Electricity systems in the limit of free solar photovoltaics and continent-scale transmission

- Electricity demand shows much less variability at the daily time scale than the variability of solar.
- Initially adding solar power is valuable because 100% of the solar is used and it supplants fossil fuel use, and the marginal value of solar is larger under deeply decarbonized scenarios.
- As the amount of solar generation increases, there is excessive generation during the day, but the solar is still unable to meet nighttime demand.

- At near-current cost levels, a zero-emission electricity system with abundant free solar generation could be more costly than a system with 100% natural gas, no emission reduction, and no free solar.
- Taking full advantages of low-cost solar will depend on developing and deploying low-cost approaches to temporally shift either energy supply (e.g., storage) or electricity loads (e.g., load-shifting).
Electricity systems in the limit of free solar photovoltaics and continent-scale transmission

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SUMMARY
Solar photovoltaics, with sufficient power generation potential, low-carbon footprint, and rapidly declining costs, could supplant fossil fuels and help produce lower-cost net-zero emissions energy systems. Here we used an idealized linear optimization model, including free lossless transmission, to study the response of electricity systems to increasing prescribed amounts of solar power. Our results show that there are initially great benefits when providing solar power to the system, especially under deep decarbonization scenarios. The marginal value of additional solar power decreases substantially with increasing cumulative solar capacities. At costs near today’s levels, the modeled zero-emission electricity system with free solar generation equaling twice the annual mean demand is more costly than a carbon-emitting natural-gas-based system supplying the same electricity demand with no solar. Taking full advantage of low-cost solar will depend on developing and deploying low-cost approaches to temporally shift either energy supply (e.g., storage) or electricity loads (e.g., load-shifting).

INTRODUCTION
Rapid decarbonization of electricity generation is expected to play an important role in limiting the accumulation of atmospheric carbon dioxide (CO2) and the adverse consequences of climate change. As transportation, heating, residential, commercial, and industrial uses of energy become increasingly electrified, decarbonization of electricity generation contributes to emission reductions in these sectors and is a central strategy that seeks to decarbonize the entire economy (Saunders et al., 2018). Efforts to replace fossil fuel carbon emission sources with low carbon emission power generation technologies have led to increasing interests in renewable energy, including the deployment of solar photovoltaics (denoted as solar hereafter), which is now a mature technology that some have proposed to deploy at multi-terawatt scale within a decade (Haegel et al., 2019; Zhang et al., 2021). The technical potential of direct solar energy generation, given system performance, topographic limitations, and environmental and land-use constraints, is more than enough to meet projected global primary energy demand in 2050 and is orders of magnitude larger than the technical potential of wind or biomass electricity generation (Creutzig et al., 2017). Costs of solar plummeted in the past decade, making it economically competitive in many electricity markets (e.g., the global weighted-average levelized cost of electricity, LCOE, for utility-scale solar photovoltaic [PV] in 2020 of $0.057/kWh is at the lower end compared to new fossil fuel-fired electricity projects) albeit often with policy support (Gielen et al., 2019; IRENA, 2020; Ramasamy and Feldman, 2021). Recent studies have concluded that solar energy can contribute a much higher portion of global electricity market supply by 2050 (e.g., >50%) than previous estimates after reviewing factors including cost reduction potential and policy conditions (Creutzig et al., 2017; Victoria et al., 2021).

Unlike firm generation technologies (e.g., natural gas and nuclear), electricity produced by solar depends on local weather conditions, and diel and seasonal cycles – it is not always available in the quantities needed to meet electricity demand (Shaner et al., 2018). As solar penetration increases, first midday demand is satisfied, and then early morning and late afternoon periods, but solar is not able to directly meet the demand that persists at night. Initially, when deployment is limited, nearly all power generated by solar can be used, but at high levels of penetration, additional solar power (in the absence of storage or load-shifting options) provides little additional usable solar generation. Previous studies have shown
substantial declines in the marginal value of solar as penetration increases (Mills and Wiser, 2013, 2015; Ueckerdt et al., 2015; Sivaram and Kann, 2016), with details depending on scenarios considered. In this study, our central question focuses on how the value of freely provided solar varies with the amount of solar power provided, emissions constraints, and other factors, but for context, we also examine what would be needed to make the best use of free solar power with free electricity transmission. We use an idealized linear optimization model, Macro Energy Model (MEM), that considers techno-economic factors only and determines both capacity expansion and electricity dispatch (Dowling et al., 2020; Tong et al., 2020; Yuan et al., 2020; Ruggles et al., 2021; Duan et al., 2022). A schematic diagram (Figure 1) illustrates the basic model configuration and technologies used in this analysis and details are described in STAR Methods. A broad range of scenarios are examined, in which solar generation (defined as the annual mean solar generation) is gradually increased and allowable carbon emissions from fossil fuel generation are decreased. Input data required to run the model (e.g., cost information, hourly electricity demand, and renewable resources) are derived for the United States. All dollar values presented in this study are year-2019 dollars. We focus on changes in the optimized system cost (with solar considered to be free) and capacity associated with other technologies to satisfy electricity demand. In other words, how much can the given amount of free solar power help in meeting electricity demand under near-current technology costs?

Our analysis focuses on providing a fundamental understanding regarding changes in the value of solar power in decarbonized electricity systems and what would be needed to make better use of abundant cheap solar generation, which could shed light on future energy system planning and policy-making processes. Our analysis considers a highly idealized framework and does not try to capture the realistic market status. We focus on the qualitative features of our results, and numerical values presented here should not be overinterpreted. Our study provides simple and transparent cost-optimized calculations, with the hope to inspire discussions on such topics and future works that use complicated models and consider more sophisticated assumptions.

RESULTS
In this section, we first examine changes in system cost associated with other generation and storage technologies for a suite of simulations involving different amounts of emission reduction constraints with free solar power provided. We then calculate the percentage of meeting electricity demand where solar is the least-cost generator, hereafter denoted as solar dispatch (in cases of multiple sources of zero-cost
electricity, we consider the solar power not to have been necessary). Our results indicate that expansion of solar generation can provide substantial benefits to the electricity systems, especially under deep decarbonization scenarios. In our configurations considering near-current cost estimates and an idealized least-cost framework, a zero-emission electricity system with free solar generation equaling to twice annual mean demand (i.e., a nameplate solar capacity equals to \( \frac{C}{7.3} \) times annual mean demand) could be more costly than a system with 100% natural gas, no emission reduction, and no free solar generation. Additional figures and tables supporting findings presented in this study can be found in the Supplementary information.

Response of system cost to free solar generation

Figure 2A shows changes in electricity system cost in response to increasing quantities of free solar generation under various emission reduction constraints. Year-2019 demand and concurrent renewable resource data are used and sensitivity tests using year-2016 to year-2018 inputs are plotted in Figure S1. In cases with solar generation fixed to zero (nameplate solar capacity equaling to zero), cheap and flexible natural gas and natural gas-with-CCS sources are the dominating electricity suppliers under modest emission reduction constraint scenarios, whereas nuclear is substantially used when deep emission reduction constraints are applied (Figure S2). Adding free solar power to the system reduces costs associated with deploying other technologies, leading to substantial decreases in system cost and great marginal values (Figures S2 and S3). That is, initial additions of solar to the system have high marginal values and produce substantial reductions in system costs. The marginal value of initially adding solar power per unit of annual mean demand is larger than the marginal value of initially adding other low-carbon emission technologies examined here (i.e., wind and nuclear). This difference in value is likely owing to better correlations between solar generation and daily peak demand than wind or nuclear (e.g., the correlation coefficient between demand and solar profiles decreases when removing frequencies higher than daily/multiple-days’ timescale using approaches, such as the moving average). Meanwhile, the marginal value of initially adding solar power is larger under deep emission reduction constraints, in which cheap and flexible natural gas and natural gas-with-CCS generations are greatly excluded from the system. Under deep emission reduction constraints, solar power provides the most value to the system.
reduction constraints, including free solar reduces the utility and value of low-emission firm generation sources (i.e., nuclear) and increases electricity generation from wind.

In our analysis, electricity demand shows much less variability at the daily time scale than the variability of solar (Figures 2B and S4). At first, added solar power is very valuable because 100% of the solar generation is used and it supplants fossil fuel use. But as the amount of solar generation increases, there is excess generation during the day, but the solar generation is still unable to meet nighttime demand. Thus, to make better use of this solar power, mechanisms are needed to either bring the solar energy into the night (storage) or bring the nighttime demand into the day (load shifting). For example, solar-powered heating in the daytime could potentially help to meet evening heating loads using improved heat storage technologies. Owing to current high costs of storage, the marginal value of adding each additional unit of free solar drops rapidly to zero as solar generation reaches ~0.8 times the annual mean demand under all emission reduction constraints, after which adding additional solar does not affect the least-cost solution (e.g., technology mixture and system cost) very much (Figure 2A). This is true as free given solar generation continuous increasing (Figure S3).

In our simulations, system costs with sufficient free solar generation (e.g., 2 times annual mean electricity demand) under deep emission reduction constraints are higher than system costs when natural gas dominates with no free solar (Figure 2A). For example, the system cost under 99% emission reduction levels with free solar generation equaling twice the annual mean demand (i.e., a nameplate solar capacity of ~7.3 times annual mean demand, point f in Figure 2A) is $0.052/kWh, which is 41% higher than the system cost with no emissions reduction, no free solar generation, and 100% natural gas (point a in Figure 2A, $0.037/kWh). System cost under 100% emission reduction levels with free solar generation equaling to 2 times annual mean electricity demand is $0.082/kWh, more than twice compared to that with no emissions reduction, no free solar generation, and 100% natural gas. Meanwhile, despite providing a substantial amount of free solar power, wind and nuclear capacities are built under deep emission reduction constraints. Our results thus suggest that at near current cost levels, while solar power can provide great benefits to electricity systems initially, it is less cost-effective to rely primarily on solar plus storage to power the night-time demand compared to using wind and/or nuclear with less storage (Figures 2 and S3). This is because a combination of these technologies plus modest storage could provide less-costly electricity to supply night-time demand. Furthermore, once wind and/or nuclear capacity is built, that capacity is also available during the daytime, reducing the need for large amounts of solar generation. In contrast to solar, increasing the prescribed generation of wind and nuclear in the same manner could continuously reduce the need for additional generation capacities and eventually reduce the need for storage (Figures S3 and S6). When considering the least-cost solution using near current cost estimates for solar (Table S1), the lowest system cost is achieved with solar generation ~0.4 times the annual mean demand under deep emission reduction constraint scenarios. Again, the least-cost solution provided here depends on the cost ratios of different technologies as inputs. Our framework is idealized, and we focus on qualitatively understanding changes in the value of solar under various emission reduction conditions. Many factors that are important in real-world planning are not included here, and numerical values should not be overinterpreted.

Our central cases examined above consider near-current cost estimates from EIA, while costs of wind and storage are expected to continue to decrease in the future. We further conducted simulations, in which fixed costs of generation technologies and battery storage are calculated based on the year-2050 cost projections from the National Renewable Energy Laboratory (NREL) 2021 Annual Technology Baseline (ATB) report under moderate technology innovation scenarios. Compared to the near-current EIA cost estimates, the derived year-2050 fixed cost from NREL ATB for wind and storage are ~32 and 31% lower, respectively, whereas the fixed costs for natural gas and natural gas-with-CCS remain roughly the same. Simulation results using future costs show consistent conclusions as to the EIA cost cases (Figure S7): introducing free solar to the system shows great benefits in reducing system costs initially, and then the value of solar diminishes to approximately zero as cumulative solar generation increases. Because of the lower projected technology costs, systems costs under deep decarbonization scenarios are substantially reduced, while scenarios considering a >99% emission reduction constraint still show equivalent or larger system costs compared to that without free solar or emission reduction, and only fossil fuel generation. If the ratio of storage cost to wind cost were to decline by a factor of three, this would be sufficient for storage to replace wind power in meeting nighttime demand (Figure S8).
To examine the impact of choosing different reanalysis datasets on optimization results, we add simulations using wind and solar profiles calculated based on the ERA5 reanalysis product. Results using ERA5 show behaviors consistent with our default cases using MERRA-2 (Figure S9). Optimization solutions are relatively weather-independent with weak or absent carbon reduction constraints because fossil fuel sources dominate power generation. For deep decarbonization scenarios (e.g., 99% emission reduction), the marginal value of additional solar decreases to zero slightly more quickly with the ERA5 profiles.

Simulations using wind and solar profiles averaged over all grid cells in the US (instead of the top 25% approach) are shown in Figure S10, which are qualitatively the same as our central cases (the R² of the correlation between the two cases is 0.93). Compared to the top 25% approach, averaging over broader areas lead to lower annual mean capacity factors for both wind and solar, and increases system costs under deeply decarbonized scenarios.

**Changes in solar dispatch**

Figure 3 shows changes in solar dispatch in meeting annual electricity demand. As mentioned above, because MEM does not specify dispatch orders among different technologies with zero variable cost, it is assumed here that electricity generated from solar is dispatched after electricity generated from other zero-variable-cost technologies (i.e., wind and nuclear), but before electricity generated from natural gas and natural gas-with-CCS. That is, we consider times when using free solar would reduce system costs. We focus on the 0 and 99% emission reduction cases in detail.

When there is no free solar in the system, natural gas dominates as the cheapest way to meet demand under modest emission reduction constraints, whereas nuclear is preferred under deep emission reduction constraints (Figures 4 and S2). When the given solar generation gradually increases, solar dispatch increases initially (Figure 3) as it is used to replace other generation technologies and reaches stable as

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**Figure 3.** Percentage of annual electricity demand that is met by solar (at times when other zero-cost electricity was unavailable), denoted as useful solar generation or solar dispatch. Because of the relatively high cost of electricity storage, the optimizer builds additional generating capacity of wind or nuclear to meet nighttime demand. This capacity is then available to use during the day.
the cumulative solar capacity increases. When solar generation reaches 2 times annual mean demand, without an emission reduction constraint (e.g., 0% emission reduction), cheap and flexible natural gas can be used to fill gaps between electricity supply and needs, and solar is exclusively used to satisfy daily electricity demand (solar dispatch of >50% of demand). Under deep emission reduction constraints, solar’s inability to provide electricity during the night provides a potential nighttime market for wind and nuclear power, and once these capacities are built, they can be used to provide electricity during the day, leading to much less need for solar except for meeting daily peak demand (Figure 4). In our model results, if we put solar last in the dispatch order of zero-cost generators, solar dispatch contributes <20% of annual demand under the 99% emission reduction constraint (<5% under the 100% emission reduction constraint) because of the abundance of zero variable cost wind and nuclear power. Our 99 and 99.9% decarbonization scenarios with abundant solar power are dominated by wind power generation, but in the absence of solar power, these scenarios have primarily nuclear generation (Figure S2). Our results indicate that if electricity storage technologies are expensive, then the least costly way to provide power at night is to generate electricity at night, either with nuclear or wind and perhaps with limited amounts of storage.

There are only two ways that solar generation can be used to power the night-time demand: either the electricity supply must be shifted from day to night (storage), or the demand must be shifted from night to day (or both). As the least-cost capacities and dispatch profiles computed by MEM depend on the ratios of costs among different technologies, and not absolute costs, for storage we conduct simulations, in which the fixed costs of storage vary from 1 × to 0.2 × the default near-current level and the fixed costs for all generating technologies remain unchanged. To examine the impact of load flexibility, we add an idealized
Load-shifting ability that allows a specified quantity of electricity demand to be shifted in time (both forward and backward) with no additional costs. We prescribe the magnitude of load-shifting ability as:

\[
\text{load shifting ability} = \frac{\text{total allowable shifted demand}}{\text{total electricity demand}}
\]

where total allowable shifted demand sets the maximum allowable amount of electricity demand being shifted (in units of kWh * hour) divided by total electricity demand (in units of kWh). In our analysis, one kWh electricity demand shifted by 10 h is numerically equal to shifting 10 kWh electricity demand by 1 h. There is no limit on the magnitude or how many hours the demand can be shifted as long as the total shifted demand is less or equal than the total allowable shifted demand limits (e.g., a load-shifting ability of 0.2 corresponds to the ability to shift 20% of the annual load by 1 h or to shift load equivalent to a single day’s mean demand 20% later or earlier in the year). Our assumptions thus represent the upper boundary scenarios, in which an idealized load-shifting approach is used. Adding other constraints on the load-shifting process that are likely in the real world (e.g., the maximum magnitude of demand to be shifted each hour) would reduce its potential benefits to variable renewables compared to our idealized assumptions. We prescribe solar generation to be 100 times annual mean electricity demand (effectively infinite) and focus on changes in solar dispatches.

Figure 5 shows changes in solar dispatch as a function of storage cost and load-shifting ability under the 99% emission reduction constraint. Under the default condition (storage cost at benchmark value and zero load-shifting ability), solar dispatch is only 21% of the annual demand (less than 6% under 100% emission reduction constraint). Reducing storage costs and/or increasing load-shifting abilities can both improve solar dispatch. Our results indicate that, even with abundant free solar power, a substantial reductions in storage cost would be required to produce a system with costs comparable to a natural gas-dominated system. With zero load-shifting ability storage costs need to be reduced by ~40% to allow solar to power more than 30% of the system. Load-shifting can play a role similar to that of storage, except that instead of shifting the electrical energy in time, the electrical demand is shifted in time. In reality, solar
power is not free, and flexibility provided by storage or load-shifting can benefit wind or nuclear as well depending on factors such as costs or policy circumstances.

**DISCUSSION**

In this study, we use an idealized least-cost optimization model to examine changes in the value of solar power under different emission reduction constraints. Our results show that when there is no or little solar generation capacity, adding additional solar power in the electricity system leads to high marginal values of solar because the added solar provides substantial benefits in reducing system costs, especially in deeply decarbonized systems. The marginal value of adding solar per unit additional solar generating capacity decreases substantially as the cumulative solar capacity increases because more of the generation is curtailed. Considering the near-current EIA cost estimates and free lossless transmission, we find substantially larger system costs with abundant free solar generation under deep emission reduction scenarios, compared to system costs in natural gas-dominated systems with zero free solar. This cost difference is mainly owing to the fact that solar cannot provide night-time demand, and the cost of alternative generation technologies and storage is relatively high. This conclusion holds under cost projections for the year 2050, such as those from the NREL ATB report, which project the cost of installing wind power and building storage will have decreased by more than 30% compared to their near-current EIA costs.

With deep emission reduction constraints (e.g., 99 and 100% emission reduction) and abundant free solar generation, the current high cost of storage results in substantial deployment of other generation technologies (e.g., wind and nuclear). These other technologies provide power both at night and during the day, with the result that solar is needed to satisfy ≤ 20% of annual electricity demand. The value of solar increases as the cost of storage or the cost of load flexibility decreases because more of the daytime solar generation can be used to meet nighttime demand. Therefore, achieving higher levels of solar utilization requires low-cost approaches that can provide system-level flexibility, such as cheaper storage and load-shifting ability.

**Limitations of the study**

Using an idealized linear-optimization model and under the cost-minimizing framework, we examined the response of an idealized electricity system to increasing quantities of free solar generation. Various emission reduction constraint scenarios were studied, under which generation from fossil fuel sources is limited. Our study focuses on the dynamic relationships among different technologies. We examine how the value of solar generation changes under different decarbonization scenarios. Caveats should be emphasized when interpreting the results presented in this analysis.

The model used in our analysis is highly idealized compared to other works that consider more detailed assumptions and models (Brown and Botterud, 2021; Cole et al., 2021; Williams et al., 2021). For example, MEM assumes a power system with no pre-existing capacity of any technology (unless given) at the beginning of optimization. Existing infrastructure does not make it easy to use abundant daytime solar electricity at night. The construction process is very idealized, and the costs of different technologies remain constant during the simulations, which differs from the real-world situations. For example, we have shown that a more rapid decreasing of the storage cost might reduce the use of wind if substantial free solar power exists (Figure S8). Our model uses hourly time steps. In the real world, the reliability of the power system can depend on grid events occurring on timescales of milliseconds to minutes. Here we focus on the temporal mismatch between electricity demand and solar generation and assume perfect, lossless electricity conduction. Other constraints, including transmission, could also pose barriers to the effective use of abundant cheap solar generation. Our model assumes perfect foresight regarding demand needs and renewable resources. These assumptions could confer advantages on solar and wind compared to firm generation (i.e., nuclear) relative to more realistic representations. Nevertheless, some of our conclusions, such as great marginal values of initially adding solar power to electricity systems followed by substantial reduction and that it is less cost-effective to rely primarily on solar plus storage to power the night-time demand at near-current cost levels, are consistent with previous studies (Mills and Wiser, 2013, 2015; Ueckerdt et al., 2015; Sivaram and Kann, 2016; Cole et al., 2018; Baik et al., 2022).

In this analysis, we consider the possibility of reducing the storage cost and providing additional load-shifting ability. Although reducing the costs of other low-carbon emission technologies could decrease system
costs, the reduced cost technologies would further compete with solar and would decrease the value of the free solar power. For example, the marginal value of solar would increase if wind or nuclear is removed from the system (Figure S5). The same situation occurs when considering other low-carbon emission options (e.g., biomass, hydropower, and advanced nuclear). In addition to the configuration used here, previous studies have shown that technologies such as long-duration energy storage could support variable renewables by providing inter-season and multi-year storage (Albertus et al., 2020; Dowling et al., 2020). We examine this feature using our central cases plus power-to-gas-to-power (PGP). Our results (Figure S11) show that at near current cost levels (Dowling et al., 2020), including PGP helps reduce systems costs under deeply decarbonized emission constraints but has little impact on low to modest emission reduction scenarios. Concentrated solar power (CSP) is often coupled with the thermal energy storage system (Romero et al., 2015). The inclusion of thermal energy storage could allow solar power to be stored and shifted more easily and provide higher marginal values with higher installed capacities. Costs of CSP technologies have dropped substantially in the past decades and could play an increasingly important role in the future (IRENA, 2020). Electrification of other sectors such as transportation and heating could increase system flexibility in the future, helping alleviate the intermittency issue associated with renewables (Bellocci et al., 2020; Bogdanov et al., 2021; Ruhnau, 2021).

In the article, we investigate the potential impact of cheaper battery storage and adding a load-shifting component. We represent the load-shifting process in a highly idealized manner such as no limitations on the magnitude and duration of demand shifted. Our analysis does not try to predict future change in the storage cost or technology innovations, and we consider such highly idealized simulations to develop fundamental understandings regarding the dependence of utilization of solar power on the future reductions in storage costs and increases in systematic flexibilities. We hope that our results can inspire future discussions and studies considering more sophisticated assumptions.

Least-cost solutions do not consider many practical considerations faced by system planners such as environmental and social considerations, which might lead to a preference for one technology over another (e.g., the nuclear waste disposal issue) (Seetharaman et al., 2019).

STAR METHODS
Detailed methods are provided in the online version of this paper and include the following:

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- RESOURCE AVAILABILITY
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  - Data and code availability
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SUPPLEMENTAL INFORMATION
Supplemental information can be found online at https://doi.org/10.1016/j.isci.2022.104108.

ACKNOWLEDGMENTS
This work is supported by a gift from Gates Ventures LLC to the Carnegie Institution for Science.

AUTHOR CONTRIBUTIONS
L.D. conducted simulations and drafted the article. L.D., T.H.R., and K.C. contributed to simulation designs, data analysis, and editing of the article.

DECLARATION OF INTERESTS
The authors declare no competing interests.
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STAR METHODS

KEY RESOURCES TABLE

| REAGENT or RESOURCE | SOURCE | IDENTIFIER |
|---------------------|--------|------------|
| Deposited data      |        |            |
| MERRA-2 weather records | Modern-Era Retrospective Analysis for Research and Application, Version 2 (MERRA-2) | https://daac.gsfc.nasa.gov/ |
| ERAS weather records | European Center for Medium-Range Weather Forecasts | https://cds.climate.copernicus.eu/cdsapp#!/home |
| Electricity demand | Ruggles et al. (2020) | https://www.nature.com.stanford.idm.oclc.org/articles/s41597-020-0483-x |
| Near-current EIA technology costs | Energy Information Administration (EIA) | https://www.eia.gov/outlooks/archive/aeo20/pdf/AEO2020%E2%80%93Electricity.pdf |
| NREL future cost projections | National Renewable Energy Laboratory 2021 Annual Technology Baseline (ATB) | https://data.openei.org/submissions/4129 |
| Life cycle carbon emissions | Schlömer, S. et al. (2014) | https://www.ipcc.ch/site/assets/uploads/2018/02/ipcc wg3_ar5_annex-iii.pdf |
| Key model outputs | Github | https://github.com/LDuan3008/Value_of_free_solar_2021. |
| Model codes and post-processing scripts | Github | https://github.com/LDuan3008/Value_of_free_solar_2021. |

Software and algorithms

| Software and algorithms | Source | Identifier |
|-------------------------|--------|------------|
| Macro Energy Model      | Ruggles et al. (2021) and GitHub | https://www-sciencedirect-com.stanford.idm.oclc.org/science/article/pii/S2666792421000433 | https://github.com/LDuan3008/Value_of_free_solar_2021. |
| Gurobi v9.0             | Gurobi Optimization | https://www.gurobi.com/ |
| Python v3.7             | Python Software Foundation | https://www.python.org/ |

RESOURCE AVAILABILITY

Lead contact
Further information and requests for resources should be directed to and will be fulfilled by the lead author, Lei Duan (leiduan@carnegiescience.edu).

Materials availability
This study did not generate new materials.

Data and code availability
- Data: Key model outputs that are used to support findings presented in this study have been deposited at GitHub and are publicly available as of the date of publication using the following link: Github: https://github.com/LDuan3008/Value_of_free_solar_2021.
- Code: All original codes, including model codes and post-processing scripts, have been deposited at GitHub with the same link above and are publicly available as of the date of publication.
- Any additional information required to reanalyze the data reported in this paper is available from the lead contract upon request.

METHOD DETAILS

Model descriptions
In this analysis, we represent electricity systems using a relatively simple, transparent, macro energy model (MEM) (Dowling et al., 2020; Tong et al., 2020; Yuan et al., 2020; Ruggles et al., 2021; Duan et al., 2022). We consider generation technologies such as natural gas, natural gas with carbon capture and storage (natural
gas-with-CCS), wind, solar, and nuclear, and battery storage. The stylized electricity system in MEM is represented as a linear-optimization problem, the objective function of which is constructed to minimize the system cost with different technologies under given electricity demands and renewable resources. Hourly time resolution is used (Nicolosi et al., 2010) and we consider optimizations over one calendar year period. MEM considers techno-economic factors only, including a fixed cost associated with all technologies and a variable cost specified for natural gas and natural gas-with-CCS. Fixed cost of a technology includes the fixed capital investment representing the purchase cost for each technology and installation, and fixed operation & management (O&M) costs:

\[
C_{\text{fixed cost}} = C_{\text{capital cost}} + CRF + C_{\text{O&M}}
\]

where \(C_{\text{capital cost}}\) represents the overnight capital cost, \(C_{\text{O&M}}\) represents the fixed O&M cost, and \(CRF\) represents the capital recovery factor, which is calculated based on discount rate \(R\) and lifetime \(N\):

\[
CRF = \frac{R \cdot (1 + R)^N}{(1 + R)^N - 1}
\]

Variable cost includes variable O&M cost and fuel costs as appropriate.

In this analysis, we consider nuclear generation to be running constantly and thus the variable O&M and fuel costs are part of the fixed cost. Cost assumptions for all generation technologies are taken directly from the near-current estimates of Energy Information Administration (EIA) 2020 Annual Energy Outlook (note that based on EIA’s cost estimates natural gas has a lower LCOE than solar, wind or nuclear), which are summarized in Table S1 (EIA, 2020). We do not consider other constraints, such as the inverter loading for solar power, that could be important to take into account in real-world planning but has minor impact on our optimization framework here. MEM determines both generation/storage capacity and electricity dispatch at each hourly time step based on ratio of costs among the modeled generation and storage technologies. That is, if all cost inputs decrease or increase by the same fraction, the optimized technology capacities and dispatches would be the same while system costs would change. Electricity supply from all sources (generation and storage technologies) must equal total sinks (i.e., electricity demand and curtailment) for each hour at the electricity exchange node. No lost load is allowed and thus 100% of electricity demand is satisfied in all simulations shown here.

**Demand and resource data**

Hourly profiles of year-2016 to 2019 electricity demand and concurrent renewable potential (i.e., solar and wind capacity factors) are provided to the model. Our central cases show results using the year-2019 inputs and others are plotted in the Supplementary information. Hourly demand data were original collected and provided by the U.S. Energy Information Administration (EIA) that cover all the contiguous United States. However, substantial quantities of missing and outlier values exist in the original data. A cleaning approach is then applied to create the final complete and usable data records used this analysis (Ruggles et al., 2020).

Wind and solar capacity factors are estimated using The Modern-Era Retrospective Analysis for Research and Application, Version 2 (MERRA-2) reanalysis satellite weather data, which has a resolution of 0.5° by latitude and 0.625° by longitude (Gelaro et al., 2017). For the wind turbine, we assume a hub height of 100 m. The wind speed at the corresponding height is interpolated based on values at 10 m and 50 m by employing a power law. A piecewise function is used to calculate wind capacity factor: (i) below a cut-in speed \(u_i\) of 3 m s\(^{-1}\) the capacity factor is zero, (ii) between the cut-in speed of 3 m s\(^{-1}\) and rated speed \(u_r\) of 12 m s\(^{-1}\) the capacity factor is \(u_r^{3}/u_i^{3}\), (iii) between the rated speed of 12 m s\(^{-1}\) and the cut-out speed \(u_{co}\) of 25 m s\(^{-1}\) the capacity factor is 1.0, and (iv) above the cut-out speed of 25 m s\(^{-1}\) the capacity factor is zero. We assume a single-axis tracking solar panel system with north-south direction, with a tilt of 0° and a maximum tuning angle of 45°. Solar zenith angle and incidence angle are calculated based on geographic location and local time. The in-panel solar radiation is then calculated, separating the direct and diffuse radiation components based on an empirical piecewise model, in combination with surrounding panel temperature to calculate hourly averaged solar capacity factors (Reindl et al., 1990; Huld et al., 2010; Pfenninger and Staffell, 2016).

We first calculate both wind and solar capacity factors at each grid cell at the original reanalysis product’s resolution, and then integrate different grid cells by calculating the area-weighted mean values to generate continental-scale hourly profiles. Our central scenarios consider cases, in which only the top 25% grid cells
in the continental U.S. that have the largest capacity factors are aggregated by doing an area-weighted average calculation (annual mean capacity factor results from year 1980–2019 for solar and wind are compared in Figure S12). We also conducted cases that average all grid cells in the continental U.S. (see Discussion below). Our capacity factor calculations represent a first order estimate of the spatial and temporal characteristic of renewable resources. Since demand and resources are prescribed before optimizations, the model has perfect knowledge of forthcoming demand peaks and power shortages for all renewable generation.

To test the impact of choosing different reanalysis datasets on optimization results, we apply the same approaches of calculating hourly solar and wind profiles to the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA5 (Hersbach et al., 2020), which has been shown to have better quality than MERRA-2 (Jourdier, 2020; Sianturi et al., 2020). Comparisons between results using renewable profiles from ERAS and MERRA-2 are discussed in the Results section.

Simulation designs
To study the system response to increasing solar power, we specify nameplate solar generation capacity before optimizations start, and let the rest of the system compete. Since solar generation capacity is prescribed, solar power is effectively free regarding the optimization process. There is no pre-fixed capacity other than solar in the system. The specified annual mean solar generation (denoted as solar generation in this analysis) represents the average level of hourly solar generation potential across the entire simulation year. Solar generation can thus be calculated as the specified nameplate solar generation capacity times the annual mean capacity factor of solar:

\[
\text{solar generation} = \text{nominal solar capacity} \times \text{annual mean capacity factor}
\]

Total solar generation can then be represented as solar generation times hours of a year. Our model does not consider details regarding where to put solar panels, and with given solar generation capacity, available solar power at hourly time resolution is fixed as well. In our central cases, we increase the nameplate solar generation capacity so that solar generation increases from zero to four times annual mean demand. Because the annual mean capacity factor of solar for the year 2019 is \(0.27\), this represents a nameplate solar generation capacity range of zero to \(7.3\) times annual mean electricity demand. Ideally the given solar generation is far more enough to meet all demand, but due to the mismatch between electrify needs and solar supply, the model does not always use all the given solar power. We also test cases, in which annual mean generation of other low-emission technologies (i.e., wind and nuclear) are specified.

To examine the impact of decarbonization on the value of solar, each prescribed generation case is performed under various scenarios, in which allowable carbon emissions from fossil fuel sources (i.e., natural gas and natural gas-with-CCS) are gradually reduced. While renewables and nuclear are not carbon-neutral (i.e., their lifecycle CO\(_2\) emissions are larger than zero), the magnitude of lifecycle CO\(_2\) emissions from these technologies are much smaller compared to fossil fuel-based sources (Schlömer et al., 2014).