Further, it is important to note that prices for solar technologies have decreased recently. The Energy Information Administration, for example, has decreased its expected LCOE for solar PV technologies in 2016 to \$0.21/kWh (US DOE 2010c).

MARKAL was used to evaluate each of the 12 cost trajectories for CSPV in Fig. 2, assuming no CO_2 mitigation target. Of the 12 runs, the CSPV technology achieved market penetration only for the trajectories with cost reductions of 70 % or more. For the 80 % reduction in cost, CSPV penetration was approximately 14 % of market share in 2050. Electricity production by technology category for selected sensitivities is shown in Fig. 3.

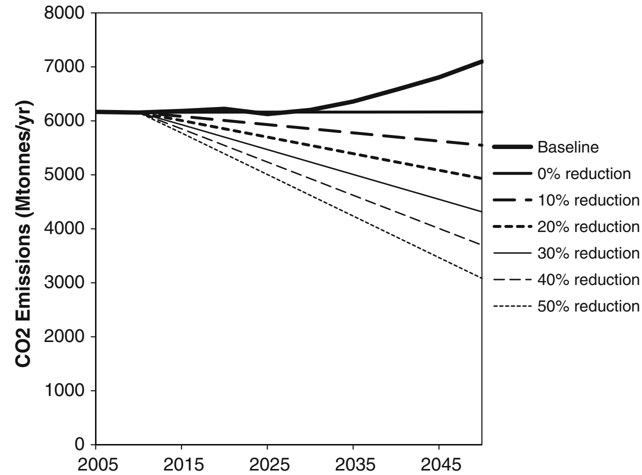

Fig. 4 System-wide CO_2 constraints representing various mitigation targets

Step 2. Investigating sensitivity to CO_2 mitigation target

Next, we examined how CO_2 mitigation targets may affect the competiveness of CSPV. In this sensitivity analysis, we held the technology cost at its baseline value (approximately \$0.40/kWh), but evaluated the optimized CSPV penetration for six different CO_2 mitigation targets. The mitigation targets are implemented as a constraint that decreases US energy system CO_2 emissions linearly from 2010 to 2050, so that 2050 emissions represent a specific percentage of 2005 emissions. The CO_2 mitigation constraints that were examined are shown in Fig. 4.

Many options are available to the model for achieving the CO_2 mitigation targets. These include CSPV as well as other low- and zero-carbon renewables such as wind, geothermal, biomass combustion and high efficiency combined-cycle turbines. MARKAL can also use CCS on coal and natural gas capacity to capture combustion emissions. Within end-use sectors, the model can adopt more efficient technologies or switch to lower-emitting fuel options. The model selects the most cost-effective manner to meet the specified target.

Electricity production profiles for the 10, 30 and 50 % CO_2 mitigation targets, using a baseline CSPV cost (approximately \$0.40/kWh), are shown in Fig. 5.

To achieve a 10 % CO_2 mitigation target, the model chose a path primarily comprised of increased use of natural gas. At 30 %, the model elects to phase out conventional coal, which is replaced in the mid-term by natural gas, and in the longer-term by coal with CCS, wind, and solar thermal. The 50 % mitigation target

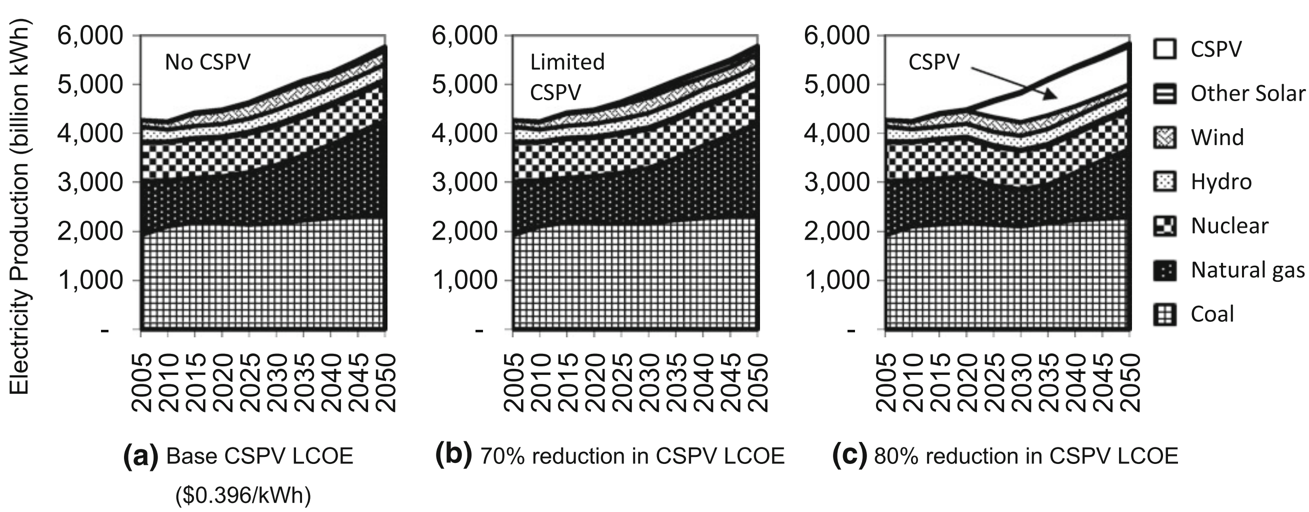

Fig. 3 Electricity production by technology for the levelized cost trajectories, assuming no CO_2 mitigation policy. *NGA* is used as an abbreviation for natural gas

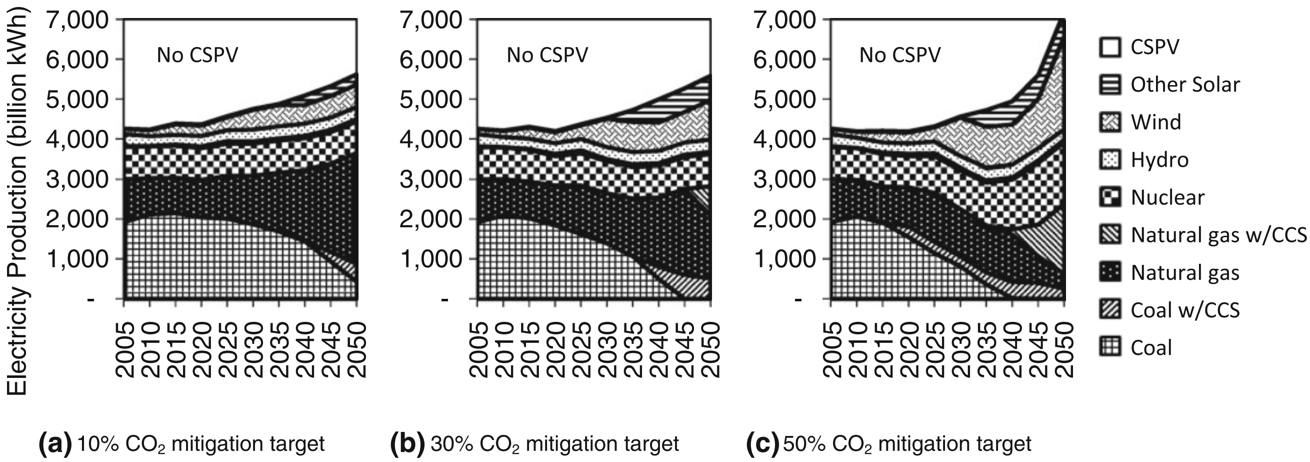

Fig. 5 Electricity production by technology for CO_2 mitigation targets of 10, 30 and 50 %, assuming a baseline CPSV cost of \$0.396/kWh

results in additional nuclear power, as well as CCS on natural gas technologies. Only in the 50 % CO_2 reduction case does CSPV achieve market share by 2050. This market share is less than 0.5 %, however, and is not visible in the figure.

Step 3. Investigating combined impacts of cost and mitigation target

Next, we examined 84 sensitivities that represent combinations of the various CSPV cost reductions and CO_2 mitigation targets shown in Figs. 2 and 4. The resulting electricity production from CSPV and other technologies in 2050 for a subset of these runs is reported in Table 2.

While the one-at-a-time parametric analysis (Steps 1 and 2) indicated only limited penetration potential for CSPV, the nested parametric analysis yields a different outcome. The results suggest that there are opportunities for CSPV market penetration if the cost of the technology can be reduced, and that these prospects are increased with the adoption of a CO_2 mitigation target. CSPV penetrated the market in 41 of the 84 sensitivity runs, achieving an optimized market share as high as 44 % given a cost reduction of 80 % and a CO_2 reduction target of 30 %.

Table 2 is useful for providing insight into the set of technologies with which CSPV competes, as well as how this set changes under increasingly stringent CO_2 mitigation targets. For example, without a CO_2 mitigation target, an 80 % reduction in cost allows CSPV to displace natural gas and wind. Under the 30 % CO_2 mitigation target and an 80 % reduction in cost, CSPV displaces coal with CCS and wind. Interestingly, even with the emergence of CSPV as a low-cost, zero-carbon electricity source, coal-fired generation remains part of the electricity production mix. In the next section we examine CSPV competition for market share in more detail.

Analysis and discussion

Examining the drivers for CSPV penetration

Over the set of nested sensitivities, the 2050 market share for CSPV ranges from 0 to over 44 %. In general, the primary trend shown in Table 2 is intuitive: moving toward more stringent CO_2 mitigation targets and less expensive CSPV (e.g., down and to the right) tends to yield higher CSPV adoption. A secondary and perhaps counter-intuitive trend is also apparent: for any given CSPV cost (reading down a given cost column), the penetration of CSPV appears to peak and then decrease as the CO_2 reduction target increases to 50 % CO_2. Why is the penetration of an inexpensive, zero-CO_2-emitting technology diminishing with a more stringent CO_2 reduction target?

Examining the behavior of other technologies in Table 2 provides some insight: the technologies that increase market share at the expense of CSPV include coal with CCS, natural gas with CCS, and "other solar," which consists primarily of centralized solar thermal. A common trait of all of these technologies is that they each provide baseload power (central solar thermal is modeled as having integrated molten salt storage, allowing it to produce electricity at night).

Why would baseload power be favored over our inexpensive, zero-carbon technology? The answer lies in the interactions between the electric sector and the rest of the energy system. For any given season in MARKAL (summer, winter, or intermediate), baseload power technologies are modeled as producing electricity at the same rate during nighttime and daytime hours. Nighttime demands for electricity are typically less than in the daytime, constraining the output of baseload technologies. For very stringent mitigation targets, however, the daily profile for electricity demands changes as fuel switching leads to a

Table 2 Electricity output in 2050 (billion kWh) for selected technologies

Technology	CO_2 Policy Target	Reduction in CSPV LCOE							
		Base	50%	55%	60%	65%	70%	75%	80%
CSPV	None	-	-	-	-	-	30	110	780
	30%	-	-	70	320	290	1,100	2,000	2,400
	40%	-	510	640	800	800	1,100	1,500	1,900
	50%	20	90	100	170	160	680	1,100	1,400
Coal	None	2,300	2,300	2,300	2,300	2,300	2,300	2,300	2,300
	30%	-	-	-	-	-	-	-	-
	40%	-	-	-	-	-	-	-	-
	50%	-	-	-	-	-	-	-	-
Coal with CCS	None	-	-	-	-	-	-	-	-
	30%	510	510	530	550	550	480	340	300
	40%	390	420	440	450	440	420	410	410
	50%	250	240	240	230	230	270	240	150
Natural gas	None	2,000	2,000	2,000	2,000	2,000	1,900	1,900	1,400
	30%	1,600	1,600	1,600	1,500	1,500	1,600	1,600	1,500
	40%	740	580	550	490	500	400	460	610
	50%	370	380	380	370	370	360	360	360
Natural gas with CCS	None	-	-	-	-	-	-	-	-
	30%	740	740	780	680	690	-	-	-
	40%	860	910	960	1,000	990	1,300	1,200	980
	50%	1,800	1,800	1,800	1,700	1,700	1,600	1,500	1,400
Nuclear	None	790	790	790	790	790	790	790	790
	30%	790	790	790	790	790	790	790	790
	40%	1,500	1,400	1,400	1,400	1,400	790	790	790
	50%	1,500	1,500	1,500	1,500	1,500	1,500	1,500	1,500
Wind	None	290	290	290	290	290	280	250	180
	30%	990	990	890	770	780	760	530	370
	40%	1,700	1,300	1,100	920	940	900	660	540
	50%	2,300	2,300	2,300	2,200	2,300	1,800	1,500	1,400
Other solar	None	60	60	60	60	60	60	60	60
	30%	610	610	610	610	610	610	60	60
	40%	610	610	610	610	610	610	610	610
	50%	610	610	610	610	610	610	610	610
All other	None	370	370	370	370	370	360	360	360
	30%	370	370	360	360	360	360	350	300
	40%	320	360	340	320	320	290	280	260
	50%	330	310	310	300	310	250	240	200

transition to electricity in many end-use sectors. For example, transitioning from a 40% CO_2 reduction target to a 50% CO_2 reduction target increased the market penetration of light-duty electric vehicles in 2050 from 27 to 46 % of the fleet. This increase in vehicle electrification has particularly important implications on baseload power. Because 75 % of charging is assumed in this analysis to occur at night, vehicle electrification expands nighttime demand for electricity, thus increasing the penetration potential of baseload power technologies. Similarly, the more stringent CO_2 target also leads to fuel switching from natural gas and oil to electricity for residential space heating, further increasing nighttime electricity loads and favoring baseload power. Without additional cost reductions or an ability to store electricity for use at night, the CSPV technology loses market share to baseload technologies. The energy system-wide coverage and the modeled load duration profile are important features in developing these insights, and thus demonstrate how the approach can complement more traditional LCOE comparisons.

Assessing breakthrough potential

Next, the ability of reductions in the cost of CSPV to yield tangible reductions in mitigation costs is explored. For each of the nested parametric solutions, MARKAL calculated a NPV of energy system costs over the modeling time horizon. This value included the capital, operations and maintenance, and fuel costs of all technologies that comprised the energy system over the modeled time horizon (2005 through 2055). A discount rate of 5 % was used to convert future costs into 2005 dollars. Note that energy system cost is not the same as the overall cost to the economy because MARKAL does not incorporate macroeconomic considerations. Further, the energy system cost does not include estimates of benefits associated with CO_2 or air pollutant emission reductions.

The NPV of the baseline run (e.g., using approximately \$0.40/kWh LCOE for CSPV and no CO_2 reduction target) can be compared to that of any of the sensitivities to obtain an estimate of the associated CO_2 mitigation costs. At a baseline CSPV cost, for example, the NPV costs of achieving the 30, 40, and 50 % CO_2 mitigation targets are estimated to be \$480 billion, \$800 billion and \$1.3 trillion, respectively. Reducing CSPV cost by 80 %, however, reduces these mitigation costs to \$45 billion, \$375 billion, and \$1.0 trillion. Figure 6 shows the relationship between CSPV and mitigation costs for three mitigation targets.

These results suggest that reducing CSPV cost has the potential to yield considerable reductions in CO_2 mitigation costs. These reductions begin to occur if the CSPV cost can be lowered by 50 % to around \$0.20/kWh, close to DOE's revised LCOE estimate for CSPV in 2016. With an 80 % CSPV cost reduction, equivalent to approximately \$0.079/kWh, the cost of achieving the 50 % CO_2 mitigation target is reduced by \$270 billion, or nearly 30 %, compared to the costs of achieving the target without CSPV. These savings can, to some degree, be used to indicate the value of investment in development of CSPV.

Mitigation cost reduction levels that constitute a "breakthrough" are subjective. Interpolating the values in Fig. 6 allows us to estimate CSPV LCOE targets that may achieve specific reductions in mitigation costs. For example, for the 50 % CO_2 target, mitigation cost reductions of 5, 10 and 20 % may be achievable via decreasing CSPV LCOE values to approximately \$0.12/kWh, \$0.11/kWh and \$0.09/kWh, respectively. While there is considerable uncertainty underlying these values, the results suggest that reductions in the cost of PV have the potential to positively impact the cost-effectiveness of potential mitigation efforts.

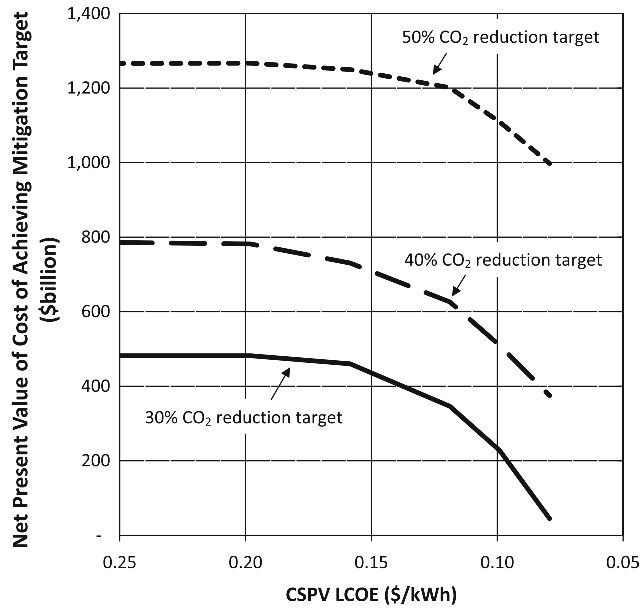

Fig. 6 Costs of achieving CO_2 mitigation targets as a function of CSPV LCOE

Conclusions

In this article, the MARKAL energy system model was used to evaluate the potential for a centralized solar PV (CSPV) technology to achieve "breakthrough" cost reductions in meeting various CO_2 mitigation targets. We identified how reductions in cost of CSPV could impact the market penetration of the technology, including an estimate of its penetration potential, both under baseline conditions and under a range of CO_2 mitigation targets. Finally, the impact of reductions in CSPV cost on CO_2 mitigation program costs for 30, 40 and 50 % CO_2 mitigation targets was calculated.

While this exercise is informative regarding the potential prospects of CSPV, a more important outcome is the demonstration of a modeling approach for evaluating and comparing the breakthrough potential of alternative technologies. At the center of the modeling approach is the MARKAL energy system optimization model. This model allows prospective technologies to be evaluated within an energy system-wide context, and facilitates consideration of factors such as capital stock turnover, fuel supply and demand relationships, the dispatchability of the technology, and current and potential policies related to GHG mitigation, energy, and the environment. Optimization is an important feature in the approach as it facilitates identification of breakpoints at which one technology is favored over another. Optimization also provides some indication of the penetration potential once this breakpoint cost has been achieved. Using MARKAL within a nested parametric analysis allows sensitivities to be examined not just to single model parameter, but also allows combinations of factors to be identified that may yield a breakthrough. For example, the CSPV technology did not achieve a high level of penetration either considering LCOE reductions or CO_2 reduction targets alone. Instead, combinations of these factors led to substantial market penetration. Further, the contextual considerations affected not only the CSPV technology, but also the overall competitive landscape, including the costs of competing technologies. Another important aspect of the approach is its ability to identify complex interactions among multiple technological and contextual factors. This ability was illustrated in the relationship between CO_2 target, electric vehicle utilization, and baseload power generation.

Perhaps one of the most important attributes of the approach is that it allows the abstract concept of a "breakthrough" to be quantified in terms of a system-wide metric, such as the cost of meeting a CO_2 mitigation target. Further, the approach can be extended to compare the potential of multiple prospective breakthrough technologies, comparing, for example, a new electricity production technology with cost reductions in electric vehicles and improvements in stationary storage.

There are caveats that should be considered when interpreting the results presented here. For example, mitigation costs represent energy system costs only and do not account for macro-economic impacts or benefits (health or environmental) associated with CO_2 and air pollutant emission reductions; end-use energy demands are modeled as being inelastic and do not respond to price signals. A drawback of our approach is the degree to which it is model-centric. As a result, many structural and parameter choices made in modeling can affect the results and conclusions. There is also considerable uncertainty inherent in estimating future energy demands and technology characteristics. While some uncertainties can be address by expanding the parametric analysis there is an associated computational cost. Nonetheless, we believe the approach is useful in producing valuable insights regarding future technology penetration opportunities. The development of such insights is critical in energy and environmental planning.

The work presented here represents only a starting point. We expect future steps in analyzing the CSPV technology will include identifying how the use of stationary storage impacts the technology's prospects. Further, we intend to use the overall breakthrough analysis framework to explore and compare the breakthrough implications of various technologies across the energy system. We would also like to explore the effects of considering demand elasticities and making technological learning endogenous to the model, as well as considering uncertainties in the timing and stringency of mitigation strategy. Also, the general nested parametric sensitivity analysis approach is model independent, so MARKAL could be replaced by one or more other models that include more detailed representations of load duration curves, temporal and spatial detail in renewable resource, matching of diurnal energy supply and use profiles, and consideration of system reliability.

Notes on modeling

For this analysis, we used version 5.9b of the MARKAL source code. The database used with MARKAL was version 1.1 of the US EPA 9-region database. Several modifications to this database were made, however. These include: (a) updating the electric light-duty vehicle characterizations, (b) incorporating a representation of the Corporate Average Fuel Economy (CAFE) that results in a fleet-wide increase in efficiency to 54.5 miles per gallon by 2025, and (c) updating emission limits on the electric sector to approximate the recently-adopted Cross-State Air Pollution Regulation and inclusion of hypothetical cap-and-trade constraints for various levels of CO_2 mitigation (US CFR 2011; US EPA 2011a, b). This version of the MARKAL 9-region database has been archived and is available upon request. Please contact the corresponding author (loughlin.dan@epa.gov) for more information.

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