LBNL-2001356

Sunsetting coal power in China

Authors:

Fredrich Kahrl[1], Jiang Lin, Xu Liu, Junfeng Hu[2]

[1]**3rdRail Inc., Berkeley, California**

[2]**North China Electric Power University**

Energy Analysis and Environmental Impacts Division
Lawrence Berkeley National Laboratory

International Energy Analysis Department

September, 2019

This work was supported by the Energy Foundation China, the William and Flora Hewlett Foundation, and the MJS Foundation, through the U.S. Department of Energy under Lawrence Berkeley National Laboratory Contract No. DE-AC02-05CH11231

Acknowledgements

This work was supported by the Energy Foundation China, the William and Flora Hewlett Foundation, and the MJS Foundation, through the U.S. Department of Energy under Lawrence Berkeley National Laboratory Contract No. DE-AC02-05CH11231.

We thank Charles Goldman for reviewing and providing valuable comments on an earlier draft of this study.

Table of Contents

List of Figures

List of Tables

Abstract

Reducing CO_2 emissions from coal-fired electricity generation in China will be critical to efforts 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 optimistic assumptions about the commercial availability of carbon capture and storage. This paper uses an analytical model to examine 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 yr^{-1} of solar and wind capacity and 15 GW yr^{-1} of energy storage from 2020 to 2025, growing to 250 GW yr^{-1} and 90 GW yr^{-1}, respectively, from 2025 to 2040. Significant changes in the planning, market, and regulatory institutions in China's electricity system would be needed to enable this transition.

1. Introduction

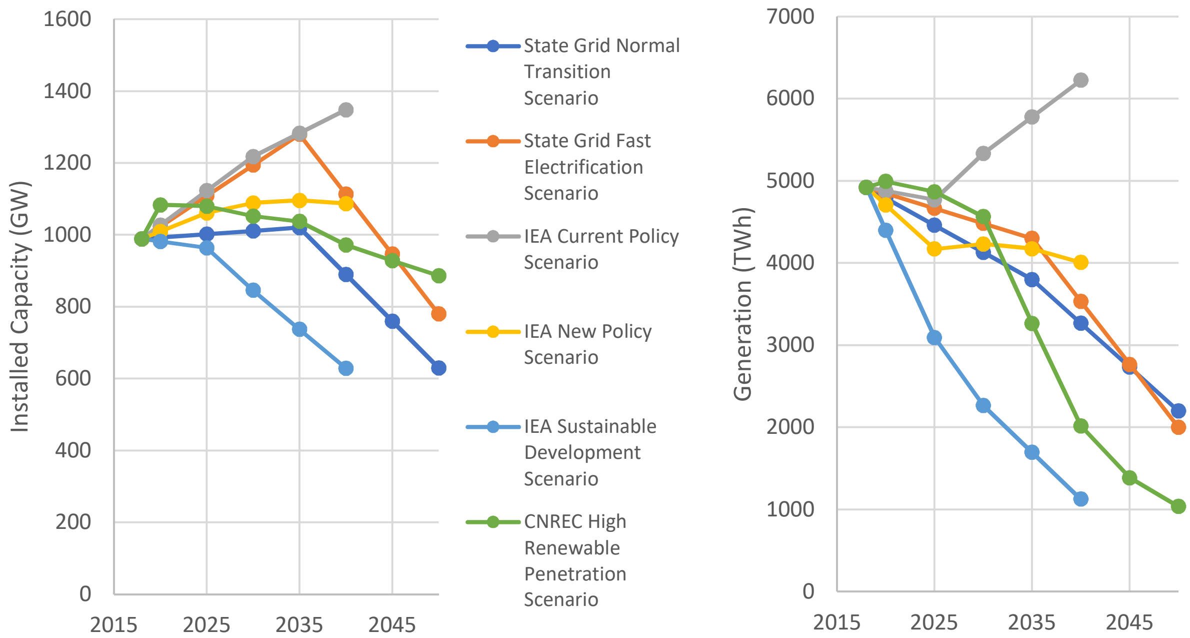
Reducing greenhouse gas (GHG) emissions from China's electricity sector is critical for reducing the risks of climate change. China's electricity sector currently accounts for 14% of global energy-related CO_2 emissions.[i] Over the longer term, a near-zero emission electricity sector is also expected to play an important role in reducing GHG emissions in China's transportation, building, and industrial sectors through electrification.[ii]

Most of China's electricity sector CO_2 emissions are from coal-fired power generation. Although the share of coal generation in China's electricity generation mix decreased from 76% in 2010 to 65% in 2017, total coal generation increased by 925 TWh (+29%) over this time period as a result of sustained electricity demand growth.[iii]

Expectations of continued electricity demand growth in China, driven by economic growth and electrification, raise questions about the extent to which the country's coal power generation can be reduced to meet global targets for limiting anthropogenic warming by mid-century. Recent Intergovernmental Panel on Climate Change (IPCC) estimates suggest that a decline in global primary coal consumption from 166 EJ (2017 estimate) to 19-24 EJ by 2050 is compatible with limiting warming to 1.5°C above pre-industrial levels.[iv] China's electricity sector currently consumes double this amount (45 EJ of primary coal in 2017).[v]

Forecasts of China's long-term energy and electricity needs tend to retain a significant amount of installed coal capacity and generation to 2040 and 2050 (Figure 1), equivalent to approximately 9-18 EJ yr^{-1} of primary coal consumption.[vi] The three studies shown in Figure 1, and other long-term abatement studies for China,[vii] 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 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 viable at scale.[viii] Moreover, this pathway is at odds with trends in leading states in U.S. and parts of Europe, where solar PV and wind, firmed with energy storage, are emerging as the dominant low-emissions technologies.[ix]

Figure 1. Installed Coal Capacity and Annual Generation in Studies of China's Long-Term Electricity Needs[x]



This study examines the resource, economic, and institutional implications of substantially reducing or replacing China's coal generation with mostly renewable energy resources by 2040, based on our assumption that there are limits to the scalability of nuclear, large hydro, and CCS over this time frame. The analysis is based on an analytical model that evaluates the amount of coal generation capacity needed to reliably meet national electricity demand, given a portfolio of renewable and other non-coal generation and energy storage resources. The results and conclusions discuss the kinds of institutional changes that would be needed to enable China to transition to a mostly renewable electricity system by 2040.

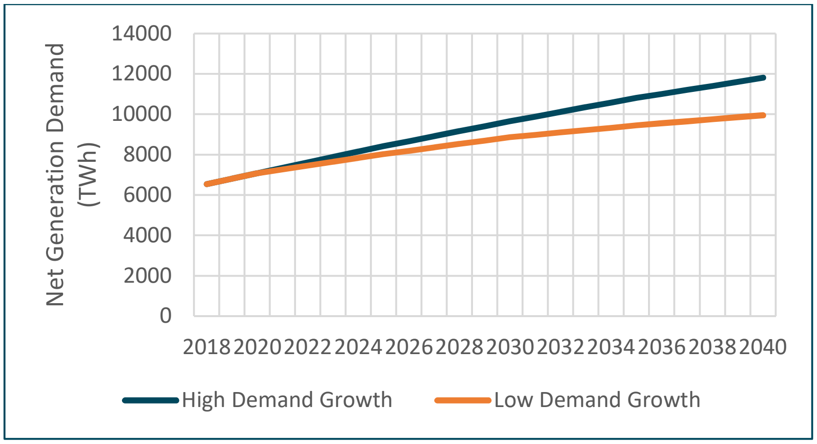
2. Methods and Assumptions

The analytical 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.

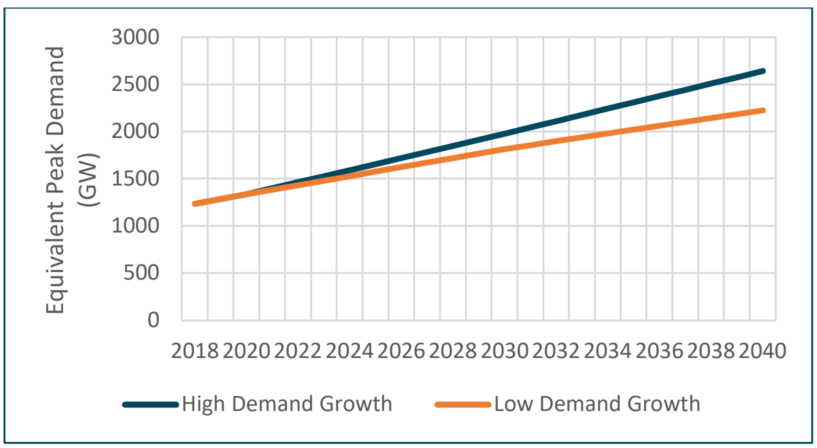
We use two demand scenarios in the analysis: a high demand (HD) scenario, calibrated to the State Grid Corporation of China's (SGCC's) Accelerated Electrification scenario in its *China Energy and Electricity Outlook*; and a low demand (LD) scenario, calibrated to the Sustainable Development scenario in the International Energy Agency's (IEA's) 2018 *World Energy Outlook* (Figure 2).[xi] 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.

Figure 2. Annual and Peak Electricity Demand in the High and Low Demand Scenarios

Annual Electricity ("Net Generation") Demand[xii]



Annual ("Equivalent") Peak Demand[xiii]



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 scaleable low-CO_2 to zero-CO_2 generation resources, consistent with current policy and industry trajectories in parts of the United States and Europe.[xiv] Generation portfolios in both scenarios contain the same amount of conventional hydropower, natural gas, and nuclear generation capacity, using conservative assumptions about the scaleability of these resources (see Appendix). However, the HR scenario has significantly more wind, solar PV, and energy storage capacity.

We adjust solar PV, wind, and battery capacity in the HR scenario until all coal generation capacity is retired by 2040 in the LD scenario. We adjust solar PV, wind, and battery 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 Appendix 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 study 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.[xv] 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 scaleability, 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. For calculating the contribution of solar PV, wind, battery storage, and pumped hydro storage to peak capacity needs, the model uses linear effective load carrying capability (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.

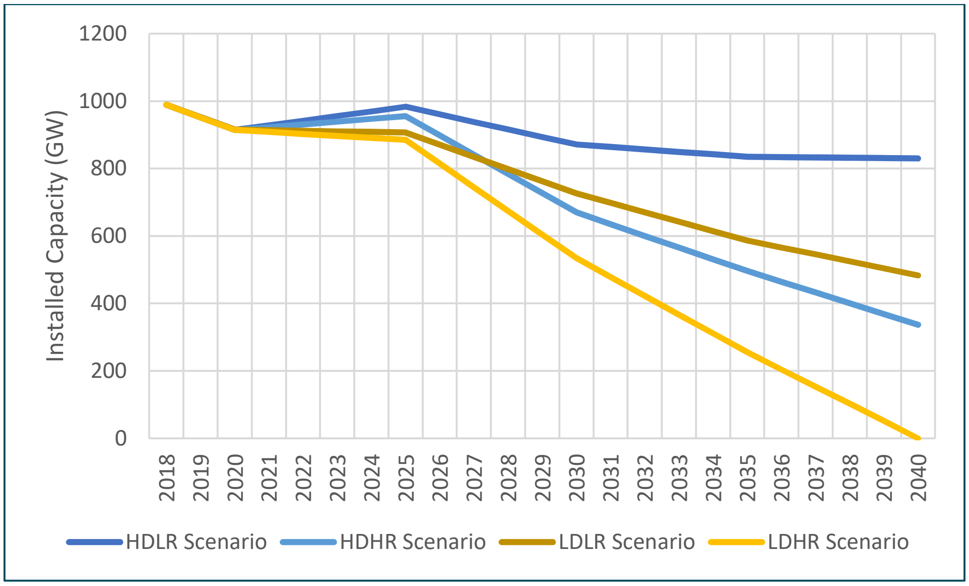
The model is designed to balance the transparency needed for intuition with the complexity needed for rigor and accuracy. We use sensitivity analysis to provide additional depth to the analysis. The Appendix contains a detailed description of the model and model inputs.

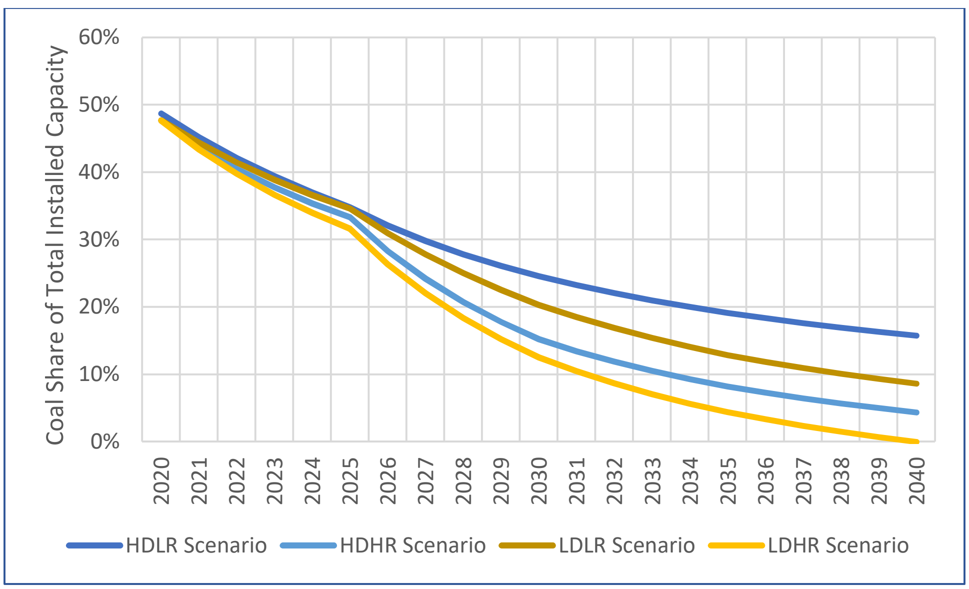
3. Results

Figure 3 shows the installed capacity of and annual generation from coal plants in each of the four scenarios. Coal generation in the HR scenarios falls to zero by 2040, though the HDHR scenario still maintains around 340 GW of coal generation capacity for reliability (reserve) needs. Coal generation in the LDLR scenario falls to approximately 300 TWh yr^{-1} by 2040 but the HDLR scenario still has 1,600 TWh yr^{-1} of coal generation in 2040. As a reminder, the supply portfolio in the HDLR scenario is designed to avoid building new coal generation. The supply portfolio in the LDHR scenario is designed to reduce coal generation to zero 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.

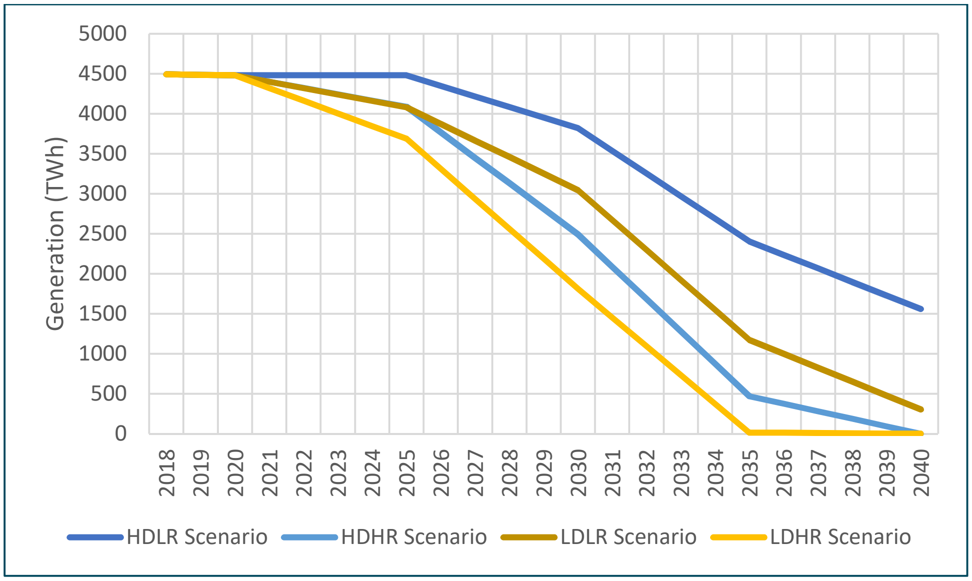
Figure 3. Installed Capacity of and Annual Generation from Coal Plants in the Four Scenarios

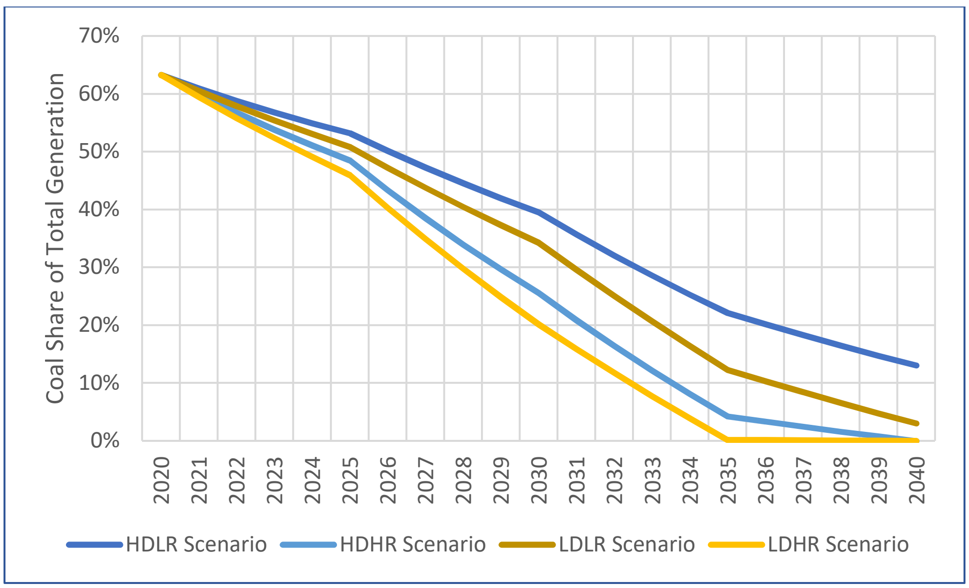
Coal Installed Capacity and Share of Total Installed Capacity





Annual Coal Generation and Share of Total Annual Generation





All four of these scenarios include large increases in solar PV (+1,525-2,325 GW) and wind generation (+1,516-2,416 GW) and battery storage capacity (+900-1,400 GW), as well as significant increases in nuclear (+55 GW), natural gas (+124 GW), conventional hydropower (+77 GW), and pumped hydropower generating capacity (+31-71 GW). Installed solar and wind generating capacity in the LR scenario in 2040 is comparable to forecasts by SGCC ("Accelerated Electrification" scenario), the China National Renewable Energy Centre (CNREC, "Below 2" scenario), and IEA ("Sustainable Development" scenario), but installed solar and wind capacity in the HR scenario is higher than in these studies (Table 1).[xvi]

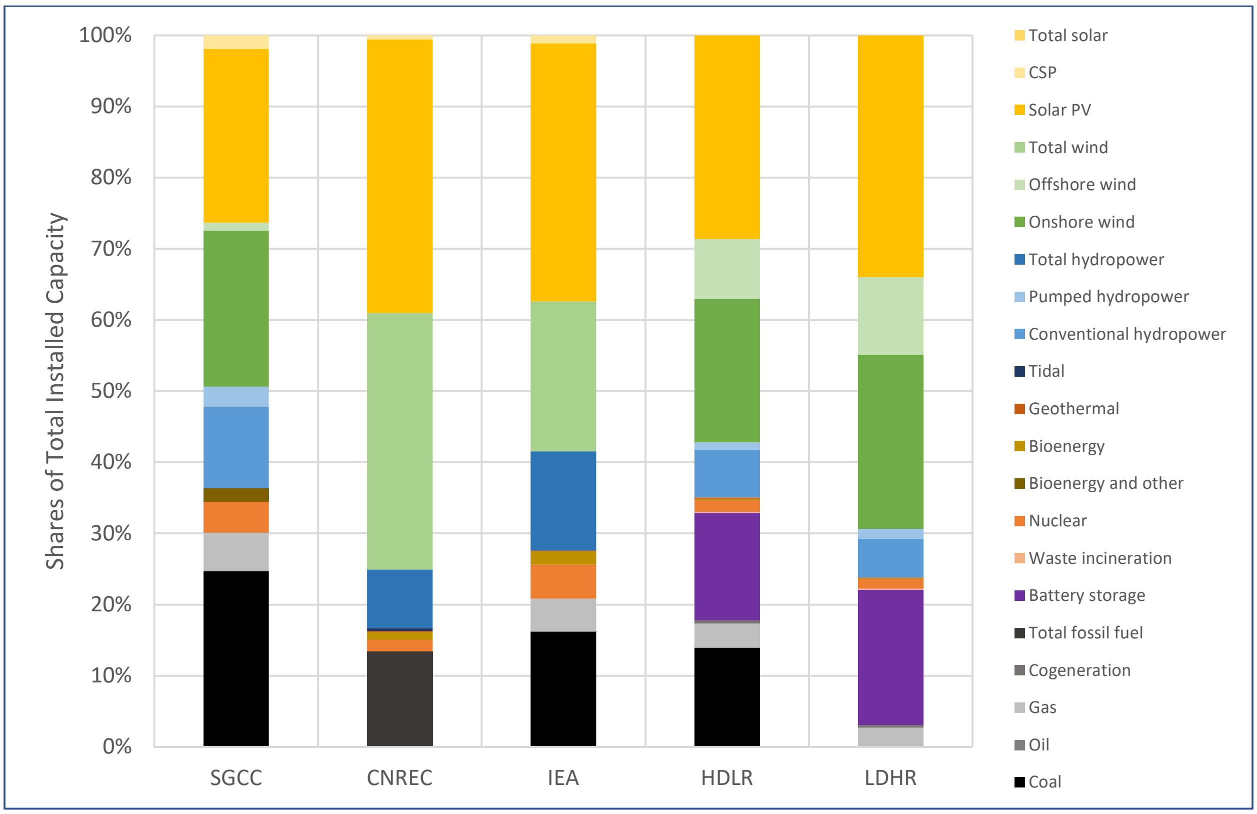
Table 1. Comparison of Installed Solar and Wind Capacity in 2040 in the LR and HR Scenarios Relative to Other Studies

	SGCC	CNREC	IEA	HDLR	LDHR

	Accelerated Electrification	Below 2	Sustainable Development	Scenario	Scenario
Solar PV	1,100	2,242	1,506	1,700	2,500
CSP	87	36	48		
Onshore Wind	987			1,200	1,800
Offshore Wind	50			500	800
Total Wind		2,105	875		

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 4).[xvii] The HDLR and LDHR scenarios compensate for the absence of this capacity through a combination of solar PV, wind, and battery storage.

Figure 4. Capacity Mix in the HR and LR Scenarios Compared with Other Long-Term Studies for China



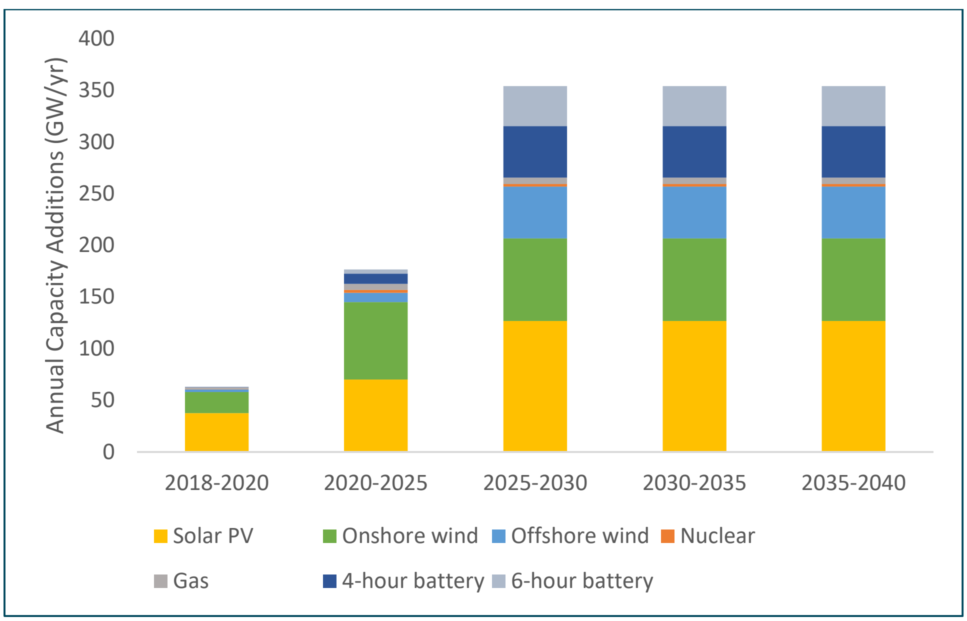
The CNREC, SGCC, and IEA studies do not include large-scale battery storage, and indeed this is the first study that we are aware of that does so. The results highlight the importance of energy storage for reducing and replacing coal generation in China, particularly if there are limits to the scalability of hydropower, nuclear, and natural gas generation. The ratio of solar PV capacity to battery capacity of approximately 2 to 1 in both the HR and LR scenarios is consistent with long-term planning studies in the United States,[xviii] but the scale of battery deployment in this study (900-1,400 GW) is much larger than what has been contemplated for any country.

In this analysis, the need for new generation capacity can be categorized into two functions: (1) meeting growth in annual and peak electricity demand, and (2) replacing the energy and capacity from existing coal plants. Between 43% (LDHR scenario) and 64% (HDLR scenario) of the annual energy (GWh yr^{-1}) generated by new generation capacity is used to meet new annual energy demand, and between 50% (LDHR) and 98% (HDLR) of the firm capacity provided by new generation capacity is used to meet new peak electricity demand. Thus, even without retiring and replacing existing coal generation, China will need to dramatically expand the size of its electricity system to meet expected growth in electricity demand.

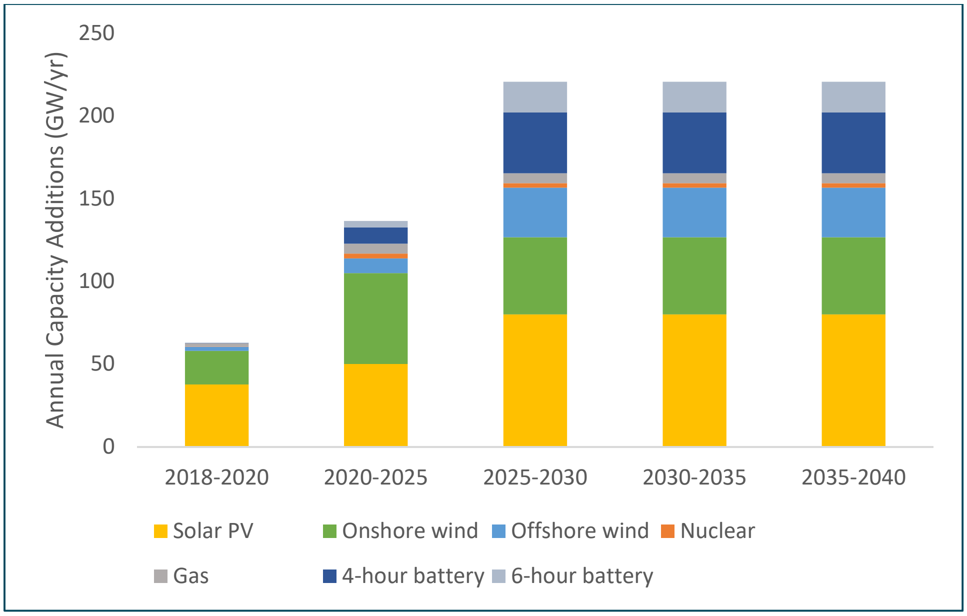
Figure 5 shows annual generation capacity additions for solar PV, onshore wind, offshore wind, nuclear, gas, and 4-hour and 6-hour battery storage in the HR and LR scenarios. From 2020 to 2025, these additions include 50-70 GW yr^{-1} of solar PV, 55-75 GW yr^{-1} of onshore wind, 9 GW yr^{-1} of offshore wind, and 14 GW yr^{-1} of 4-hour and 6-hour battery 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 55-89 GW yr^{-1} of 4-hour and 6-hour battery storage. For reference, annual solar PV and onshore wind capacity additions in China from 2017 to 2018 were 45 GW and 20 GW (53 GW and 16 GW from 2016 to 2017), respectively, with negligible additions of offshore wind and battery storage.[xix]

Figure 5. Annual Installed Capacity Additions in the HR and LR Scenarios

High Renewable Scenario



Low Renewable Scenario



Non-coal 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 onshore wind with 500 GW of solar PV requires an additional 200 GW of 6-hour battery storage to have the same effect on coal generation needs. Alternatively, that 500 GW of onshore wind could be replaced with approximately 100 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 and storage. In the LDHR scenario, reducing demand by 100 GW through demand response would avoid the need for approximately 300 GW of solar PV and 150 GW of battery storage.

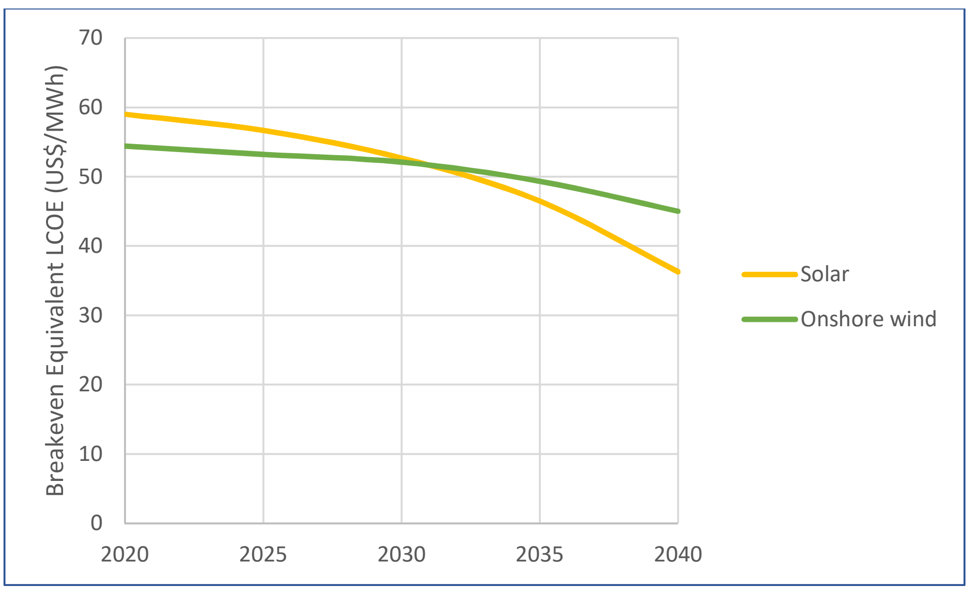
The large annual renewable and storage capacity additions in Figure 5 will naturally raise questions around scalability and feasibility, but ultimately the most important questions surround cost, institutions, and transition.[xx] Simply because natural gas and nuclear generation have higher capacity factors and are more familiar to policymakers and system operators does not necessarily make them more scalable or lower cost. We discuss institutions and transition issues in the next section. Given the large uncertainties around future technology costs and fuel (coal) prices, we do not use relative costs to drive technology selection in the model and instead ask: What would be the breakeven cost of solar PV, wind, and battery storage technologies, relative to coal generation, to make the portfolios in the LR and HR scenarios cost-effective without CO_2 prices?

Marginal resource costs are a more helpful indicator than system average costs for considering breakeven costs, because the value of solar PV, wind, and battery 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;[xxi] to 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.

Battery 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 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 batteries' energy costs and depends 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.

The use of equivalent costs in these rules accounts for the declining capacity values of solar PV, wind, and battery storage and higher curtailment of solar and wind generation as their penetrations increase. Equivalency implies that costs for solar PV, wind, and battery storage must continue to decline for these resources to remain competitive as their marginal value declines. Figure 6 shows breakeven levelized cost estimates for solar PV and onshore wind relative to the equivalent long-run marginal cost of coal generation in the LDHR scenario, using generic assumptions for coal operating and capacity costs and ELCC values and capacity factors from the analysis.[xxii] These estimates illustrate the need for continued declines in solar PV and, to a lesser extent, wind costs as their reliability (ELCC) value decreases and curtailment of their output increases.

Figure 6. Implied Marginal Breakeven Costs (2018 US$/MWh) for Solar PV and Wind to Replace New Coal Generation Over Time, LDHR Scenario



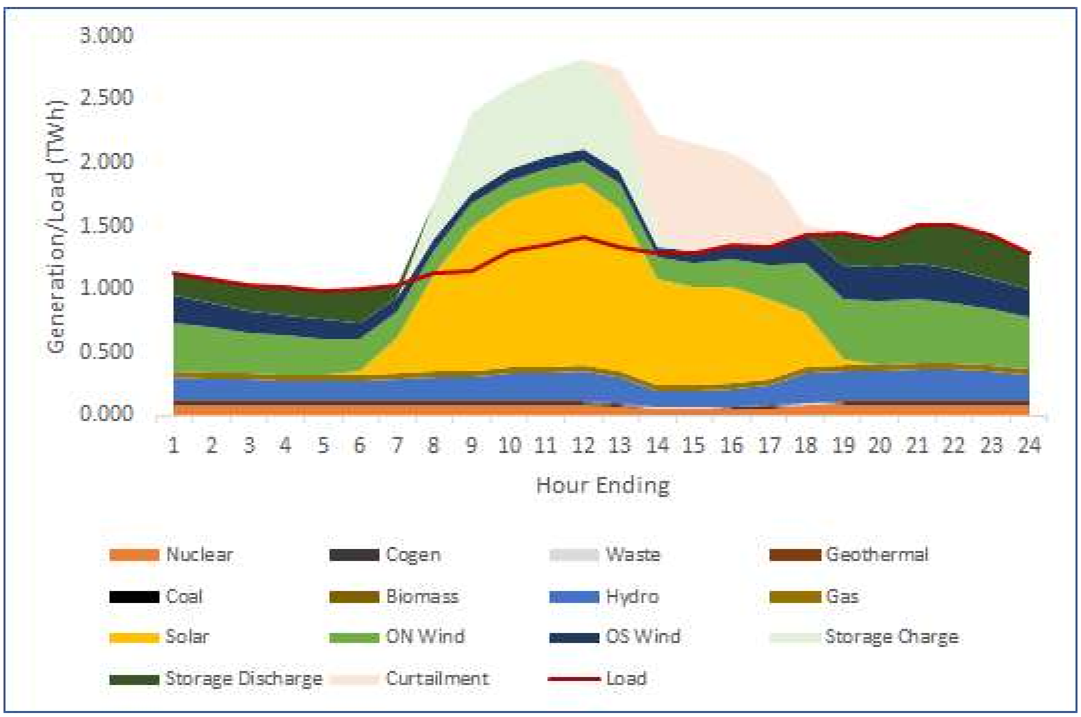
Retirement of existing coal generation capacity in the LDHR scenario implies a roughly 20-year lifetime and constant retirement rate for existing coal plants, which is consistent with historical accounting conventions for coal generating facilities in China.[xxiii] Thus, in the LDHR scenario all new electricity demand would be met with non-coal generation, all coal generation would operate to the end of what has historically been its financial life and then retire, and when it retires it would be replaced by non-coal generation.

In the HDLR scenario, where non-coal 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.

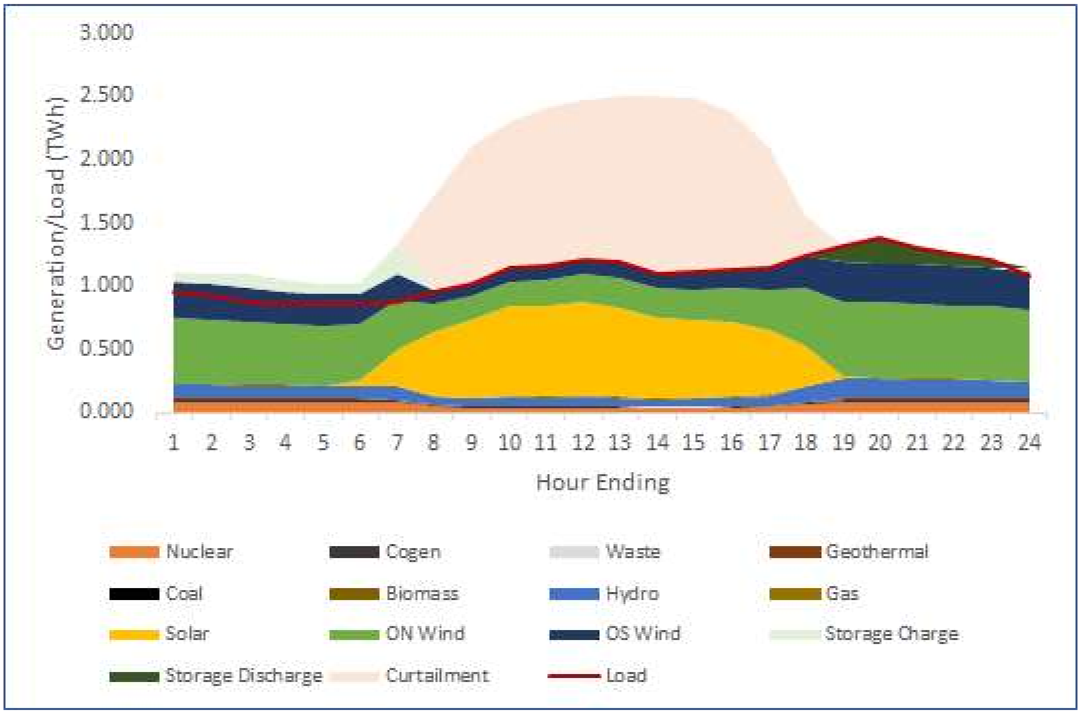
Transitioning to an electricity system that has 1.7-2.5 TW of solar PV generation and 1.7-2.6 TW of wind generation will require significant changes in electricity system operations and economics. Figure 7 shows dispatch plots from the model in summer and spring 2040. These plots illustrate that generation capacity is built to meet summer peak demand, which means that in the spring most energy is provided by renewable energy, curtailment is high, and storage utilization declines.

Figure 7. Daily System Dispatch in the LDHR Scenario for Summer and Spring

Summer



Spring



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 requires 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 and efficient utilization of storage resources requires an economic framework for system operations, such as electricity spot (balancing) markets.

The results here are robust in direction and magnitude. Higher demand growth requires more resource effort. For instance, retiring all coal generation in the HD scenario and replacing incremental coal generation with solar PV and storage would require 4 TW of PV and 2 TW of battery storage. The lack of scalability in specific resources (e.g., offshore wind, nuclear) will require greater scale in others (e.g., solar PV and batteries), as discussed above. Given the scale of the analysis, generation constraints tend to be less important for the results, but ELCC value assumptions for solar PV in particular have important implications for the results. Lower ELCC values for solar PV would require larger investments in energy storage to offset their lower capacity value. The importance of ELCC values for the future of coal power in China has implications for the intersection between reliability planning and nascent electricity markets, as discussed below.

4. Conclusions and Discussion

Reducing and ultimately retiring all of China's coal generation capacity over the next two decades may prove to be technically and economically feasible, but doing so will require that, beginning in the early 2020s, all new electricity demand be met with non-coal generation and all existing coal generation be replaced with non-coal generation at least by the end of its original depreciation schedule.

For transitioning to a mostly renewable electricity system without coal generation, meeting these two requirements would require: (1) a rapid scaleup in solar and wind generation and battery storage deployment, on the order of 250 GW yr^{-1} of solar and wind and 90 GW yr^{-1} of battery storage from 2025 to 2040; (2) continued cost declines in solar and wind and significant cost reductions in battery 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.

The difference in electricity demand between the low and high demand scenarios in this analysis also suggests the importance of policy efforts to restrain growth in China's electricity demand. 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[xxiv] and emerging issues around electrification and the end-use efficiency of new electric equipment in transportation, buildings, and industry.

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 and hundred gigawatt per year 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 (e.g. land use) 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 PV 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.

China's most important transition issue is the hundreds of billions of dollars of capital invested in existing coal generation facilities.[xxv] 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 historical depreciation schedules for coal generating facilities are maintained. 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 capacity value — for instance, energy storage and demand response.

5. References

China Electricity Council (CEC). 2018. *Basic Electricity Statistics 2017* (2017 年电力统计基本数据一览表). Online at: http://www.cec.org.cn/guihuayutongji/tongjxinxi/niandushuju/.

China Electricity Council (CEC). 2019. *Basic Electricity Statistics 2018* (2018 年电力统计年快报基本数据一览表). Online at: http://www.cec.org.cn/guihuayutongji/tongjxinxi/niandushuju/.

Energy Information Administration (EIA). 2019. *Electric Power Monthly: May 2019*. Washington, D.C.: Department of Energy.

He, Gang and Dan Kammen. 2014. "Where, when and how much wind is available? A provincial-scale wind resource assessment for China." *Energy Policy* 74: 116-122. Available at: https://rael.berkeley.edu/wp-content/uploads/2015/08/He-Kammen_2014_Energy-Policy_Where-when-and-how-much-wind-is-available_a-provincial-scale-wind-resource-assessment-for-China_APC.pdf.

He, Gang and Dan Kammen. 2016. "Where, when and how much solar is available? A provincial-scale solar resource assessment for China." *Renewable Energy* 85: 74-82. Available at: https://rael.berkeley.edu/wp-content/uploads/2015/08/He-and-Kammen-Solar-Resource-for-China-2015.pdf.

International Energy Agency (IEA). 2018. *World Energy Outlook 2018*. Paris: OECD/IEA.

Ming, Zach, Arne Olson, Gerrit De Moor, Huai Jiang, and Nick Schlag. 2019. *Long-Run Resource Adequacy under Deep Decarbonization Pathways for California*. San Francisco: Energy and Environmental Economics.

China National Energy Administration (NEA). 2013. http://www.nea.gov.cn/2013-02/20/c_132180424_2.htm. 我国中长期发电能力及电力需求发展预测

Olson, Arne. 2015. "Western Interconnection Flexibility Assessment: Update to TEPPC." https://www.wecc.biz/Administrative/WECC_FlexStudy_TEPPC_2015-05-07.pptx.

Schlag, Nick, Dan Mullen, and Kush Patel. 2019. "Moving beyond 'rules of thumb' for smart, cost effective storage deployment." *Utility Dive*. Online at: https://www.utilitydive.com/news/moving-beyond-rules-of-thumb-for-smart-cost-effective-storage-deployment/553674/.

State Grid Corporation of China (SGCC). 2018. *China Energy and Electricity Outlook 2018* (中国能源电力发展展望). Beijing: SGCC.

Appendix A: Model Description and Inputs

A.1 Model Overview

This model 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.

A.2 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) data in the model are from the 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.

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

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 A-2 shows base case annual average growth rates by time period for each scenario.

Table A-2. Base Case Annual Average Growth Rates by Time Period and Demand Growth Scenario

Scenario	Unit	2018-2020	2020-2025	2025-2030	2030-2035	2035-2040
Low demand	%/yr	4.00%	3.50%	2.75%	2.25%	1.75%

High demand	%/yr	4.00%	2.50%	2.00%	1.25%	1.00%

These annual average growth rates lead to the net generation forecasts lead in Table A-3. These forecasts imply that net generation increases by factors of 1.5 (low demand scenario) and 1.8 (high demand scenario) from 2018 to 2040. Based on CEC estimates, net generation in 2018 was 6,550 TWh.

Table A-3. Net Generation Forecasts by Model Year and Demand Growth Scenario

Scenario	Unit	2020	2025	2030	2035	2040
Low demand	TWh	7,085	8,028	8,875	9,456	9,952
High demand	TWh	7,085	8,427	9,664	10,816	11,811

We benchmarked these forecasts against a range of long-term demand forecasts from Chinese companies, Chinese organizations, and international organizations (Table A-3 and Table A-3). 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.[1]

Table A-4. Long-Term Electricity Demand Forecasts Used to Benchmark Net Generation Forecasts for this Study

Organization	Metric	Scenario	Unit	2020	2025	2030	2035	2040	2050
SGCC	GEC	1	TWh	7,500	9,100	10,300	10,900	11,600	
		2	TWh	7,700	9,600	11,100	12,100	12,800	
NEA	GEC	1	TWh	7,000		10,000			12,000
		2	TWh	8,000		11,000			15,000
IEA	NG	1	TWh		7,996	8,695		9,970	
		2	TWh		8,485	9,534	10,434	11,187	
		3	TWh		8,604	9,821		11,883	

Notes: GEC refers to gross electricity consumption; NG refers to net generation. The difference between these two metrics is generator own-use, which averaged 4.8% in China in 2017 (CEC data). We assume that the IEA data are in terms of NG rather than GEC. SGCC forecasts are from SGCC (2018). Scenarios 1 and 2 are the normal transition and fast electrification scenarios, respectively. NEA forecasts are from NEA (2013). Scenarios 1 and 2 are low and high growth scenarios. IEA forecasts are from IEA (2018). Scenarios 1, 2, and 3 are the sustainable development, new policies, and current policies scenarios, respectively.

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 55% by 2040. This value (55%) was the system load factor for CAISO in 2015 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 RM_y value of 15% for each model year in the analysis.

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

Table A-5 shows total reliable capacity needs (CN_y values) for the low and high demand scenarios.

Table A-5. Total Reliable Capacity Needs in the Low and High Demand Scenarios

Scenario	Unit	2020	2025	2030	2035	2040
Low demand	GW	1,337	1,576	1,816	2,021	2,226
High demand	GW	1,337	1,654	1,978	2,311	2,642

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}).

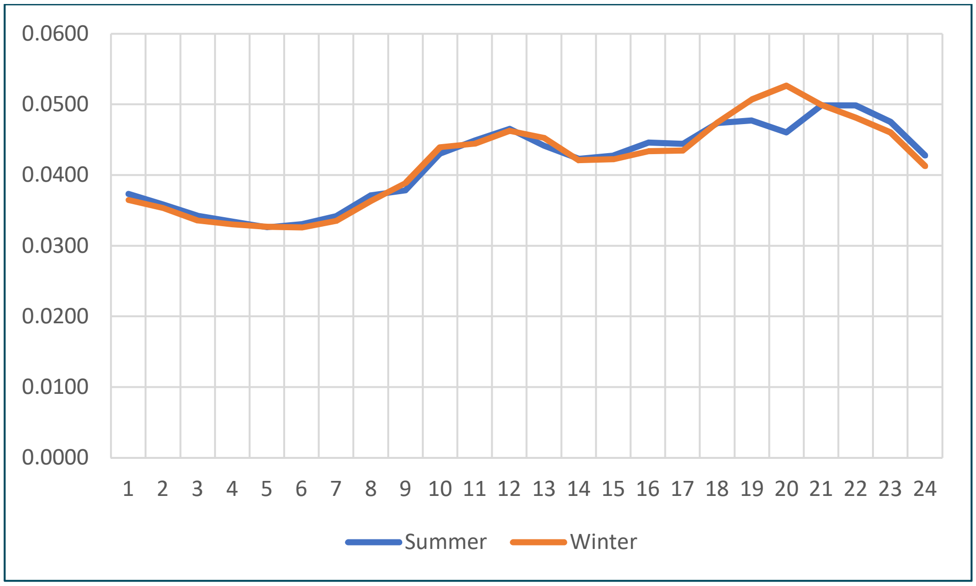
$$DG_{ymhs} = DG_{ym} \times \beta_{hs}$$

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 A-8). As a sensitivity, we tested whether using average 2015 summer and winter load shapes for the California Independent System Operator (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.

Figure A-8. Summer and Winter Normalized Load Shapes



For monthly generation (发电量) shares, we use CEC data for 2010 to 2016.[1] 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 A-6.

Table A-6. Monthly Total Generation Shares

Month	1	2	3	4	5	6	7	8	9	10	11	12
Share	8%	7%	8%	8%	8%	8%	9%	9%	8%	8%	8%	9%

A.3 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 0).

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 2018 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 A-7 and Table A-8 show non-coal installed capacity by year in the high renewable and low renewable scenarios.

Table A-7. Total Installed Capacity of Non-Coal Resources in the Low Renewable Scenario (GW)

	2018	2020	2025	2030	2035	2040
Solar PV	175	250	400	767	1133	1500
Onshore wind	184	225	400	683	967	1250
Offshore wind	0	5	50	200	350	500
Geothermal	0	1	3	5	8	10
Hydro	323	325	344	363	381	400
Nuclear	45	45	53	60	68	75
Gas	76	80	98	115	133	150
Pumped hydro	29	30	33	35	38	40
4-hour battery	0	1	50	233	417	600
6-hour battery	0	0	20	97	173	250
Cogeneration	26	26	26	26	26	26
Biomass	9	9	9	9	9	9
Waste incineration	7	7	7	7	7	7

Table A-8. Total Installed Capacity of Non-Coal Resources in the High Renewable Scenario (GW)

	2018	2020	2025	2030	2035	2040
Solar PV	175	250	600	1167	1733	2300
Onshore wind	184	225	600	983	1367	1750
Offshore wind	0	5	50	283	517	750
Geothermal	0	1	3	5	8	10
Hydro	323	325	344	363	381	400
Nuclear	45	45	53	60	68	75
Gas	76	80	98	115	133	150
Pumped hydro	29	30	35	43	52	60
4-hour battery	0	1	50	283	517	750
6-hour battery	0	0	20	147	273	400
Cogeneration	26	26	26	26	26	26
Biomass	9	9	9	9	9	9
Waste incineration	7	7	7	7	7	7

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 IEA's 2018 *World Energy Outlook*. 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, and batteries through an interactive 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 battery 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.

Table A-9. CNREC, SGCC, and IEA Forecasts of Installed Capacity for Different Generation Resources (2040 or 2050)

	CNREC	CNREC	SGCC	SGCC	IEA	IEA	IEA
Year	**2050**	**2050**	**2050**	**2050**	**2040**	**2040**	**2040**
Scenario	Stated policies	Below 2	Normal Transition	Fast Electri-fication	Current policies	New policies	Sustain. develop-ment
Solar PV	2157	2803	1270	1560	612	935	1506
CSP	8	33		160	6	16	48
Wind	2062	2664	970	1370	428	590	875
Geothermal	20	20			1	2	3
Total hydro	532	532	610	710	488	510	578
Tidal	50	50			1	1	1
Nuclear	120	120	180	230	135	148	198
Gas	—	—	210	310	269	232	191
Biomass	55	57	60	130	48	58	79

Notes: "Biomass" for SGCC includes "other." "Total hydro" includes conventional hydropower and pumped hydropower.

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, battery storage needs if CSP has onsite storage capacity. Tidal power is similar in profile to hydropower output and could substitute for several resources.

A.4 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 A-10 shows the maximum capacity factors used for different resources in the analysis.

Table A-10. Maximum Capacity Factors for Non-Dispatchable Resources

Resource	Value	Source
Solar PV	0.20	He and Kammen (2016)

Onshore wind	0.25	Based on He and Kammen (2014)
Offshore wind	0.30	Based on He and Kammen (2014)
Geothermal	0.75	Based on capacity factors in the U.S.; data are from the U.S. Energy Information Administration (EIA, 2019)
Hydropower	0.40	Based on the average annual capacity factor for conventional hydro in 2017 (0.42); CEC (2018)
Nuclear	0.80	Based on the average annual capacity factor for nuclear in 2017 (0.79); CEC (2018)
Cogeneration	0.50	Based on the average annual capacity factor for cogeneration in 2017 (0.50); CEC (2018)
Waste incineration	0.60	Based on the average annual capacity factor for waste incineration in 2017 (0.60); CEC (2018)

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.

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

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 0. 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.[1] As with 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.

Table A-11. Monthly Hydropower Generation Shares

Month	1	2	3	4	5	6	7	8	9	10	11	12
Share	6%	5%	6%	7%	8%	10%	12%	11%	11%	9%	8%	7%

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).

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

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}).

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

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 A-12. Residual Generation Technology Assumptions Used in the Analysis

2020	2025	2030	2035	2040
Gas	Gas	Gas	Coal	Coal

Table A-12 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.

Table A-13. Maximum Capacity Factors for Biomass, Natural Gas, and Coal Generation

Resource	Value	Source
Biomass	0.54	Based on the average annual capacity factor for biomass in 2017 (0.50); CEC (2018)
Natural gas	0.80	Based on a rule-of-thumb estimate for natural gas units; assumes a 20% planned and forced outage rate
Coal	0.80	Based on a rule-of-thumb estimate for coal units; assumes a 20% planned and forced outage rate

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).

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

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) 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 shortest duration battery, then the longer duration battery, and finally 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 ≥ net load(h)
        If (-)maximum charge rate + SOC(h-1) ≤ storage capacity

charge(h) = maximum charge rate

Else

charge(h) = SOC(h-1) – storage capacity

Else

If SOC(h-1) + net load(h) ≤ 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 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 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 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 A-14. CO_2 Emission Factors

Resource	Value (tCO_2/MWh)	Assumption
Coal	0.9	Based on a commonly used value of 2.72 tCO_2/tce and a net heat rate of 320 kgce/MWh; this yields an emission factor of 0.87 tCO_2/MWh, which we round to 0.9 tCO_2/MWh
Gas	0.4	Based on a commonly used value of 1.63 tCO_2/tce and a net heat rate of 240 kgce/MWh; this yields an emission factor of 0.39 tCO_2/MWh, which we round to 0.4 tCO_2/MWh
Cogeneration	0.9	Assuming that the primary fuel for cogeneration is coal, and that all emissions for electricity plus heat are allocated to electricity

A.5 Capacity Balance Module

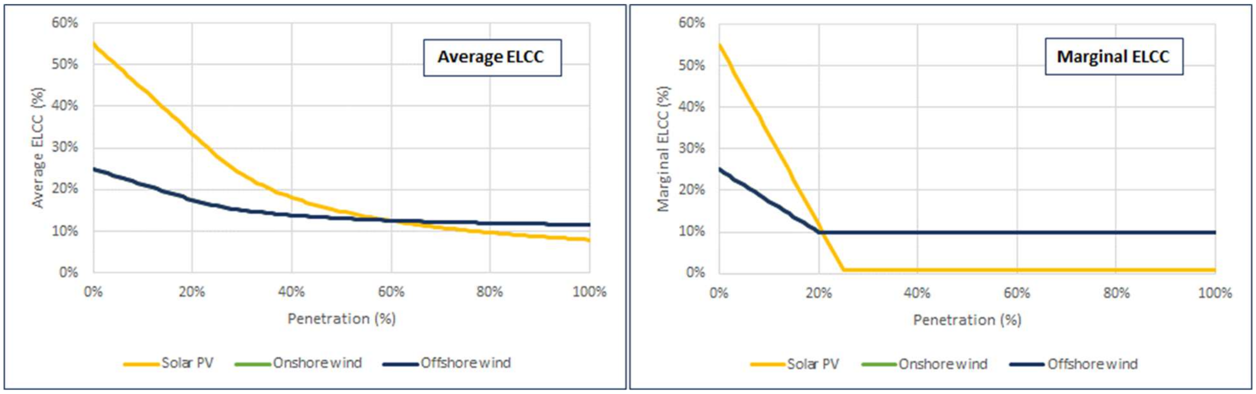
The capacity balance module ensures that available generation capacity is adequate to meet the regionally coincident peak demand forecast plus a 15% reserve margin (Table @@). The module first calculates and sums reliable capacity for all other resources. It then calculates installed coal capacity as 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 effective load carrying capability (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, ELCC values should be 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.

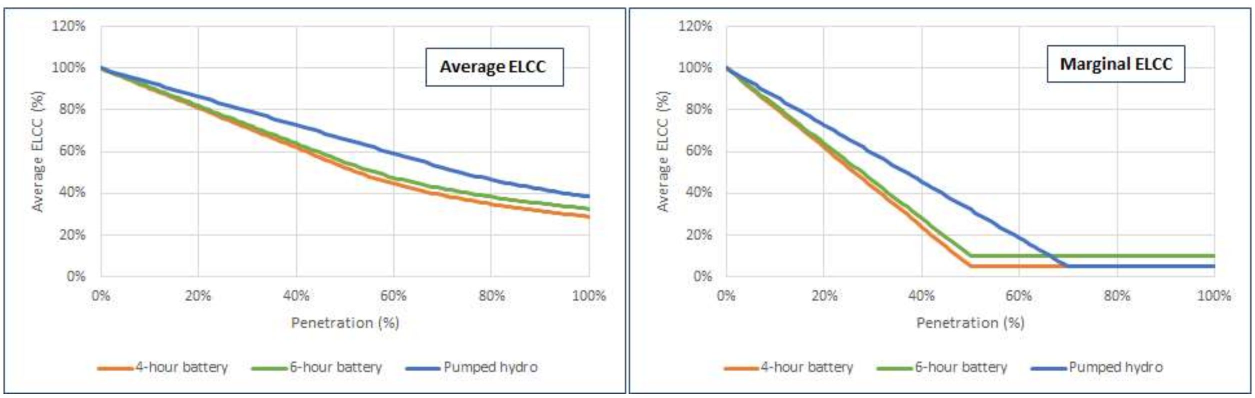
Figure A-9 shows marginal and average ELCC values for solar, onshore wind, and offshore wind generation that we use in the analysis. Figure A-10 show marginal and average ELCC values for different kinds of storage used in the analysis.

Figure A-9. Average and Marginal ELCC Values for Solar, Onshore Wind, and Offshore Wind



Note: We assume onshore and offshore wind have the same ELCC values.

Figure A-10. Average and Marginal ELCC Values for Battery and Pumped Hydro Storage



These ELCC "curves" are drawn from analyses of different electricity systems in the United States and were chosen to reflect operationally conservative values.[1] 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 saturation 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 A-14 and Table A-15 show 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 battery and pumped hydro storage, penetration is defined as the share of regional equivalent peak demand.

Table A-15. Penetrations and Average ELCC Values Used in the Analysis, High Electricity Demand Scenario

High Electricity Demand Scenario										
	Low RE Scenario					High RE Scenario				
	2020	**2025**	**2030**	**2035**	**2040**	**2020**	**2025**	**2030**	**2035**	**2040**
Solar PV										
Penetration	6%	8%	14%	18%	22%	6%	12%	21%	27%	30%
Average ELCC	49%	46%	41%	36%	31%	49%	42%	32%	26%	24%
Onshore Wind										
Penetration	7%	10%	15%	20%	23%	7%	16%	22%	27%	31%
Average ELCC	23%	21%	19%	18%	17%	23%	19%	17%	16%	15%
Offshore Wind										
Penetration	0%	2%	5%	9%	11%	0%	2%	8%	12%	16%
Average ELCC	25%	25%	23%	22%	21%	25%	25%	22%	21%	19%
4-Hour Battery										
Penetration	0%	3%	14%	21%	26%	0%	3%	16%	26%	33%
Average ELCC	100%	97%	88%	81%	75%	100%	97%	85%	76%	70%
6-Hour Battery										
Penetration	0%	1%	6%	9%	11%	0%	1%	9%	14%	17%
Average ELCC	100%	99%	96%	93%	91%	100%	99%	93%	88%	85%
Pumped hydro										
Penetration	3%	2%	2%	2%	2%	3%	2%	3%	3%	3%
Average ELCC	99%	99%	99%	99%	99%	99%	99%	99%	99%	99%

Table A-16. Penetrations and Average ELCC Values Used in the Analysis, Low Electricity Demand Scenario

Low Electricity Demand Scenario										
	Low RE Scenario					High RE Scenario				
	2020	**2025**	**2030**	**2035**	**2040**	**2020**	**2025**	**2030**	**2035**	**2040**
Solar PV										
Penetration	6%	9%	15%	21%	26%	6%	13%	23%	29%	30%
Average ELCC	49%	46%	39%	33%	28%	49%	41%	31%	25%	24%
Onshore Wind										
Penetration	7%	11%	17%	22%	27%	7%	16%	24%	30%	34%
Average ELCC	23%	21%	19%	17%	16%	23%	19%	16%	15%	15%
Offshore Wind										
Penetration	0%	2%	6%	10%	13%	0%	2%	8%	14%	17%
Average ELCC	25%	25%	23%	22%	20%	25%	25%	22%	20%	19%
4-Hour Battery										
Penetration	0%	4%	15%	24%	31%	0%	4%	18%	29%	39%
Average ELCC	100%	97%	87%	78%	71%	100%	97%	84%	72%	64%
6-Hour Battery										
Penetration	0%	1%	6%	10%	13%	0%	1%	9%	16%	21%
Average ELCC	100%	99%	95%	92%	89%	100%	99%	92%	87%	82%
Pumped hydro										

Penetration	3%	2%	2%	2%	2%	3%	3%	3%	3%	3%
Average ELCC	99%	99%	99%	99%	99%	99%	99%	99%	99%	98%

For conventional hydropower, biomass, and waste incineration, we assume that capacity contributions are equal to 2018 capacity factors (Table A-10), 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

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

Where CNy is the total reliable capacity need, IC_r is the installed capacity of resource type r (solar PV, onshore wind, offshore wind, 4-hour battery storage, 6-hour battery 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 type s (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, which would be mothballing or inefficient.

A.6 Resource Profiles

The below tables show the resource profiles used for solar PV, onshore wind, and offshore wind. We assume that onshore and offshore wind have the same resource profile, though the model allows users to input different profiles for each resource.

Solar Resource Shape

	Month											
HE	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
6	0.0000	0.0000	0.0000	0.0027	0.0157	0.0197	0.0129	0.0020	0.0002	0.0000	0.0000	0.0000
7	0.0000	0.0003	0.0067	0.0204	0.0236	0.0244	0.0254	0.0224	0.0178	0.0098	0.0016	0.0000
8	0.0257	0.0388	0.0546	0.0633	0.0640	0.0589	0.0560	0.0586	0.0647	0.0686	0.0583	0.0364
9	0.0863	0.0873	0.0912	0.0916	0.0879	0.0840	0.0838	0.0874	0.0921	0.0977	0.0988	0.0927
10	0.1147	0.1093	0.1060	0.1022	0.0986	0.0951	0.0958	0.1004	0.1045	0.1118	0.1186	0.1195
11	0.1288	0.1222	0.1135	0.1072	0.1038	0.1010	0.1022	0.1071	0.1108	0.1188	0.1296	0.1342
12	0.1347	0.1263	0.1159	0.1091	0.1059	0.1041	0.1055	0.1099	0.1131	0.1207	0.1320	0.1395
13	0.1329	0.1250	0.1147	0.1086	0.1057	0.1044	0.1057	0.1093	0.1121	0.1194	0.1295	0.1377
14	0.1271	0.1187	0.1112	0.1058	0.1030	0.1020	0.1033	0.1060	0.1086	0.1147	0.1219	0.1293
15	0.1146	0.1102	0.1046	0.1007	0.0976	0.0967	0.0980	0.0997	0.1021	0.1052	0.1080	0.1135
16	0.0919	0.0937	0.0925	0.0900	0.0871	0.0874	0.0886	0.0896	0.0892	0.0859	0.0823	0.0843
17	0.0432	0.0619	0.0677	0.0689	0.0686	0.0713	0.0722	0.0706	0.0652	0.0459	0.0195	0.0128
18	0.0003	0.0063	0.0212	0.0283	0.0314	0.0373	0.0394	0.0339	0.0194	0.0014	0.0000	0.0000
19	0.0000	0.0000	0.0001	0.0014	0.0071	0.0133	0.0108	0.0033	0.0003	0.0000	0.0000	0.0000
20	0.0000	0.0000	0.0000	0.0000	0.0001	0.0003	0.0004	0.0000	0.0000	0.0000	0.0000	0.0000
21	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
22	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
23	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
24	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Onshore Wind Resource Shape

	Month											
HE	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1	0.0437	0.0417	0.0419	0.0432	0.0446	0.0467	0.0499	0.0503	0.0476	0.0453	0.0427	0.0429
2	0.0438	0.0416	0.0411	0.0422	0.0435	0.0433	0.0440	0.0459	0.0448	0.0445	0.0421	0.0424
3	0.0437	0.0414	0.0400	0.0409	0.0422	0.0405	0.0394	0.0417	0.0423	0.0432	0.0417	0.0422
4	0.0434	0.0413	0.0398	0.0395	0.0406	0.0382	0.0365	0.0390	0.0411	0.0422	0.0411	0.0421
5	0.0429	0.0407	0.0396	0.0384	0.0388	0.0357	0.0332	0.0369	0.0402	0.0409	0.0404	0.0420
6	0.0427	0.0405	0.0396	0.0366	0.0351	0.0303	0.0264	0.0322	0.0382	0.0403	0.0402	0.0419
7	0.0425	0.0402	0.0380	0.0328	0.0310	0.0267	0.0204	0.0259	0.0320	0.0382	0.0399	0.0416
8	0.0408	0.0387	0.0364	0.0311	0.0305	0.0266	0.0190	0.0238	0.0274	0.0333	0.0375	0.0404
9	0.0391	0.0378	0.0371	0.0322	0.0309	0.0270	0.0180	0.0226	0.0272	0.0315	0.0352	0.0390
10	0.0390	0.0388	0.0384	0.0338	0.0318	0.0274	0.0175	0.0212	0.0274	0.0323	0.0357	0.0392
11	0.0395	0.0403	0.0398	0.0355	0.0332	0.0290	0.0184	0.0209	0.0277	0.0339	0.0375	0.0403
12	0.0401	0.0419	0.0410	0.0374	0.0358	0.0321	0.0224	0.0233	0.0295	0.0354	0.0393	0.0412
13	0.0411	0.0436	0.0424	0.0401	0.0392	0.0362	0.0301	0.0276	0.0324	0.0370	0.0406	0.0417
14	0.0418	0.0451	0.0436	0.0426	0.0424	0.0404	0.0362	0.0349	0.0355	0.0389	0.0417	0.0419
15	0.0422	0.0455	0.0449	0.0449	0.0448	0.0444	0.0421	0.0397	0.0381	0.0416	0.0421	0.0419
16	0.0422	0.0448	0.0453	0.0469	0.0471	0.0479	0.0474	0.0431	0.0425	0.0419	0.0417	0.0423
17	0.0424	0.0441	0.0448	0.0478	0.0496	0.0514	0.0531	0.0496	0.0456	0.0427	0.0428	0.0431
18	0.0425	0.0441	0.0447	0.0478	0.0493	0.0532	0.0596	0.0551	0.0509	0.0461	0.0445	0.0431
19	0.0418	0.0433	0.0444	0.0482	0.0498	0.0545	0.0653	0.0622	0.0558	0.0480	0.0452	0.0425
20	0.0411	0.0426	0.0445	0.0482	0.0498	0.0573	0.0695	0.0663	0.0569	0.0486	0.0451	0.0421
21	0.0407	0.0419	0.0441	0.0483	0.0491	0.0571	0.0686	0.0662	0.0571	0.0492	0.0450	0.0420
22	0.0406	0.0407	0.0436	0.0480	0.0485	0.0541	0.0653	0.0622	0.0557	0.0490	0.0453	0.0417
23	0.0413	0.0400	0.0428	0.0474	0.0470	0.0513	0.0611	0.0572	0.0534	0.0482	0.0461	0.0415
24	0.0413	0.0396	0.0423	0.0463	0.0456	0.0487	0.0566	0.0521	0.0508	0.0479	0.0465	0.0409

Offshore Wind Resource Shape												
	Month											
HE	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1	0.0437	0.0417	0.0419	0.0432	0.0446	0.0467	0.0499	0.0503	0.0476	0.0453	0.0427	0.0429
2	0.0438	0.0416	0.0411	0.0422	0.0435	0.0433	0.0440	0.0459	0.0448	0.0445	0.0421	0.0424
3	0.0437	0.0414	0.0400	0.0409	0.0422	0.0405	0.0394	0.0417	0.0423	0.0432	0.0417	0.0422
4	0.0434	0.0413	0.0398	0.0395	0.0406	0.0382	0.0365	0.0390	0.0411	0.0422	0.0411	0.0421
5	0.0429	0.0407	0.0396	0.0384	0.0388	0.0357	0.0332	0.0369	0.0402	0.0409	0.0404	0.0420
6	0.0427	0.0405	0.0396	0.0366	0.0351	0.0303	0.0264	0.0322	0.0382	0.0403	0.0402	0.0419
7	0.0425	0.0402	0.0380	0.0328	0.0310	0.0267	0.0204	0.0259	0.0320	0.0382	0.0399	0.0416
8	0.0408	0.0387	0.0364	0.0311	0.0305	0.0266	0.0190	0.0238	0.0274	0.0333	0.0375	0.0404
9	0.0391	0.0378	0.0371	0.0322	0.0309	0.0270	0.0180	0.0226	0.0272	0.0315	0.0352	0.0390
10	0.0390	0.0388	0.0384	0.0338	0.0318	0.0274	0.0175	0.0212	0.0274	0.0323	0.0357	0.0392
11	0.0395	0.0403	0.0398	0.0355	0.0332	0.0290	0.0184	0.0209	0.0277	0.0339	0.0375	0.0403
12	0.0401	0.0419	0.0410	0.0374	0.0358	0.0321	0.0224	0.0233	0.0295	0.0354	0.0393	0.0412
13	0.0411	0.0436	0.0424	0.0401	0.0392	0.0362	0.0301	0.0276	0.0324	0.0370	0.0406	0.0417
14	0.0418	0.0451	0.0436	0.0426	0.0424	0.0404	0.0362	0.0349	0.0355	0.0389	0.0417	0.0419
15	0.0422	0.0455	0.0449	0.0449	0.0448	0.0444	0.0421	0.0397	0.0381	0.0416	0.0421	0.0419
16	0.0422	0.0448	0.0453	0.0469	0.0471	0.0479	0.0474	0.0431	0.0425	0.0419	0.0417	0.0423
17	0.0424	0.0441	0.0448	0.0478	0.0496	0.0514	0.0531	0.0496	0.0456	0.0427	0.0428	0.0431
18	0.0425	0.0441	0.0447	0.0478	0.0493	0.0532	0.0596	0.0551	0.0509	0.0461	0.0445	0.0431
19	0.0418	0.0433	0.0444	0.0482	0.0498	0.0545	0.0653	0.0622	0.0558	0.0480	0.0452	0.0425
20	0.0411	0.0426	0.0445	0.0482	0.0498	0.0573	0.0695	0.0663	0.0569	0.0486	0.0451	0.0421
21	0.0407	0.0419	0.0441	0.0483	0.0491	0.0571	0.0686	0.0662	0.0571	0.0492	0.0450	0.0420
22	0.0406	0.0407	0.0436	0.0480	0.0485	0.0541	0.0653	0.0622	0.0557	0.0490	0.0453	0.0417
23	0.0413	0.0400	0.0428	0.0474	0.0470	0.0513	0.0611	0.0572	0.0534	0.0482	0.0461	0.0415
24	0.0413	0.0396	0.0423	0.0463	0.0456	0.0487	0.0566	0.0521	0.0508	0.0479	0.0465	0.0409

[i] International Energy Agency, *World Energy Outlook 2018* (Paris: OECD/IEA, 2018).
[ii] Teng et al., *Pathways to Deep Decarbonization in China* (New York: SDSN/IDDRI, 2015); IEA (2018).
[iii] Data are from the China Electricity Council (CEC), http://www.cec.org.cn/.
[iv] IEA (2018); IPCC, *Global warming of 1.5°C* (Genf: IPCC, 2019).
[v] IEA (2018).
[vi] 9-18 PJ is based on a range of 1,000 to 2,000 TWh per year, from the figure, and assuming 40% net efficiency. See China National Renewable Energy Centre (CNREC), *China Renewable Energy Outlook 2018* (Beijing, CNREC, 2018), State Grid Corporation of China (SGCC), *China Energy and Electricity Outlook* (Beijing: SGCC, 2018); IEA (2018).
[vii] See, for instance, Jiang, K., He, C., Xu, X., Jiang, W., Xiang, P., Li, H., & Liu, J. (2018). Transition scenarios of power generation in China under global 2° C and 1.5° C targets. *Global Energy Interconnection*, *1*(4), 477-486; Jiang, K., et al. "Emission scenario analysis for China under the global 1.5° C target." *Carbon Management* 9.5 (2018): 481-491.
[viii] Reiner, David M. "Learning through a portfolio of carbon capture and storage demonstration projects." *Nature Energy* 1, no. 1 (2016): 15011.
[ix] In the United States, as of 2019 four states (California, Hawaii, Maine, Minnesota) had committed through statute or state goal to 100% renewable electricity systems by 2040 to 2050; seven states have committed to 100% clean energy goals (Connecticut, New Jersey, New York, New Mexico, Nevada, Washington, and Wisconsin), relying on existing nuclear plants and new renewable generation to achieve these goals. In Europe, Germany and Spain have committed to 100% renewable electricity systems by 2050.
[x] CNREC's projections are "fossil fuels" and not coal generation specifically, but coal accounts for the majority of fossil fuels in the CNREC estimates.
[xi] SGCC (2018); IEA (2018).
[xii] Net generation demand is final electricity consumption plus transmission and distribution losses.
[xiii] Equivalent peak demand is the sum of non-coincident peak demand from China's six regional grids.
[xiv] See, for instance, Mahone et al., *Deep Decarbonization in a High Renewables Future* (Sacramento: California Energy Commission, 2018) and Xcel Energy, "Upper Midwest Integrated Resource Plan," Docket No. E002/RP-19-368, 2019.
[xv] These divergence between forecast and actual has been most pronounced for solar PV, battery storage, and to a lesser extent wind. For examples, see, for instance, California Public Utilities Commission, *33% Renewables Portfolio Standard: Implementation Analysis Preliminary Results* (San Francisco: CPUC, 2009); He et al., "SWITCH-China: A Systems Approach to Decarbonizing China's Power System," *Environmental Science & Technology* 50, 5467-5473 (2016).
[xvi]CNREC (2018); SGCC (2018); IEA (2018)
[xvii] *Ibid*.
[xviii] Energy and Environmental Economics (E3), *Long-Run Resource Adequacy under Deep Decarbonization Pathways for California* (San Francisco: E3, 2019).
[xix] Data are from the China Electricity Council (CEC), http://www.cec.org.cn/.
[xx] The scale of wind and solar PV resource development implied here is below technical potential. Eurek et al. (2017) estimate a technical potential of 19.8 TW for onshore wind and 3.6 TW for offshore wind in China. See Eurek et al., "An Improved Global Wind Resource Estimate for Integrated Assessment Models," *Energy Economics* 64, 552-567 (2017). He and Kammen (2016) estimate that China's solar potential is between 4.7 and 39.3 TW. See He and Kammen, "Where, when and how much solar is available? A provincial-scale solar resource assessment for China," *Renewable Energy* 85, 74-82 (2016).
[xxi] Equivalent costs are the equivalent marginal cost of capacity and energy for coal and solar and wind units. To make capacity costs equivalent, the coal capacity cost must be scaled by $\frac{ELCC}{CF \times 8760}$; to make energy equivalent, the wind and solar LCOE must be scaled by $\frac{1}{Curtailment\ rate}$.
[xxii] The calculations here use an operating cost for coal of 325 yuan/MWh, a capacity cost of 475 yuan/kW-yr, and an exchange rate of 6.88 CNY/USD. The breakeven equivalent costs are calculated using the approach described in the previous endnote.

[xxiii] Hu et al., ""Using natural gas generation to improve power system efficiency in China," *Energy Policy* 60, 116-121 (2013); Lin et al., "Challenges and strategies for electricity market transition in China," *Energy Policy* 133 (2019).
[xxiv] Guan et al., "Structural decline in China's CO2 emissions through transitions in industry and energy systems," *Nature Geoscience* 11, 551-555 (2018); Kahrl et al., "Past as Prologue? Understanding energy use in post-2002 China," *Energy Economics* 36, 759-771 (2013).
[xxiv] Lin et al. (2019).