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Title
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Permalink
https://escholarship.org/uc/item/4337x7x9

Journal
iScience, 24(9)

ISSN
2589-0042

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Lin, Jiang
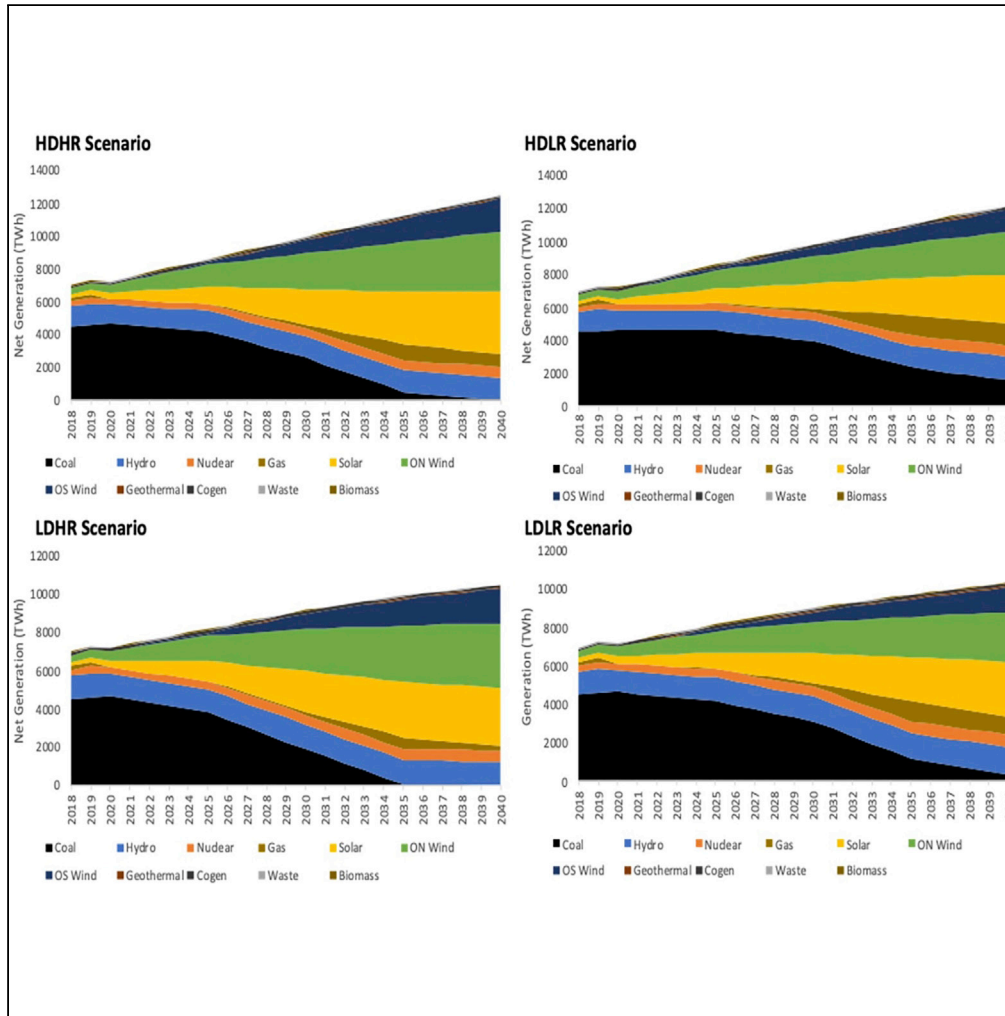Liu, Xu
et al.

Publication Date
2021-09-01

DOI
10.1016/j.isci.2021.102939

Peer reviewed

Article
Sunsetting coal power in China

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Highlights
Retiring all coal
generation capacity by
2040 is feasible in China

New electricity demand
should be met with
noncoal generation

All coal plants should be
replaced by the end of its
original depreciation time

A rapid scale-up in solar,
wind, and storage
resources is needed

Article

Sunsetting coal power in China

Fredrich Kahrl,[1,3] Jiang Lin,[2,3,6,*] Xu Liu,[2,4] and Junfeng Hu[2,5]

SUMMARY

Reducing CO_2 emissions from coal-fired electricity generation in China is critical to limit global warming. Long-term projections of China's electricity supply tend to assume that coal generation will be a mainstay of China's electricity system through 2050, due to limitations in the scalability of hydropower, nuclear, and natural gas generation and the commercial availability of carbon capture and storage. This paper examines the resource, economic, and institutional implications of reducing and replacing coal generation in China with mostly renewable energy and energy storage by 2040. We find that the scale of solar, wind, and storage resources needed to do so is on the order of 100–150 GW/year of solar and wind capacity and 15 GW/year of energy storage from 2020 to 2025, growing to 250 GW/year and 90 GW/year, respectively, from 2025 to 2040. We then also evaluate the sensitivities if coal plants are retired by 2050.

INTRODUCTION

Reducing CO_2 emissions from coal-fired electricity generation in China is critical for reducing the risks of climate change. Coal generation in China currently accounts for 14% of global energy-related CO_2 emissions and is the world's single largest sectoral source of CO_2 emissions (International Energy Agency (IEA), 2018). Although the share of coal generation in China's electricity generation mix is declining (from 76% in 2010 to 62% in 2019), total coal generation is still increasing (by 1329 TWh (+41%) from 2010 to 2019) as a result of electricity demand growth (China Electricity Council (CEC), 2020)

Expectations of continued electricity demand growth in China, driven by economic growth and electrification, raise questions about the extent to which CO_2 emissions from coal generation can be reduced to meet global goals for limiting anthropogenic warming. Recent Intergovernmental Panel on Climate Change estimates suggest that limiting global warming to 1.5°C above preindustrial levels is consistent with a decline in global primary coal consumption from 166 EJ yr^{-1} in 2017 to 19–24 EJ yr^{-1} by 2050 (International Energy Agency (IEA), 2018; Intergovernmental Panel on Climate Change (IPCC), 2019). China's electricity sector currently consumes double this amount (45 EJ of primary coal in 2017) (International Energy Agency (IEA), 2018)

Long-term forecasts of China's electricity supply tend to retain a significant amount of installed coal capacity and coal generation to 2040 and 2050, equivalent to coal consumption of 9–18 EJ yr^{-1} (Figure 1) (International Energy Agency (IEA), 2018; China National Renewable Energy Center (CNREC), 2018; State Grid Corporation of China (SGCC), 2018). The three studies shown in Figure 1, and other long-term abatement studies for China (Jiang et al., 2018a, 2018b), follow a similar logic: Given the scale of expected electricity demand in China (10–12 PWh yr^{-1} by 2040), there are limits to the scalability of nuclear power and hydropower and reliably meeting demand will require keeping some amount of coal generation, ideally with carbon capture and storage (CCS). However, it is unclear if and when CCS will be commercially viable at scale (Reiner, 2016). Moreover, this pathway is at odds with trends in many U.S. states and parts of Europe, where solar PV and wind, firmed with energy storage, are emerging as the dominant low-emission technologies.

This study examines the resource, economic, and institutional implications of substantially reducing or replacing coal generation in China with mostly renewable energy and energy storage by 2040, assuming there are limits to the scalability of nuclear power, large hydropower, and CCS over this time frame. As far as we know, this is the first study to rigorously explore the implications of a full transition away from coal generation in China.

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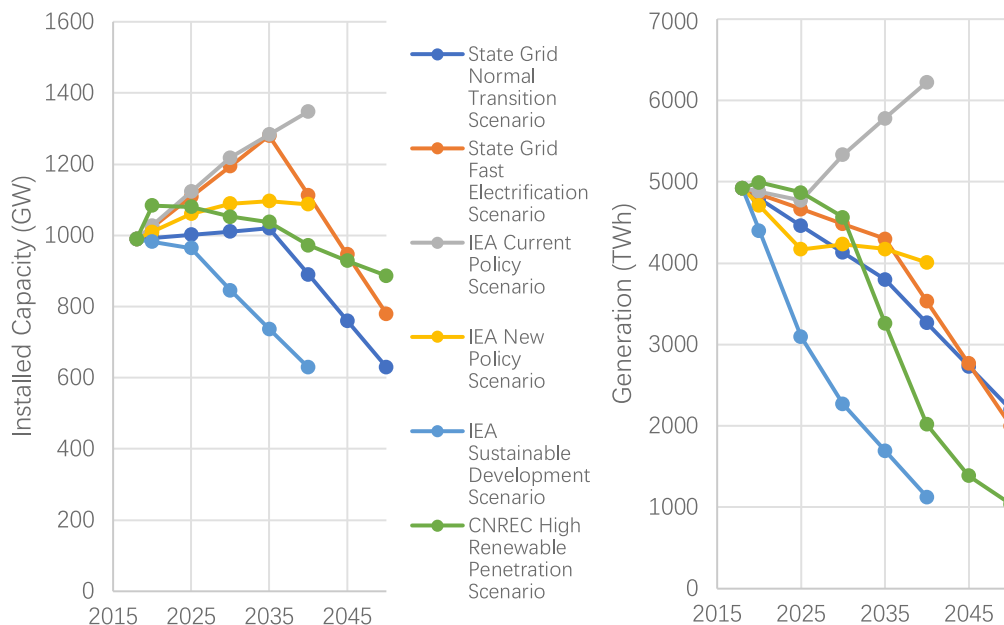https://doi.org/10.1016/j.isci. 2021.102939

Figure 1. Installed coal capacity and annual generation in studies of china's long-term electricity needs
Notes: IEA is the International Energy Agency; CNREC is the China National Renewable Energy Center. CNREC's projections are "fossil fuels" and not coal generation specifically, but coal accounts for the majority of fossil fuels in the CNREC estimates.

The analysis is based on a bottom-up analytical model (see method details) that determines the amount of coal generation capacity needed to reliably meet the sum of peak electricity demands in China's six regional electric grids from 2020 to 2040, given a portfolio of renewable and other noncoal generation and energy storage resources. The model accounts for the declining contribution of solar PV, wind, and energy storage to system reliability using effective load carrying capability (ELCC) curves and includes hourly dispatch (one day per month) with basic operating constraints and a storage dispatch logic. The model uses publicly available data inputs, balancing simplicity and transparency with the rigor needed for accuracy.

RESULTS

Installed capacity and generation mix

The analysis is organized around two electricity demand scenarios—low demand (LD) and high demand (HD)—and two electricity supply scenarios—high renewable (HR) and low renewable (LR)—creating a total of four scenarios. The supply portfolio in the high-demand low-renewable (HDLR) scenario is designed to avoid building new coal generation capacity. The supply portfolio in the low-demand high-renewable (LDHR) scenario is designed to eliminate the need for coal generation capacity by 2040. Installed coal capacity in the HDHR and LDLR scenarios is determined by the combination of a demand scenario and the HR and LR portfolios in the HDLR and LDHR scenarios.

Figures 2A and 2B shows the installed capacity and annual generation mixes in each of the four scenarios. Coal generation in the HR scenarios falls to zero by 2040, though the HDHR scenario still maintains around 310 GW of coal generation capacity for reliability (reserve) needs. Coal generation in the LDLR scenario falls to approximately 350 TWh yr^{-1} by 2040 but the HDLR scenario still has 1,600 TWh yr^{-1} of coal generation in 2040.

All four of these scenarios include large increases in solar PV generation capacity (+1,500–2,300 GW), wind generation capacity (+1,500–2,400 GW) and 4-h and 6-h energy storage capacity (+900–1,400 GW), as well as significant increases in nuclear (+55 GW), natural gas (+105 GW), conventional hydropower (+70 GW), and pumped hydropower generating capacity (+30–70 GW). Installed solar and wind generating capacity in the LR scenario in 2040 is comparable to forecasts by China's State Grid (SGCC, "Accelerated

A Installed Capacity Mix
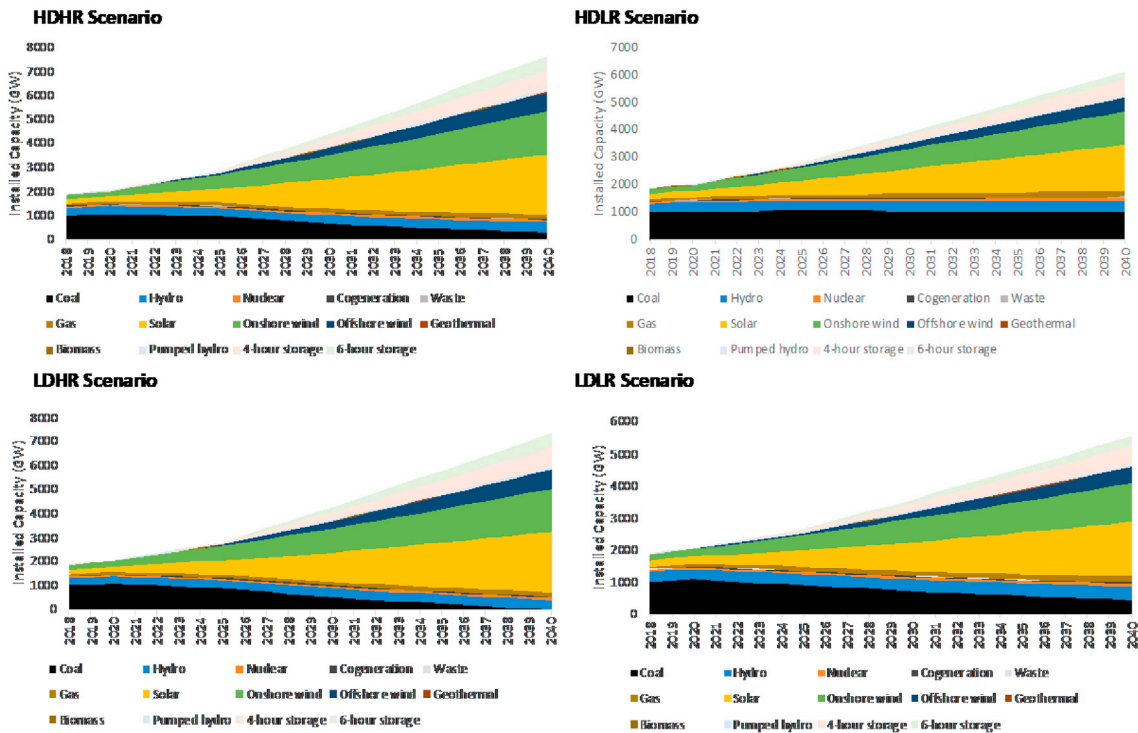
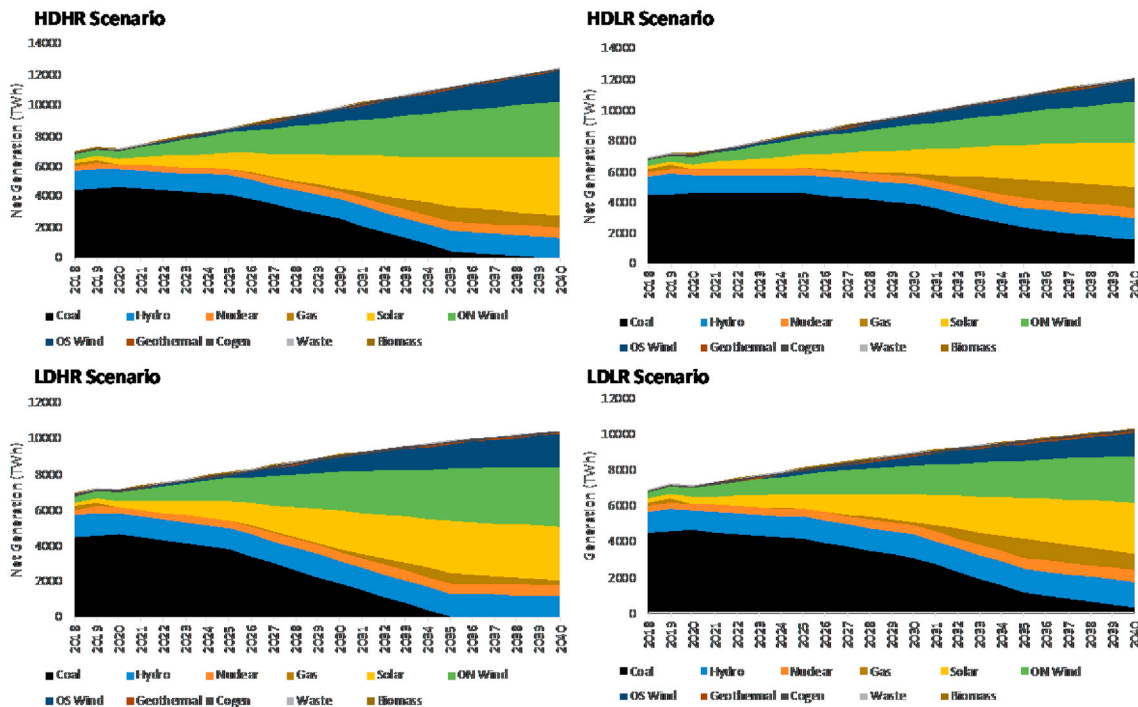

B Annual Generation Mix

Figure 2. Installed capacity mix and annual generation mix in the four scenarios

(A) Installed Capacity Mix in the Four Scenarios, (B) Annual Generation Mix in the Four Scenarios,
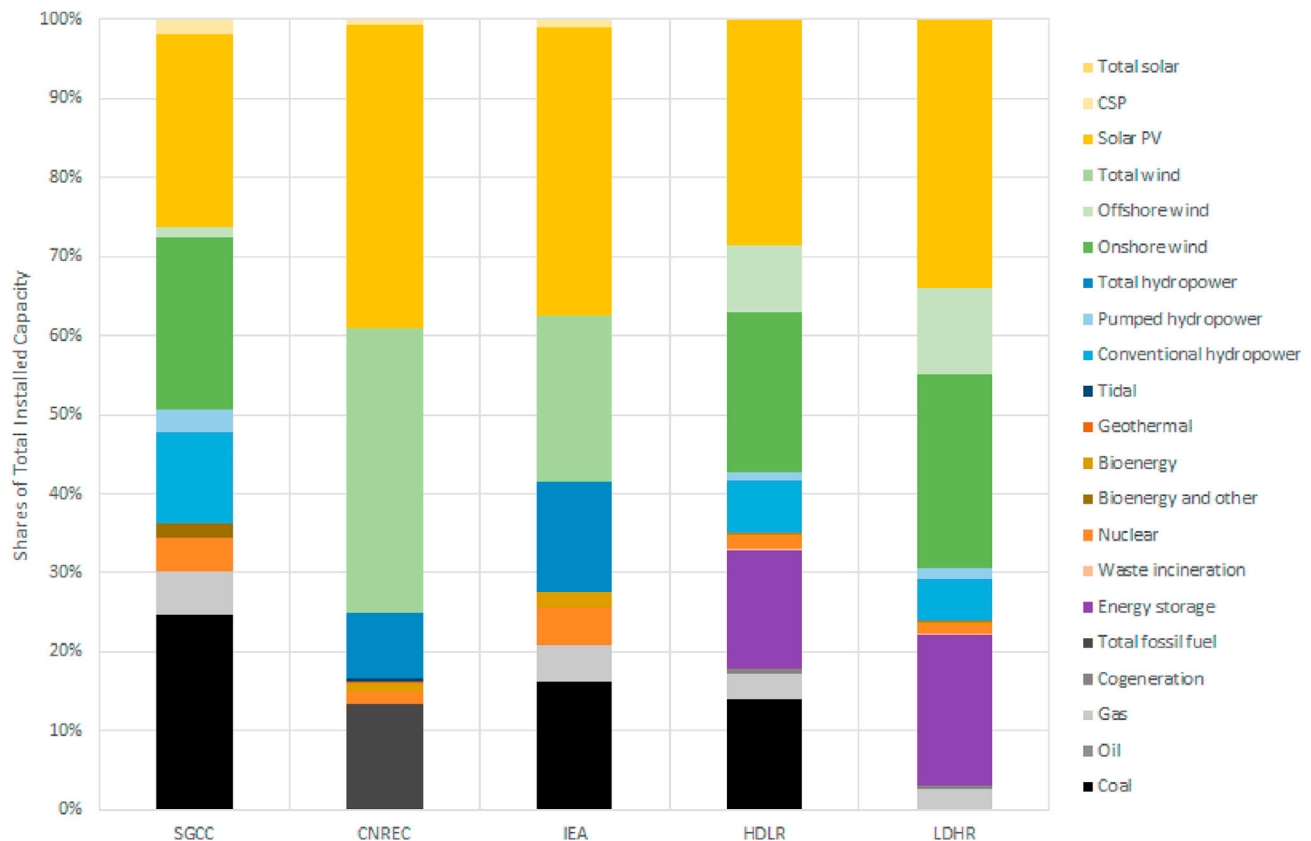
Figure 3. Capacity Mix in the HR and LR Scenarios Compared with Other Long-Term Studies for China

Electrification" scenario), the China National Renewable Energy Center (CNREC, "Below 2" scenario), and the International Energy Agency (IEA, "Sustainable Development" scenario), but installed solar and wind capacity in the HR scenario is higher than in these studies (Figure 3).

The generation capacity mix in the HDLR and LDHR scenarios differs from the SGCC, CNREC, and IEA scenarios in two key ways: (1) both the HDLR and LDHR scenarios have significantly less hydropower, nuclear, and natural gas capacity, based on a conservative assumption that these resources have scalability limits and (2) the LDHR scenario has no coal capacity (Figure 3). The HDLR and LDHR scenarios compensate for the absence of hydropower, nuclear, natural gas, and coal capacity through a combination of solar PV, wind, and energy storage.

The CNREC, SGCC, and IEA studies do not include large-scale energy storage, and indeed, this is the first study that we are aware of that does so. The results highlight the importance of energy storage for reducing and replacing coal generation capacity in China, particularly if there are limits to the scalability of hydropower, nuclear, and natural gas generation. The approximately 2-to-1 ratio of solar PV capacity to energy storage capacity in both the HR and LR scenarios is consistent with long-term planning studies in the United States (Energy and Environmental Economics (E3), 2019), but the scale of energy storage deployment in this study (+900–1,500 GW by 2040) is larger than what has been contemplated for any country.

Figure 4 shows annual generation capacity additions for solar PV, onshore wind, offshore wind, nuclear, natural gas, pumped hydro, and 4-h and 6-h energy storage in the HR and LR scenarios. From 2020 to 2025, these additions include 56–76 GW yr^{-1} of solar PV, 56–76 GW yr^{-1} of onshore wind, 10 GW yr^{-1} of offshore wind, and 14 GW yr^{-1} of 4-h and 6-h energy storage. From 2025 to 2040, they include 80–127 GW yr^{-1} of solar PV, 47–80 GW yr^{-1} of onshore wind, 30–50 GW yr^{-1} of offshore wind, and 56–89 GW yr^{-1} of 4-h and 6-h energy storage. For reference, annual solar PV and onshore wind capacity additions in China from 2018 to 2019 were 30 GW and 25 GW (45 GW and 20 GW 2017 to 2018, 53 GW and
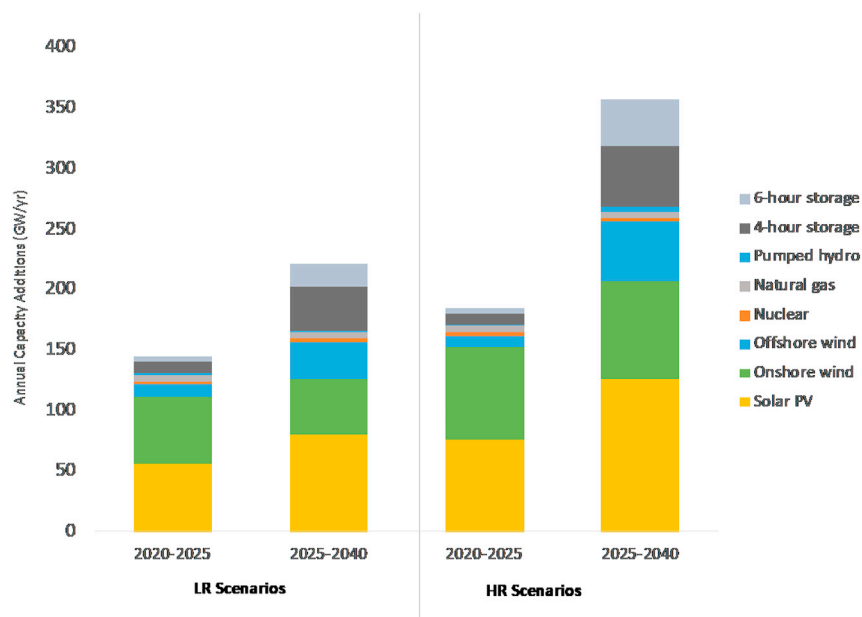
Figure 4. Average annual installed capacity additions in the HR and LR scenarios

16 GW from 2016 to 2017), respectively, with negligible additions of offshore wind and nonhydro storage (China Electricity Council (CEC), 2020).

Noncoal resources within the HR and LR portfolios have some degree of substitutability but may be constrained by physical limits. For instance, onshore and offshore wind capacity in these portfolios can be reduced by increasing the capacity of solar PV but doing so will require additional energy storage to offset the declining reliability value of solar PV. In the LDHR scenario, replacing 500 GW of offshore wind with 500 GW of solar PV would require an additional 30 GW of 6-h energy storage to have the same effect on coal generation needs. Alternatively, that 500 GW of offshore wind could be replaced with approximately 60 GW of additional natural gas or nuclear generating capacity.

The analysis highlights the importance of demand response for reducing peak demand in predominantly renewable electricity systems, by reducing the need for providing low capacity factor (low utilization) reserve capacity with solar PV, wind, and storage. In the LDHR scenario, reducing peak demand by 100 GW through demand response would avoid the need for approximately 600 GW of solar PV and 300 GW of energy storage.

Retirement of existing coal generation capacity in the LDHR scenario implies a roughly 20-year lifetime and constant retirement rate for existing coal plants. China's Ministry of Finance allows depreciation schedules for coal units to range from 20 to 30 years (Ministry of Finance (MoF), 2017), though recent industry practice has often been 20 years (Hu et al., 2013; Lin et al., 2019; Yuan et al., 2019). Coal units in China typically have a design life of 30 years (Pan and Pan, 2014). Thus, in the LDHR scenario, all new electricity demand would be met with noncoal generation, all coal generation would operate to the end of what has historically been its financial life (but not design life) and then retire, and when it retires, it would be replaced by noncoal generation.

To assess the implications of a 2050, rather than a 2040, retirement date for coal plants in the LDHR scenario, we examine a sensitivity that extends the load forecast and supply portfolios to 2050. Relaxing the retirement date to 2050 reduces the combined solar PV, onshore wind, and offshore additions from 255 GW yr^{-1} to 175 GW yr^{-1} between 2035 and 2050 and reduces total energy storage additions from 90 GW yr^{-1} to 50 GW yr^{-1}.

In the HDLR scenario, where noncoal generation supplies all new demand but coal generation continues to supply a significant amount of energy, CO_2 emissions from coal generation (1.4 GtCO$_2$ yr^{-1}) remain high in

2040 and total electricity sector CO_2 emissions (2.0 $GtCO_2$ yr^{-1}) in 2040 are approximately half of total estimated 2018 emissions (4.1 GtCO2 yr^{-1}), assuming that all combustion emissions are uncontrolled. In all other scenarios, total CO_2 emissions range from 0.2 $GtCO_2$ yr^{-1} (LDHR scenario) to 0.7 $GtCO_2$ yr^{-1} (LDLR scenario). This suggests the importance of replacing energy from existing coal plants on a larger scale, even if some coal generation capacity is maintained for reliability, as in the HDHR scenario.

Cost implications

The large annual renewable and storage capacity additions in Figure 4 will naturally raise questions around scalability and feasibility, but ultimately the most important questions surround cost, institutions, and transition. Simply because natural gas and nuclear generation have higher capacity factors and may be more familiar to policymakers and system operators does not necessarily make them more scalable or lower cost. Given the large uncertainty around solar, wind, and storage costs and coal prices in China, we do not use relative costs to drive technology selection in the model and instead ask: In principle, what would be the breakeven cost of solar PV, wind, and energy storage technologies, relative to coal generation and without CO_2 prices, to make these resources cost-effective in this analysis?

Marginal resource costs are a more helpful indicator than average costs for considering breakeven costs because the system value of solar PV, wind, and energy storage declines at higher penetrations. A few high-level rules provide guidance on marginal breakeven costs. To economically displace the energy and capacity (reliability) value of new coal plants, the long-run marginal cost (levelized cost) of solar PV and wind generation must be lower than the "equivalent" long-run marginal cost of coal generation— the cost of new coal generation adjusted to account for the lower and declining reliability (ELCC) value and any curtailment of solar and wind generation. To economically displace the energy of existing coal plants, the levelized cost of solar PV and wind generation must be lower than the short-run marginal (operating) cost of coal generation.

Energy storage displaces coal generation in two ways: (1) by providing "residual" energy or energy during periods when the system would otherwise not have sufficient energy (e.g., during nighttime periods when solar PV is not generating) and (2) by providing reserve capacity. For (1), the marginal breakeven point for storage would be the short-run (existing coal) and long-run (new coal) marginal cost of coal, but the cost of storage in this role depends on energy (charging) costs and on system conditions. For (2), the net capacity cost of energy storage must be lower than the equivalent marginal net capacity cost of new or existing coal generation.

Declining reliability (ELCC) values and for solar and wind generation, increasing curtailment imply that the cost of solar, wind, and energy storage must continue to decline for these technologies to be cost-effective. Figure 5 illustrates this point, by showing a range of breakeven equivalent levelized cost estimates for solar PV and onshore wind relative to the equivalent long-run marginal cost of coal generation in the LDHR scenario. The range in Figure 5 is based on 2018 provincial benchmark tariffs for coal and should be viewed with caution because these tariffs are not strictly cost based (see supplemental information).

Although marginal breakeven costs are useful for building intuition, they are not a substitute for detailed planning analyses that evaluate the total system cost impacts of portfolio choices, accounting for the interactions among solar, wind, and storage resources. Planning analyses should ideally occur within the context of a stakeholder process, where methods and inputs can be vetted by stakeholders.

Electricity dispatch

Transitioning to an electricity system that has 1.7–2.5 TW of solar PV generation and 1.7–2.6 TW of wind generation will require significant changes in electricity system operations and economics. Figure 6 shows dispatch plots from the model in summer and spring 2040. These plots illustrate that, because generation capacity is built to meet summer peak demand, solar PV and wind generation provide most system energy during the spring, solar and wind curtailment is high, and storage utilization declines. Solar PV curtailment increases nonlinearly as it is increasingly used as a summer peaking resource, with average solar curtailment rising from around 10% of total solar generation in 2035 to nearly 35% in 2040.

Figure 5. Implied marginal breakeven costs (2018 US$/MWh) for solar PV and wind relative to new coal generation, LDHR scenario

Note: The ranges in Figure 5 are based on low (Ningxia), average (Hebei), and high (Guangdong) benchmark tariffs for coal in 2018. See the supplemental information for detailed information on methods and inputs.

Overbuilding of generation capacity to meet seasonal demand is not new to the electricity sector, including in China, but the notion of doing so with renewable generation and storage is newer and would require socialization. System operators in China already have experience using solar and wind curtailment as a physical operating strategy but transitioning to economic curtailment of these resources, with potentially high levels of springtime curtailment, and efficient utilization of storage resources requires an economic framework for system operations, such as electricity spot (balancing) markets.

DISCUSSION

In light of China's recent pledge to achieve carbon neutrality by 2060, it is critical to explore concrete and scalable solutions to decarbonizing its power sector without overly relying on technologies that have yet to demonstrate economic competitiveness and scalability, such as nuclear and CCS. The generation portfolios considered in this analysis examine potential pathways for reducing the Chinese electricity system's reliance on coal through a transition to a predominantly renewable electricity system.

The analysis indicates that reducing and ultimately retiring all of China's coal generation capacity by 2040 would require that, beginning in the early 2020s, all new electricity demand be met with noncoal generation and all existing coal generation be replaced with noncoal generation at least by the end of its financial life.

As captured in the LDHR scenario, meeting these two requirements would entail (1) a rapid scale-up in solar and wind generation and energy storage deployment, on the order of 250 GW yr^{-1} of solar and wind and 90 GW yr^{-1} of energy storage from 2025 to 2040; (2) continued cost declines in solar and wind generation and significant cost reductions in energy storage; (3) significant changes in electricity system operations, transitioning to economic curtailment of solar and wind generation and efficient utilization of storage resources; and (4) a shift toward probabilistic methods for planning for electricity system reliability, to account for a growing reliance on intermittent resources.

The difference in electricity demand between the low- and high-demand scenarios in this analysis also highlights the importance of policy efforts to restrain growth in electricity demand in China. The scale of expected electricity demand growth—a nearly 2 PWh yr^{-1} difference between the low- and high-demand scenarios by 2040—implies that, to be meaningful, these efforts must address the Chinese economy's long overreliance on investment and heavy industry and emerging issues around electrification and the end-use efficiency of new electric equipment in transportation, buildings, and industry (Guan et al., 2018; Kahrl et al., 2013).
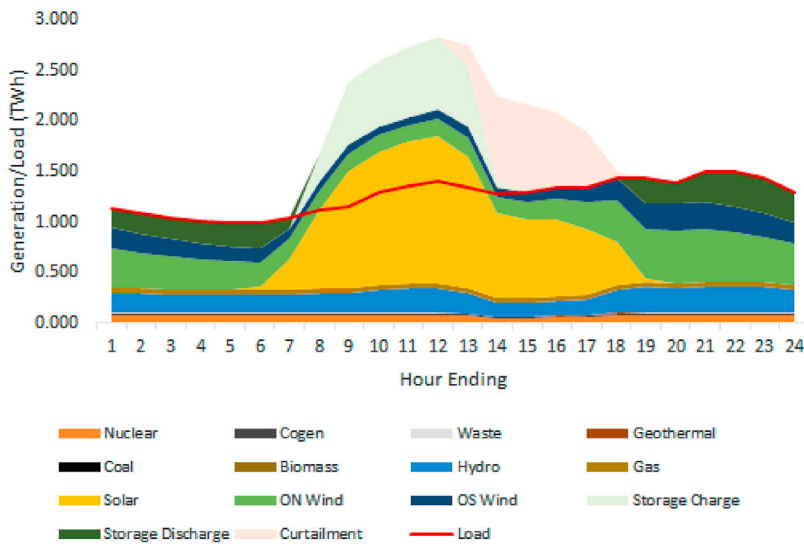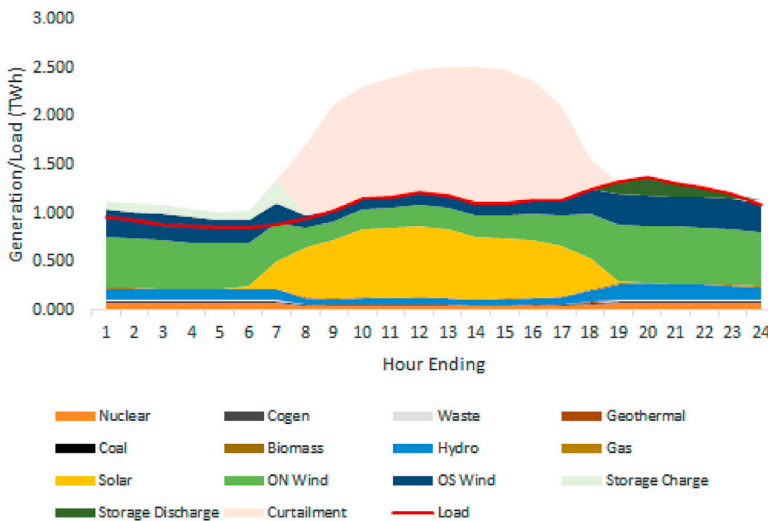
Summer

Spring

Figure 6. Daily system dispatch in the LDHR scenario for summer and spring in 2040
Note: In the above figures, storage charge is shown as a separate area rather than as part of load, for illustrative purposes.
In cases where generation exceeds load (red line), the area of storage charge will equal the difference between
generation and load. As a rule, generation plus storage discharge will equal load plus storage charge.

The electricity demand forecasts used in this analysis suggest that China would need to approximately double the size (capacity) of its electricity system by 2040 to reliably meet demand. This expected scale of growth suggests that China's most important near-term challenge is the nature and composition of new generation, rather than how to replace and retire existing coal generation.

Terawatt-scale generation expansion for solar, wind, and batteries will inevitably draw comparisons to the historical development and scale of fossil-fuel-based electricity systems, but these comparisons are neither accurate nor useful. Ultimately, key questions are around total costs; the institutional changes need to support mostly renewable electricity systems; potential environmental limits on terawatt-scale solar and wind development; and transition issues.

The existing planning and economic institutions in China's electricity sector evolved to support the rapid expansion of baseload coal and, to a lesser extent, hydropower facilities. Transitioning to an electricity system dominated by solar and wind will require fundamental changes in these institutions, including continued efforts to develop wholesale electricity markets and a shift to probabilistic methods for planning for electricity system reliability. It will also require aligning electricity planning with land use regulation, to ensure that the development of solar and wind generation on a terawatt scale does not compete with conservation and other land use priorities.

Lack of transparency around relative generation technology costs in China is an important obstacle to the transition away from coal-fired generation. For the last decade and a half, government agencies have set incentive-based feed-in tariffs across different generating technologies, but these tariffs have only loosely tracked actual generation costs. Continued transition to wholesale electricity markets in China could help to better reveal supply costs and internalize coal price risks. During this transition, and potentially even over the longer term, limiting new investment in coal-fired generating capacity will likely require strong policy commitment.

China's most important transition issue is the hundreds of billions of dollars of capital invested in existing coal generation facilities.[11] None of the scenarios evaluated in this study would necessarily require stranding coal generation assets if new investments in coal generation are not made after 2020 and if existing coal generating facilities maintain 20-year depreciation schedules. However, it is unlikely that existing facilities would maintain 20-year depreciation schedules in a competitive electricity market. More likely, retirement of existing coal generation capacity will be driven by policy or significant declines in the cost of resources that compete with coal to provide reserve capacity—for instance, energy storage and demand response. For reference, the average age of existing coal power plants in China is about 12 years and would be 32 years in 2040 (Global Energy Monitor (GEM), 2020).

This paper aims to provide order of magnitude estimates that focus discussion on questions that must be addressed to facilitate the transition to a mostly renewable electricity system in China over the next two decades. The development of new technologies, from CCS to longer-duration storage technologies to nuclear fusion, could reduce reliance on intermittent renewable generation technologies, but as the cost of these resources continues to fall and without breakthroughs in competing technologies, it is important to begin to plan for mostly renewable electricity systems.

Limitations of the study

The transparent, bottom-up analysis in this paper is intended to complement more detailed power system reliability, capacity expansion, and production cost modeling. More detailed modeling should incorporate China's unique wind, solar, and load profiles, hydropower operating constraints, and transmission network topology. Three issues raised in this study require further study in China with higher spatial and temporal resolution data and models: (1) reliability evaluation of mostly renewable electricity systems, (2) evaluation of options for changes in markets and operations, demand-side flexibility, and investments (energy storage, transmission) to reduce the costs of higher renewable penetration electricity systems; and (3) the land use implications of terawatt-scale solar and wind development.

STAR★METHODS

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  - Materials availability
  - Data and code availability
- METHOD DETAILS
  - Overview
  - Figure 5 inputs
  - Model description and inputs
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  - Other materials

SUPPORTING CITATIONS

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STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Deposited data		
Electricity Demand CEC	China Electricity Council (CEC), 2020	http://www.cec.org.cn/
Electricity Demand SGCC	State Grid Corporation of China (SGCC), 2018	https://baike.baidu.com/item/%E4%B8%AD%E5%9B%BD%E8%83%BD%E6%BA%90%E7%94%B5%E5%8A%9B%E5%8F%91%E5%B1%95%E5%B1%95%E6%9C%9B%282018%29/50400216?fr=aladdin
Electricity Demand NEA	China National Energy Administration (NEA), 2013	http://www.nea.gov.cn/2013-02/20/c_132180424_2.htm
Electricity Demand IEA	International Energy Agency (IEA), 2018	https://www.iea.org/reports/world-energy-outlook-2018
Maximum Capacity Factors for non-fossil resources	China Electricity Council (CEC), 2018	http://www.cec.org.cn/guihuayutongji/tongjxinxi/niandushuju/
Installed Capacity CNREC	China National Renewable Energy Centre (CNREC), 2018	https://www.sohu.com/a/270871707_99945497
Installed Capacity IEA	International Energy Agency (IEA), 2018	https://www.iea.org/reports/world-energy-outlook-2018
Installed Capacity SGCC	State Grid Corporation of China (SGCC), 2018	https://baike.baidu.com/item/%E4%B8%AD%E5%9B%BD%E8%83%BD%E6%BA%90%E7%94%B5%E5%8A%9B%E5%8F%91%E5%B1%95%E5%B1%95%E6%9C%9B%282018%29/50400216?fr=aladdin
Note: The sources the complete data set can be found in supplemental information		

RESOURCE AVAILABILITY

Lead contact

Further information and requests for resources should be directed to and will be fulfilled by the lead contact, Jiang Lin (j_lin@lbl.gov).

Materials availability

The study did not generate new materials.

Data and code availability

The sources of the data sets supporting the current study have been presented. The other data and codes can be available on request from the lead contact. Any additional information required to reanalyze the data reported in this paper is available from the lead contact upon request.

METHOD DETAILS

Overview

This study uses a bottom-up analytical model that was developed for the analysis. The model calculates the amount of installed coal generation capacity needed to reliably meet peak electricity demand, given user-determined load forecasts and non-coal supply portfolios.

The model consists of four modules: (1) energy and peak demand forecast, (2) generation portfolios, (3) system dispatch, and (4) capacity balance. Using user-determined annual growth rates, the energy and peak demand forecast module calculates annual net generation demand (GWh) — final electricity demand plus transmission and distribution losses. Using this net generation demand forecast, the module uses a forecast of system load factors to calculate "equivalent" national peak demand, which is the sum of non-coincident peak demands for China's six regional grids. We assume that system load factors decline over time, as demand growth shifts from industry to the residential, commercial, and transportation sectors.

We use two demand scenarios in the analysis: a high demand (HD) scenario, calibrated to the State Grid Corporation of China's (SGCC's) Accelerated Electrification scenario in its *China Energy and Electricity Outlook*; and a low demand (LD) scenario, calibrated to the Sustainable Development scenario in the International Energy Agency's (IEA's) 2018 *World Energy Outlook* (Figure S1) (International Energy Agency (IEA), 2018; State Grid Corporation of China (SGCC), 2018). In both scenarios, demand growth declines over time, from 4.0% per year (both scenarios) in 2018-2020 to 1.8% (HD) and 1.0% (LD) per year from 2035-2040. Although these scenarios equate to modest annual average demand growth rates of 2.7% (HD) and 1.9% (LD) per year between 2018 and 2040, they represent a more than doubling (2.1x, HD) and a near doubling (1.8x, LD) of the generation capacity needed to reliably meet China's electricity demand by 2040, relative to 2018.

To supply this demand, the generation portfolio module organizes user-determined installed capacities for non-coal technologies around two scenarios: a high renewable energy (HR) scenario and a low renewable energy (LR) scenario. These scenarios assume that solar and wind energy are the most economically scalable low-CO_2 to zero-CO_2 generation resources, consistent with current policy and electricity industry trends in the United States (Mahone et al., 2018; Xcel Energy, 2019; Northern Indiana Public Service Company, 2018; Public Service Company of Colorado, 2017; Bolinger et al., 2019). Generation portfolios in both scenarios contain the same amount of conventional hydropower, natural gas, and nuclear generation capacity, using conservative assumptions about the scalability of these resources. However, the HR scenario has significantly more wind, solar PV, and energy storage capacity.

We adjust solar PV, wind, and energy storage capacity in the HR scenario until all coal generation capacity is retired by 2040 in the LD scenario. We adjust solar PV, wind, and energy storage capacity in the LR scenario so that coal generation capacity in the HD scenario does not increase beyond its 2018 level, declines to 2030, and remains constant after 2030. The supplemental information contains a more detailed description of generation portfolio development. Combinations of demand and generation scenarios create four total scenarios: high demand high renewable (HDHR); high demand low renewable (HDLR); low demand high renewable (LDHR); low demand low renewable (LDLR).

The scenarios are user-driven: they assume that changes in relative technology costs will support generation portfolios rather than employing a cost-minimization logic, consistent with the emphasis in this paper on envisioning a *possible* future rather than arguing for a *particular* future. Cost-minimizing analysis is driven by cost forecast assumptions. However, over the past decade, generation cost forecasts used in least-cost electricity planning studies have often diverged significantly from actual costs (California Public Utilities Commission (CPUC), 2009; He et al., 2016). Thus there is value in complementing least-cost expansion studies with engineering accounting studies that envision a feasible future and explore the implications for resource scalability, changes in costs, and changes in institutions required to enable it.

For each model year, the dispatch module dispatches generation portfolios to meet hourly energy for one day in each of twelve months, based on net generation demand and daily load shapes for typical summer and winter days. The module incorporates a storage dispatch logic and minimum generation constraints for coal units but, for simplicity, assumes that transmission and other generation constraints are non-binding. It calculates curtailment for non-thermal resources, the post-curtailment annual generation mix, and annual CO_2 emissions for fossil fuel generation.

Drawing on generation from the dispatch, the capacity balance module calculates the reliable capacity available from each non-coal generation technology and the installed capacity of coal generation needed, as a residual, to meet peak demand plus a planning reserve margin. For calculating the contribution of solar PV, wind, and energy storage to peak capacity needs, the model uses linear ELCC curves that decline with penetration, capturing the declining contribution of these resources to system reliability as their share of system energy or peak capacity increases. The ELCC curves reflect a blend of systems with different load and resource characteristics.

The model is designed to balance the transparency needed for intuition with the complexity needed for rigor and accuracy. We examine how critical assumptions influence the results by investigating sensitivities.

Figure 5 inputs

Figure 5 shows the marginal breakeven costs for solar PV and wind generation to replace new coal generation over time, based on the "equivalent" long-run marginal cost of coal generation. Mathematically, the marginal breakeven cost point occurs when the incremental impact of both resources on total system costs is equivalent, or when the incremental cost of new coal generation ($/MWh per an additional 1 MW) is equal to the incremental cost of new solar PV or wind generation.

$$FC_C \times \theta + OC_C = LC_S \times \beta$$

Where FC_C is the fixed cost of new coal generation, θ is a conversion factor, OC_C is the operating cost of coal generation, LC_S is the levelized cost of solar, and β is an adjustment term that accounts for curtailment. The fixed costs represent the cost (or value) of firm generation capacity.

The conversion factor (θ) converts from annualized capital costs ($/kW-yr) to energy costs ($/MWh), but also adjusts coal capacity costs to account for the fact that a smaller amount of installed coal capacity is needed to meet resource adequacy requirements, per 1 MWh of output. For instance, a solar plant with a 20% capacity factor and a 0.5 ELCC value will provide 0.3 kW (= 1 MWh / (0.20 * 8760 hrs/yr) * 0.5) of firm capacity. Assuming that coal has an ELCC value of 1.0, only 0.3 kW of installed coal capacity would be needed to provide the same capacity value.

The conversion factor is thus

$$\theta = \frac{ELCC_S}{CF_S \times 8760}$$

Where $ELCC_S$ is the ELCC of solar and is a function of penetration, CF_S is the maximum capacity factor of solar, and 8,760 is the number of hours in non-leap year. We do not adjust the CF_S term for curtailment, as it is unlikely that solar would be curtailed during periods of peak demand.

The curtailment term (β) accounts for the fact that higher rates of solar and wind generation curtailment will increase the levelized costs needed for fixed cost recovery, by reducing the denominator (MWh) in the levelized cost equation. For instance, a 1 MW solar facility that is expected to have a 20% capacity factor will generate 1,752 MWh per year. If 20% of the facility's output is curtailed it will only generate 1,402 MWh per year, increasing levelized costs by 25% (= 1 / (1 – curtailment rate)).

The curtailment term is thus

$$\beta = \frac{1}{(1 - CR_S)}$$

Where CR_S is the curtailment rate of solar.

Combining these equations, the equivalent marginal breakeven cost of new solar (or wind) generation relative to new coal generation is thus

$$LC_S = \left(FC_C \times \frac{ELCC_S}{CF_S \times 8760} + OC_C \right) \times (1 - CR_S)$$

In Figure 5, the values for ELCC, CF, and CR for both solar PV and onshore wind are taken from the model. The values of FC_C and OC_C are based on the lowest, highest, and average provincial coal benchmark tariffs in 2018, average raw (5,000 kCal/kg) coal prices by province in 2018, an assumed net heat rate of 280 kgce/MWh for new coal units, and a variable O&M cost of 20 yuan/MWh. For the average, we use the estimates for Hebei, which had a benchmark coal tariff (simple average of north and south Hebei) equal to the national simple average tariff. Fixed costs are calculated as the residual between benchmark tariffs and operating costs (fuel + variable O&M cost) and are converted to yuan/kW-yr terms using a standard assumption of 5,300 fully loaded operating hours per year. Conversion to U.S. dollars uses an exchange rate of 6.9 CNY/USD (January 2020). The Table S1 shows inputs for the high, average, and low marginal breakeven cost estimates.

This approach likely overstates fixed costs, by shifting some variable taxes to fixed costs. Additionally, there is some indication that the low estimates in Figure 5 do not reflect coal fuel costs: media outlets report that

despite significant increases in coal prices over the last three years, Ningxia's benchmark coal tariff has not increased, leading generators to operate at a loss (see, for instance, 宁夏煤电企业连续三年大面积亏损将成定局！, http://www.mycoal.cn/news/show/166089/).

Although breakeven costs are useful to provide intuition, they are not a substitute for system analysis using capacity expansion and production simulation models.

Model description and inputs

The model used in this paper evaluates the coal generation capacity necessary to reliably meet electricity demand in China over time, given a user-determined portfolio of non-coal generation capacity. The model is designed to mimic a traditional generation capacity expansion model, using scenarios and user inputs instead of least-cost optimization to build reliable generation portfolios.

The model includes four main modules:

- Energy and peak demand module, which calculates total energy demand, peak demand, and total reliable capacity need;

- Generation portfolio module, which accepts user inputs for installed capacity of non-coal resources;

- Dispatch module, which calculates an hourly dispatch for one day per month in each model year;

- Capacity balance module, which determines a reliable generation capacity contribution for each resource type and ensures that the model has sufficient available generation capacity to meet a peak demand forecast plus a reserve margin.

The model's geographic scope is national, with regional peak demand requirements. The model operates in five-year increments starting in 2020 and through 2040 (five total model years).

The model is designed around two groups of scenarios: (1) low and high electricity demand scenarios, and (2) low and high renewable generation capacity scenarios. Each demand scenario is coupled with a low and high renewable generation capacity scenario, for a total of four scenarios.

Energy and peak demand module. Energy and capacity needs in the model are driven by total net generation and a system load factor, respectively. Total net generation in each year (NG_y) is the sum of electricity sales (ES_y), customer-sited generation (CG_y), and transmission losses (TL_y) in that year.

$$NG_y = ES_y + CG_y + TL_y$$

Base year (2017, 2018, 2019) data in the model are from the China Electricity Council (CEC) (China Electricity Council (CEC), 2020; China Electricity Council (CEC), 2018).

For each model year (2020, 2025, 2030, 2035, 2040), the model calculates NG_y using an annual average growth forecast.

$$NG_y = NG_0 \times \left(1 + r^D\right)^t$$

where NG_0 is net generation in the base period, r^D is the annual average growth rate for each time interval, and t is the number of years in each time interval.

Table S2.1 shows base case annual average growth rates by time period for each scenario.

These annual average growth rates lead to the net generation forecasts lead in Table S2.2. These forecasts imply that net generation increases by factors of 1.5 (low demand scenario) and 1.8 (high demand scenario) from 2019 to 2040. Based on CEC estimates, net generation in 2019 was 6,932 TWh.

We benchmarked these forecasts against a range of long-term demand forecasts from Chinese companies, Chinese organizations, and international organizations (Table S2.4.). The low demand scenario is consistent with the International Energy Agency's (IEA's) "sustainable development" scenario from its 2018 *World Energy Outlook*. The high demand scenario is consistent with State Grid Corporation of China's (SGCC's) "fast electrification scenario" in its 2018 *China Energy and Electricity Outlook*. SGCC's

estimates are based on gross, rather than net, electricity generation; adjusting the SGCC 2040 estimate to net generation makes it closer to our 2040 net generation forecast, though the SGCC forecasts for 2020-2035 are higher.

The model calculates national peak capacity generation capacity needs based on a "national equivalent" system load factor (LF_y), which captures the relationship between national net generation (NG_y) and total regional non-coincident peak generation demand (RP_y).

$$LF_y = \frac{NG_y}{RP_y \times 8760}$$

where RP_y is the sum of non-coincident peak generation demand in China's regional grids (RP_{iy}).

$$RP_y = \sum_i RP_{iy}$$

We use CEC data on regional peak generation demand (最高发受电电力) to calculate LF_y for 2017 (66%). We assume that the value of LF_y does not change between 2017 and 2020, and then declines linearly to 57% by 2040. This value (57%) was the average system load factor for the California Independent System Operator's (CAISO's) footprint from 2008 to 2018 (California Independent System Operator (CISO), various years) and implies that China's electricity system becomes "peakier" over time. Our assumptions are conservative. Using non-coincident regional peak generation demand assumes that there is no capacity reserve sharing among grid regions in China. Declines in system load factor make coal generation retirement more difficult, as more reliable capacity is needed to meet system peak. We use the same LF_y values in both the low and high demand scenarios. To determine the total reliable capacity need (CN_y), the model increases peak demand (RP_y) using a model year-specific planning reserve margin (RM_y). We use an estimated actual RM_y value of 27% for 2020 and a middle-of-the-road assumption of 15% for each subsequent model year in the analysis.

$$CN_y = RP_y \times (1 + RM_y)$$

Table S2.3 shows total reliable capacity needs (CN_y values) for the low and high demand scenarios.

As a sensitivity, we relax the retirement constraint in the LDHR scenario to 2050 rather than 2040. To calculate 2050 energy demand, we assume that annual average growth rates between 2040 and 2050 decline by 20% relative to 2030 to 2040, consistent with trend. We assume that system load factor declines linearly to 57% by 2050 rather than 2040. This leads to net generation of 13,386 TWh (HD) and 10,692 (LD) in 2050 and total capacity needs of 2,889 (HD) and 2,307 (LD).

The model's dispatch module requires hourly load (net generation) shapes for an average day in each month. To calculate hourly net generation shapes, the model first calculates daily net generation (DG_{my}) in each month in a given year by allocating annual net generation across months using historical total (national) monthly generation shares (α_m) and the number of days in each month (D_m).

$$DG_{my} = \frac{NG_y \times \alpha_m}{D_m}$$

The model calculates hourly net generation shapes (DG_{ymhs}) for winter and summer days (season s) using hourly load coefficients (β_{hs}) multiplied by daily net generation (DG_{ym}).

$$DG_{ymhs} = DG_{ym} \times \beta_{hs}$$

Hourly load coefficients (β_{hs}) for each season are calculated using normalized load shapes (hourly load divided by total daily load) inputted by users.

$$\beta_{hs} = \frac{L_{hs}}{\sum_h L_{hs}}$$

In the analysis, we use hourly load profiles that reflect current characteristic load shapes in China, drawing on typical day winter and summer load shapes from Guangxi Province (Figure S2.). As a sensitivity, we tested whether using average 2015 summer and winter load shapes for the CAISO would have a significant impact on the results, but the impacts are negligible because the model is driven primarily by peak capacity accounting rather than energy dispatch.

For monthly generation (发电量) shares, we use CEC data for 2010 to 2016. CEC does not report data for December, and annual totals minus the sum of non-December months do not provide a sensible estimate for December. As an alternative, we linearly interpolate December generation between November and January of the next year (for 2016 we use January 2016). These shares are shown in Table S3.

Generation portfolio. Total installed capacity for non-coal resources in the model is user-driven, separated into low renewable and high renewable scenarios. Installed capacity for coal generation is calculated endogenously in the capacity balance module (See Section 4).

We developed generation portfolios to achieve two outcomes:.
- For the low renewable scenario (LR), we ensure that total installed coal capacity in the high demand (HD) scenario does not increase relative to its 2020 value;
- For the high renewable scenario (HR), we ensure that total installed coal capacity falls to zero in the low demand (LD) scenario by 2040.

These two scenarios then serve to constrain the HDHR and LDLR scenarios. Table S4 shows non-coal installed capacity by year in the high renewable and low renewable scenarios.

For both portfolios, installed capacities of hydropower, natural gas, biomass, and nuclear generation were chosen to be conservatively lower than forecasts from the China National Renewable Energy Center's (CNREC's) *China Renewable Energy Outlook 2018*, State Grid's *China Energy and Electricity Development Outlook 2018*, and the International Energy Agency (IEA), 2018 *World Energy Outlook* (Table S5). We increased geothermal to 10 GW by 2040, half of CNREC's forecast for 2050. We held cogeneration and waste incineration at 2018 installed capacities, as reported by the CEC.

With other non-coal generation capacities fixed at these levels, we chose installed capacities of solar PV, wind, 4-hour storage, and 6-hour energy storage through an iterative process that aimed to achieve the two outcomes described above (no new coal generation, retire all coal generation by 2040). This iterative process sought to maintain a roughly 1:1 ratio between solar PV and total wind generation, consistent with the CNREC and SGCC studies, and a roughly 2:1 ratio between solar PV and total 4-hour and 6-hour energy storage. In practice, the distinction between onshore and offshore wind, in terms of capacity factors (25% versus 30%, respectively) and ELCC values (no difference), is sufficiently small that they could be considered a single resource.

For simplicity, we do not include concentrated solar power (CSP) or tidal power in our portfolios. CSP would reduce solar PV and, to a lesser extent, energy storage needs if CSP has onsite storage capacity. Tidal power is similar in profile to hydropower output and could substitute for several resources.

For the 2050 sensitivity, we increase solar PV capacity to 1,900 GW (LR) and 2,700 (HR), total wind capacity to 2,000 GW (LR) and 2,900 GW (HR), and total 4-hour and 6-hour energy storage capacity to 1,300 GW (HR, no change in LR) by 2050.

Dispatch module. The model calculates hourly dispatch for one day (24 hours) in each month, or 288 hours per year. The dispatch logic contains several steps.

Step 1: Schedule Non-Dispatchable Generation. In the first step, the model builds up an hourly dispatch stack for non-dispatchable generation based on generation profiles. Non-dispatchable generation includes solar PV, onshore wind, offshore wind, geothermal, hydropower, nuclear, cogeneration, and waste incineration. Dispatchable generation includes biomass, coal, and natural gas.

For each non-dispatchable technology, the model first determines the maximum annual net generation (NG_{jy}) for each non-dispatchable generation type j in year y, based on total installed capacity (TIC_{jy}) and a maximum capacity factor (MCF_j).

$$NG_{jy} = TIC_{jy} \times MCF_j \times 8760$$

Table S6 shows the maximum capacity factors used for different resources in the analysis.

For solar, onshore wind, and offshore wind generation (generation type k), the model converts annual net generation (NG_{yj}) to daily net generation for each hour (DG_{kymh}) using monthly generation shares (θ_{km}), the number of days in each month (D_m), and normalized resource profiles (γ_{kmh}).

$$DG_{kymh} = \frac{NG_{ky} \times \theta_{km}}{D_m} \times \gamma_{kmh}$$

Resource profiles are based on average simulated output for resource j for each hour of the day (1-24) in month m (P_{kmh}), divided by the sum of hourly average simulated outputs for that month.

$$\gamma_{kmh} = \frac{P_{kmh}}{\sum_h P_{kmh}}$$

Hourly resource profiles for wind and solar over larger geographic areas in China are not publicly available. Our resource profiles for solar and wind are based on simulated outputs for the Western United States using tools from the U.S. National Renewable Energy Laboratory (NREL). Resulting resource profiles are shown in Section 5. As a simplification, we assume that the profiles for onshore and offshore wind are the same.

The model assumes that hourly hydropower generation (DG_{Hymh}) has the same hourly output profile as load, varying by winter and summer seasons.

$$DG_{Hymh} = NG_{Hy} \times \theta_{Hm} \times \beta_{hs}$$

For data on monthly hydropower generation shares, we use CEC data for 2010 to 2016 (Table S3.). As with all generation, the CEC does not report hydropower generation for December, and we use the same linear interpolation approach that we do with total generation to calculate hydropower generation for December.

The model schedules nuclear, cogeneration, and waste incineration (generation type l) using a flat annual average shape, which will be net annual generation (NG_{ly}) divided by 8,760 hours per year.

$$DG_{lyh} = \frac{NG_{ly}}{8760}$$

Step 2: Enforce Minimum Generation Constraints for Coal Generation. After scheduling these non-dispatchable resources, the model builds biomass, gas, and coal generation into the stack in order to enforce minimum generation constraints for coal generation.

Biomass is treated like nuclear, cogeneration, and waste incineration (generation type l), but scheduled hourly biomass generation (DG_{Bymh}) is decreased if total hourly net generation demand (final demand plus transmission losses) (DG_{ymh}) minus the sum of hourly non-dispatchable generation (DG_{NDymh}) is larger than maximum hourly biomass generation ($NG_{By}/8760$).

$$DG_{Bymh} = \max\left(\left(\min\left(DG_{ymh} - DG_{NDymh}, \frac{NG_{By}}{8760}\right), 0\right)\right)$$

The model enables users to specify whether natural gas or coal is the residual generation technology. Residual generation balances any final difference between net generation demand and net generation. If coal is chosen as the residual generation technology, scheduled hourly coal generation (DG_{Cymh}) will be the smaller of net generation demand minus hourly non-dispatchable generation (DG_{NDymh}), hourly biomass generation (DG_{Bymh}), and hourly natural gas generation (DG_{Gymh}).

$$DG_{Cymh} = \max\left(DG_{ymh} - DG_{NDymh} - DG_{Bymh} - DG_{Gymh}, 0\right)$$

If natural gas is chosen as the residual technology, the model schedules coal generation to meet the smaller of net generation demand minus hourly non-dispatchable generation (DG_{NDymh}) and hourly biomass generation (DG_{Bymh}), meaning that the model will assume there is sufficient coal capacity available to generate this amount of energy. Actual coal dispatch (step 4) is constrained by coal capacity. This approach avoids endogeneity issues with coal generation capacity, while still allowing us to maintain minimum generation limits for coal. In practice, this assumption has little to no impact on the results.

In the analysis, we assume that gas is the residual generation technology from 2020 to 2030, and that coal becomes the residual generation technology in 2035 and 2040 as environmental considerations take on greater importance. This shift could happen, for instance, as a result of CO_2 pricing. The impacts of residual generation technology assumptions on the coal capacity results are negligible, though these assumptions do have some impact on emission results.

Table S7 shows the maximum capacity factors used for biomass, natural gas, and coal generation in the analysis. The maximum capacity factor for coal generation is used in step 4.

Once non-dispatchable generation has been scheduled, the model enforces a "fleetwide" minimum generation level for coal generators (MG_{ymh}) by taking the maximum coal generation level over the next 24-hour period (MC_{ymh}) and multiplying it by a user-inputted, year-specific minimum generation level (τ_y).

$$MG_{ymh} = MC_{ymh} \times \tau_y$$

Calculating minimum generation levels for coal before dispatching storage will lead to situations in which minimum generation levels are maintained but not actually needed. This is a conservative approach, and could reflect, for instance, system operator reserve needs. In dispatch (step 4), natural gas generation will often replace coal generation in providing meeting minimum generation needs.

Incorporating minimum generation levels makes the model dispatch more realistic, but minimum generation level assumptions (τ_y) only have a small impact on the results.

Step 3: Dispatch Storage. After scheduling non-dispatchable and enforcing generation, the model then dispatches (charges and discharges) storage. The storage logic assumes that shorter duration storage charges and discharges before longer duration storage. The model first charges and discharges the 4-hour storage, then the 6-hour storage, and finally the 8-hour storage (pumped hydro).

For each storage resource, the resource will charge when net generation demand minus non-dispatchable generation minus minimum generation ("net load" in the boxes below) is less than zero, subject to operating constraints. The resource will discharge when net generation demand minus non-dispatchable generation minus minimum generation is greater than zero subject to operating constraints. The model maintains a state of charge to ensure that charge/discharge does not violate energy limits.

The mathematics for storage operations can be complex and are easiest to understand through a description of the algorithms for charging, discharging, and managing the state of charge. In the boxes below, maximum charge rate refers to the maximum rate (gross of losses) at which the resource can charge (in TW), which is its nameplate capacity. Storage capacity refers to the resource's maximum charge rate multiplied by its duration (TWh).

Box 1: Storage charge logic

If net load(h) < 0
If maximum charge rate $\geq$ net load(h)
    If (-)maximum charge rate + SOC(h-1) $\leq$ storage capacity
        charge(h) = maximum charge rate
    Else
        charge(h) = SOC(h-1) – storage capacity
Else
    If SOC(h-1) + net load(h) $\leq$ storage capacity
        charge(h) = net load(h)
    Else
        charge(h) = SOC(h-1) – storage capacity
Else
Do not charge

In the above, (-) refers to taking the negative of a value, SOC is state of charge, h is hour, and h-1 is the previous hour.

Examples

Say we have 0.6 TW of 4-hour battery storage capacity (-0.6 TW maximum charge rate, 2.4 TWh storage capacity). In a given hour, net load is -0.8 TW, so the battery will charge. The battery's SOC is in the previous hour [SOC(h-1)] was 0.3 TWh. If the battery charges at its maximum charge rate, its SOC would increase to 0.9 TWh, which is less than its capacity (2.4 TWh) [(-)maximum charge rate + SOC(h-1) ≤ storage capacity]. Thus, the battery will charge at its maximum rate of -0.6 TW. If the battery's SOC in the previous hour was 2.1 TWh, the battery can only store 0.3 TWh of energy, so the maximum amount it can charge is -0.3 TW [SOC(h-1) – storage capacity]. In other words, we limit charging plus losses to maximum storage capacity.

If the net load in that hour is -0.2 TW [net load(h) ≥ maximum charge rate] and the SOC in the previous hour was 0.3 TWh [SOC(h-1) + net load(h) ≤ storage capacity], the battery will charge at the net load (-0.2 TW). If the previous hour's SOC was 2.3, the battery will charge at -0.1 TW [SOC(h-1) – storage capacity].

Box 2: Storage discharge logic

If net load(h) > 0
If maximum discharge rate ≤ net load(h)
    If SOC(h-1) > maximum discharge rate
        discharge(h) = maximum discharge rate × discharge efficiency
    Else
        discharge(h) = SOC(h-1) × discharge efficiency
Else
    If SOC(h-1) × discharge efficiency > net load(h)
        discharge(h) = net load(h)
    Else
        discharge(h) = SOC(h-1) × charge efficiency

Examples

Say we have 0.6 TW of 4-hour battery storage capacity (0.6 TW maximum discharge rate, 2.4 TWh storage capacity, 90% charge and discharge efficiency). In a given hour, net load is 1 TW, so the battery will discharge. The battery's SOC is in the previous hour [SOC(h-1)] was 0.7 TWh. The battery's SOC is larger than the total 0.6 TW it will discharge at its maximum discharge rate). Thus, the battery will discharge at 0.6 TW. If the battery's SOC in the previous hour was 0.3 TWh, the battery will discharge 0.27 TW and its SOC will decline to zero.

If the SOC in the previous hour was 0.7 TWh and net load is 0.5 TW, the battery will discharge at 0.5 TW. If SOC in the previous hour was 0.52 TW, the battery will discharge at 0.47 TW [SOC(h-1) × charge efficiency], capturing losses from charging.

Box 3: Storage SOC logic

If charge(h) < 0
If (-)charge(h) + SOC(h-1) <= storage capacity
    SOC(h) = (-)charge(h) × charge efficiency + SOC(h-1)
Else
    SOC(h) = SOC(h-1)Else
SOC(h) = SOC(h-1) – discharge(h) / charge efficiency

Examples

Say we have 0.6 TW of 4-hour battery storage capacity (0.6 TW maximum discharge rate, 2.4 TWh storage capacity, 90% charge and discharge efficiency). In a given hour, the battery charges at -0.4 TW and SOC in the previous hour was 0.6 TWh. Because this is less than storage capacity (2.4 TWh), the battery will charge at -0.4 TW and SOC in hour h will increase to 0.96 TWh (= -0.4 TWh/h × 0.9 + 0.6 TWh). In practice, the second (else) condition will never bind.

If the battery is not charging, either it is discharging at a positive value or zero. If battery discharge is positive, the SOC will decline by the amount discharge plus charging losses. Without adding charging losses here, charging losses would not be accounted for in SOC accounting.

To ensure that the storage logic is functioning properly, we do a check to ensure that net generation demand plus storage losses equals total final net generation.

Step 4: Curtail Non-Dispatchable Resources and Dispatch Thermal Generation.

After the three storage resources have been dispatched, any remaining negative net load represents curtailment. The model allocates curtailment (decreases generation) uniformly to non-dispatchable generation on the basis of the scheduled generation shares in Step 1.

After calculating curtailment and final "dispatch" of non-dispatchable resources, the model does a final dispatch of biomass, natural gas, and coal generation, using the same approach described in Step 2. In Step 4, however, the model restricts the maximum net generation from coal — when coal is not the residual generation technology — to the total installed capacity of coal generation calculated in the capacity balance module.

In some cases, the implied amount of installed capacity for the residual generation technology, based on residual energy dispatch, will be higher than the amount of capacity calculated in the capacity balance module. To reconcile potential differences, we do a final check to ensure that available installed capacity for the residual generation technology (coal or gas) is adequate to provide the amount of energy generated by the residual technology. If it is not, we increase the final capacity of the residual technology to the amount of capacity needed to meet residual generation needs.

The model calculates CO_2 emissions for coal, natural gas, and cogeneration generation by multiplying their final net generation by an emission factor (Table S8).

Capacity balance module. The capacity balance module ensures that available generation capacity is adequate to meet the regionally coincident peak demand forecast plus a 15% reserve margin after 2020. The module first calculates and sums reliable capacity for all other resources. It then calculates installed coal capacity as the difference between the reliable capacity need (CN_y) and the sum of reliable capacity from non-coal resources.

For solar, wind, and storage, the module accounts for their energy-limited nature by using average ELCC values. ELCC values vary with resource penetration. For instance, in a system that is saturated with solar generation, solar generation will have a marginal ELCC value of zero (adding more solar does not provide additional reliable capacity). Its average ELCC value will also decline as more solar generation is added, reflecting a lower contribution from each MW of solar to system capacity needs.

For solar and wind generation, the energy penetrations used to calculate reliable capacity are calculated net of curtailment, as total on-grid (post-curtailment) generation for each resource divided by total generation. A primary function of the dispatch module is in calculating total on-grid generation for solar and wind generation. For storage, we assume that ELCC values scale as a share of system peak demand.

Figure S3A shows marginal and average ELCC values for solar, onshore wind, and offshore wind generation that we use in the analysis. Figure S3B show marginal and average ELCC values for different durations of storage used in the analysis.

These ELCC "curves" are drawn from analyses of different electricity systems in the United States (Schlag, et al., 2015; Schlag et al., 2019; Ming et al., 2019) and were chosen to reflect operationally conservative values. These ELCC values will naturally be different for different regions in China, due to differences in load and resource profiles and resource mix. However, despite potential differences, they are likely to be approximately accurate because they capture two important characteristics of solar, wind, and storage performance: (1) ELCC values should not be zero, because these resources provide at least some reliability value; (2) ELCC values will decline with penetration, often steeply on a marginal basis, as a result of saturation.

For solar, wind, and storage, we assume that ELCC values saturate as a function of national, rather than regional, net generation and peak demand. This is a necessary assumption given that the model is national rather than regional, though it likely overstates ELCC values. This more aggressive assumption is offset by our conservative ELCC curves.

Table S9 shows penetrations and average ELCC values used in the analysis by resource type and model year. For solar PV and wind, penetrations are defined as the post-curtailment energy share of total net generation. For energy storage, penetration is defined as the share of regional equivalent peak demand.

For conventional hydropower, biomass, and waste incineration, we assume that capacity contributions are equal to 2018 capacity factors (Table S6.) reflecting the energy limits of these resources. Conservatively, we assume that cogeneration has a capacity contribution of zero. We assume that all other resources have a capacity contribution of 100%, consistent with common practice in the United States.

Installed capacity of coal in any model year (CC_y) is thus

$$CC_y = CN_y - \sum_r IC_{ry} \times \mu_{ry} - \sum_s IC_{sy} \times \phi_{sy} - \sum_t IC$$

Where CN_y is the total reliable capacity need, IC_r is the installed capacity of resource type r (solar PV, onshore wind, offshore wind, 4-hour storage, 6-hour storage, pumped hydro storage), μ_{ry} is the average ELCC value of resource r in year y, IC_{sy} is the installed capacity of resource types (conventional hydropower, biomass, and waste incineration), ϕ_{sy} is the capacity contribution of resource s in year y, and IC is the installed capacity of all other resources (geothermal, nuclear, gas).

If the installed capacity of coal generation decreases in any five-year model period, this reflects "retirement" decisions. Coal capacity can decrease in one period and increase in the next.

Resource profiles. Table S10 show the resource profiles used for solar PV, onshore wind, and offshore wind. We assume that onshore and offshore wind has the same resource profile, though the model allows users to input different profiles for each resource.

Other materials
For the model itself, please refer to the supplemental Excel file, named "Coal_retirement_model_ 10.16.20.xlsx", which is related to STAR Methods".