Decarbonization of the Indian electricity sector: Technology choices and policy trade-offs

**Assessment of India’s 2040 power generation mix considers 40 decarbonization scenarios**

| Policy dimensions | Economic dimensions |
|-------------------|---------------------|
| Annual CO₂ emissions limit | Natural gas price [$/MMBtu] |
| None              | No emissions limit |
| Moderate          | 1,146 MT CO₂ / yr |
| Stringent         | 486 MT CO₂ / yr |

**Policy dimensions**

- **None**
  - No emissions limit
- **Moderate**
  - 1,146 MT CO₂ / yr
- **Stringent**
  - 486 MT CO₂ / yr

**Economic dimensions**

- **Storage CAPEX** [$/kW]
- **VRE CAPEX** [$/kW]
  - Solar: 580, Wind: 900
  - Solar: 325, Wind: 714

**Highlights**

- We simulate 40 scenarios for the 2040 Indian electricity sector.
- Large-scale expansion of VRE, particularly solar PV, occurs in most scenarios.
- CO₂ policies are less costly and reduce more air pollution than alternatives.
- Renewables policies retain more incumbent generation than CO₂ policies.

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Decarbonization of the Indian electricity sector: Technology choices and policy trade-offs

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SUMMARY

India is the third largest CO2 emitter worldwide, and its electricity demand, which is primarily supplied by coal-fired generation, is expected to increase almost threefold over the next twenty years. Here, we simulate 40 scenarios for the 2040 Indian electricity sector, considering uncertainty in future natural gas prices and costs for batteries and variable renewable energy (VRE) technologies, under different CO2 emissions limits and renewable portfolio standard (RPS) targets. We find a large-scale expansion of VRE, particularly, solar PV, in most scenarios. Furthermore, energy storage competes with natural gas and coal to provide flexibility to integrate VRE. Given a set of technology assumptions, policies that explicitly limit CO2 emissions are more cost-effective at reducing emissions than RPS policies. The former are also more effective at reducing air pollution than RPS policies by explicitly penalizing CO2 emissions, thereby reducing coal generation more substantially than RPS policies.

INTRODUCTION

India’s electricity system is one of the largest interconnected systems of its kind globally and notable in that power generation is projected to increase nearly threefold from 2017 to 2040 according to IEA’s Stated Policies Scenarios (STEPS) (International Energy Agency, 2019). Coal-based generation has historically contributed more than 70%, and by 2030, may still contribute more than 50% of total electricity generation (International Energy Agency, 2019) (Central Electricity Authority, 2020). Although the CO2 emissions intensity of the power sector is projected to decline by nearly 50% in this time frame (Chaturvedi et al., 2018), absolute annual power sector emissions are projected to increase by ~0.6 Gton CO2 from 2017 to 2030 under STEPS (International Energy Agency, 2019). In contrast, annual emissions under IEA’s Sustainable Development Scenario (SDS)—in line with a 2°C pathway—are projected to decrease by 0.2 Gton CO2 over the same time frame. As a broader backdrop, a global conditional Nationally Determined Contribution (NDC) trajectory across all sectors is likely to fall short of the emissions reductions assessed by the IPCC (IPCC, 2018) to be consistent with 2°C by 12 Gton CO2eq in 2030 (United Nations Environment Programme, 2019). Thus, there is a need to better understand technologies and policies that can lead to emissions reduction and attainment of other societal objectives across geographies.

Prior modeling studies of the future energy system in India (Shukla et al., 2008), (Shukla et al., 2009), (Priyadarshi and Chaturvedi, 2012), (Shukla and Chaturvedi, 2013), (Chaturvedi and Shukla, 2014), (Rose et al., 2020) have considered different technology, policy, and pricing assumptions. Recognizing the major role played by India’s power sector in the country’s energy system and the power sector’s contribution to greenhouse gas (GHG) emissions (International Energy Agency, 2019), it is worth noting that these studies do not fully consider the breadth of possible outcomes under various technology, policy, and market assumptions. Some recent studies have focused on the sensitivity of energy outcomes to solar photovoltaic (PV) costs but primarily at a global level (Creutzig et al., 2017) or in regions such as China (He et al., 2020). In addition, despite the fact that India’s approach to power system emissions reduction includes VRE capacity targets as a key element (Central Electricity Authority, 2020) (Palchak et al., 2017), prior studies have not compared renewable portfolio standards (RPSs) to other emissions reduction policies, such as tradable emissions limits.

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Over the past decade, future Indian power system studies aimed at reducing CO₂ emissions have almost exclusively started from the assumption that an exogenously defined renewables generation or capacity target must be met by a future year. Through detailed production cost modeling, (Palchak et al., 2017) simulated the potential for India to successfully integrate 175 GW by 2022, while (Spencer et al., 2020) demonstrated the feasibility of reaching a 32% VRE generation share by 2030. In contrast to (Palchak et al., 2017) and (Spencer et al., 2020), where the capacity mix for the entire system was provided exogenously, several researchers have used capacity expansion models to determine a least-cost future capacity mix subject to exogenously defined VRE constraints. Using the LEAP energy systems planning model, (Kumar and Madlener, 2016) found that in an accelerated renewable energy technology scenario, 23%–36% of electricity is generated by renewables, and that a 74% CO₂ reduction is possible by 2050. (Lu et al., 2020) explored the possibility of meeting 80% of projected 2040 power demand from VRE resources. India’s Central Electricity Authority (CEA) investigated the feasibility of achieving 450 GW of VRE capacity by 2030 (Central Electricity Authority, 2020). (Deshmukh et al., 2021) examined 15 VRE build-out scenarios with up to 600 GW of VRE capacity in 2030 and various user-defined shares of solar PV and wind. In a study with larger regional scope, (Gulagi et al., 2017) compared four scenarios to meet electricity demand from 100% renewables in South Asia in 2030. None of these studies investigate an explicit CO₂ emissions limit as done in the present study.

In addition to a lack of research comparing RPSs to other emissions-focused policies in India, there is a gap between longer-term studies that use coarser modeling frameworks, and shorter-term studies that use higher-resolution models for India. As argued in (Das et al., 2021), “new modeling strategies are needed to reflect short-term flexibility requirements in long-term portfolio planning”. For example, the LEAP energy systems planning model used in (Kumar and Madlener, 2016) has no intra-annual resolution, and hence no means of handling hourly fluctuations in supply and demand. Using a simple “screening curve approach” as opposed to a more rigorous optimization-based methodology, (Deshmukh et al., 2021) heuristically determine capacity mixes to meet exogenously defined renewables targets and battery storage capacity. The India-ReEDS model used in (Rose et al., 2020) partitions a year into time slices rather than explicitly considering annual operations across all hours of the year. Our approach is similar to that of (Lu et al., 2020) who simultaneously optimize capacity expansion decisions and 8,760 h of power systems operations, although as discussed above consider only scenarios with prescribed renewables shares.

This study fills the gaps identified above and makes several noteworthy contributions. First, we refine the GenX capacity expansion model (Jenkins and Sepulveda, 2017) to project future outcomes for India, taking into account the need to balance electricity supply and demand at an hourly level. Second, we consider a wider range of VRE cost, battery cost, and natural gas price assumptions to illustrate the potential diversity of outcomes consistent with power system growth and other environmental objectives. Third, for given technology assumptions, we illustrate differences in the projected energy mix, cost of CO₂ abatement, and air pollution emissions under a renewable portfolio standard and tradable emissions limits for CO₂. Fourth, we rigorously co-optimize investment decisions for all generation and storage options along with operational dispatch decisions subject to a CO₂ emissions constraint, differentiating our work from prior research on the Indian power sector. This novelty allows us to examine which technologies would mitigate emissions at the lowest possible cost, given different cost assumptions, rather than to only examine the consequences of prescribed renewables shares for the power system. Fifth, even though CO₂ limits are expected to be more cost-effective than RPSs, we quantify the magnitude of the difference in the abatement cost between the former and the latter for different scenarios for India. Taken together, our results illustrate a range of possible technology outcomes, highlight differences in technology, emissions, and cost outcomes associated with different policy choices, and suggest that operational constraints may be important to consider in electricity system planning for India.

RESULTS

Scenarios for India’s electricity system in 2040

Focusing on the Indian electricity system (Figure 1), we find the least-cost mix of generation resources to meet the projected electricity demand in 2040—April 2039 to March 2040 in line with the CEA—using the GenX capacity expansion model, which finds the optimal expansion plan for a future year considering unit commitment, transmission, and other operational constraints (Jenkins and Sepulveda, 2017). As initial status, we obtained regional generation capacity in MW in 2017 from (Central Electricity Authority, 2017a) (Central Electricity Authority, 2018b) and projected aggregate transmission capacity between...
regions in 2037 from (Central Electricity Authority, 2016a, 2016b). We develop 40 scenarios, accounting for uncertainty in future natural gas prices and costs for energy storage and VRE technologies, as well as different policy approaches for limiting CO\(_2\) emissions, as illustrated in Figure 2. The capacity expansion planning model and additional assumptions for the various cases are detailed in the limitations of the study and STAR Methods sections, with additional details in the supplemental information.

Capacity and generation outcomes in 2040 under tradable CO\(_2\) emissions limits

Figure 3 shows a large expansion of new electricity generation capacity to meet the projected demand in 2040 across scenarios with different emissions limits and technology cost assumptions. With a CO\(_2\) emissions limit in place, there is substantial investment in renewable energy, with solar PV being the technology with the largest increase in installed capacity. Wind and solar PV also expand substantially in the unconstrained carbon scenarios with low VRE costs. In addition, battery installations reach a total of 485 GW in the scenario with the most stringent CO\(_2\) emissions limit, high natural gas cost, and low storage and VRE costs. In contrast, the amount of energy storage expansion is much lower with higher storage costs, with the lowest level of 9 GW occurring in the unconstrained carbon emissions scenario with high VRE and storage costs. There is clearly a synergy between energy storage and solar PV, with installations of the former substantially higher in scenarios with greater solar PV build-out, as also observed in (Victoria
et al., 2019). In contrast, storage expansion is not similarly correlated with wind power expansion. Note that wind power reaches its assumed national resource limit (from a recent report by India’s National Institute for Wind Energy (Chaurasiya et al., 2019) of 299 GW in several scenarios. In contrast, solar PV expansion does not reach the assumed national expansion limit, but frequently reaches installation limits imposed on each of the five zones (national and zonal installation limits for solar and wind are detailed in the supplemental information).

We also conducted sensitivity cases without a resource limit for wind power. Removing the wind capacity resource limit leads to a substantial increase in wind power capacity and generation. This has implications for other technologies. In particular, gas power plants see a large reduction in expansion and use, with the opposite effect for coal power plants. The results serve to illustrate the complex relationship between capacity expansion of different technologies and how they are impacted by imposed resource limits, which is captured by the modeling approach applied in this study. These sensitivity results are documented in Table S7.

The amount of natural gas-fired generation capacity varies widely across these scenarios, from relatively little expansion in the unconstrained carbon scenarios to as much as 320 GW in the scenarios with a stringent CO2 emissions limit and high storage costs. In the latter case, it is more cost-effective to expand natural gas capacity than energy storage, both of which provide flexibility to accommodate VRE. Moreover,
sions under the RPS policy. Consequently, CO2 emissions in the RPS scenarios are higher by a factor of two (with these stringent CO2 limit scenarios, coal capacity is reduced significantly and eliminated entirely from the system in cases with high storage costs). In contrast, under the moderate CO2 limit scenarios, coal capacity remains roughly at initial levels, and in scenarios without a CO2 limit, coal-fired generation increases significantly, reaching 442 GW in the scenario with high natural gas prices, VRE, and storage costs.

Figure 4 shows that without a carbon policy, coal remains by far the largest source of electricity generation. Natural gas becomes the largest resource under stringent CO2 emissions limits and high storage costs. In all scenarios, solar PV is the largest renewable generation resource, reaching an annual generation of more than 1,300 TWh in several of the scenarios with low storage costs. Overall, the total penetration of renewable resources (including solar PV, wind, and hydro) range between 40% and 65% in the scenarios with CO2 emissions limits. There is also substantial use of energy storage resources, with storage discharge exceeding 500 TWh in several scenarios with low storage cost, which coincides with high solar PV generation.

Comparison between tradable CO2 emissions limits and renewable portfolio standards

In the policy scenarios that include an RPS in 2040, the renewable electricity generation (solar PV, wind, and hydro) percentage from the two emissions limit policies was used as a constraint, effectively defining two RPS policies with different renewables targets. In the RPS cases, CO2 emissions in 2040 are therefore a model output rather than a constraint, whereas CO2 emissions are a constraint under the tradable emissions policies. Figure 5 reports electricity generation by different technologies in the most stringent CO2 emissions limit (486 Mton/year) cases and the cases with corresponding RPS limits. In all RPS scenarios, coal generation is higher and natural gas generation is lower than in the corresponding emissions limit scenarios, since there is no penalty for CO2 emissions under the RPS policy. Consequently, CO2 emissions in the RPS scenarios are higher by a factor of two (with low storage costs) or more (with high storage costs) than under the corresponding CO2 emissions limit scenarios.
In order to investigate the cost of CO\textsubscript{2} abatement in more detail, we compare the results from five scenarios (green piece of the pie charts).

Achieves more CO\textsubscript{2} abatement (i.e. the blue curve is typically farther to the right than the orange curve, difference is substantial. In other words, for a given abatement cost on the y axis, the carbon policy that within the RPS cases, the VRE generation is always equal to that of the equivalent CO\textsubscript{2} emission limit scenario. Note that the electricity demand is the same across the 24 scenarios for 2040. However, the total generation differs due to different levels of energy storage charging, discharging, and corresponding losses. These losses are around 15\% of the total charged energy, and only slightly fluctuate among scenarios.

Moreover, SO\textsubscript{2} and NO\textsubscript{x} emissions in the RPS scenarios are higher by a factor of two to three (with low storage costs) or five to seven (with high storage costs) than under the corresponding CO\textsubscript{2} emissions limit scenarios. Figure 6 shows the same results for the cases that originate from the CO\textsubscript{2} emissions limit of 1,146 Mton/year. The difference in emissions between the carbon constrained and RPS policies are smaller in this case, particularly under low storage costs. This is because there is less substitution from coal to natural gas in these scenarios. Note that within the RPS cases, the VRE generation is always equal to that of the equivalent CO\textsubscript{2} emission limit scenarios (green piece of the pie charts).

In order to investigate the cost of CO\textsubscript{2} abatement in more detail, we compare the results from five scenarios: 1) no carbon policy, 2) moderate CO\textsubscript{2} emissions limit, 3) RPS target identical to the result of the moderate CO\textsubscript{2} emissions limit, 4) stringent CO\textsubscript{2} emissions limit, and 5) RPS target identical to the result of the stringent CO\textsubscript{2} emissions limit. Using the no carbon policy scenario as the reference for each unique technology combination (battery cost, VRE CAPEX, and natural gas price), we calculate the amount of CO\textsubscript{2} abated and the corresponding average CO\textsubscript{2} abatement cost, which can be interpreted as the total policy cost (the difference in cost between the policy case and the reference case) normalized by CO\textsubscript{2} abatement. Figure 7 shows that for all eight sets of technology assumptions, a carbon policy is always at least as cost-effective as a means to reduce CO\textsubscript{2} emissions as an RPS, and in some cases, the difference is substantial. In other words, for a given abatement cost on the y axis, the carbon policy achieves more CO\textsubscript{2} abatement (i.e. the blue curve is typically farther to the right than the orange curve, indicating a greater reduction in CO\textsubscript{2} emissions). Similarly, for a given level of emissions abatement on the x axis, the abatement cost of the carbon policy is usually lower (the blue curve is typically below the orange curve).

In the scenarios with low storage costs (leftmost four panels), the abatement costs for the emissions limit and RPS policies are closer to one another (for a given level of CO\textsubscript{2} reduction) than when storage costs are higher.
assumed to be higher (rightmost four panels). In other words, when storage is relatively inexpensive, the outcomes under the more flexible carbon emissions limit policy are similar to the outcomes under an RPS. The reason is that both policies rely heavily on solar PV and storage to meet the policy goals, limiting the cost savings provided by policy compliance flexibility under the carbon limit. However, when storage is relatively expensive, the flexible carbon policy relies more heavily on other technology options (e.g., natural gas-fired power plants), providing cost savings relative to the less flexible RPS policy. Although earlier work, e.g. focusing on the United States (Palmer and Burtraw, 2005) (Rausch and Mowers, 2014) (Young and Bistline, 2018) (Levin et al., 2019) (Paltsev et al., 2022) or Europe (Zhu et al., 2019), has demonstrated that a carbon policy is more cost-effective than an RPS in reducing CO₂ emissions, few studies have examined these differences for India or other emerging economies.

Implications for power system operations

Increasing deployment of renewable generation in India will alter the traditional hourly dispatch of controllable thermal generation—coal and natural gas. Figure 8 displays hourly generation dispatch graphs of four critical days for selected expansion scenarios, which illustrate the intricate interplay between the available generation technologies and the need for flexibility. Because the GenX model represents hourly dispatch while projecting expansion of the Indian power grid, we can project potential future expansion portfolios that are consistent with meeting loads at an hourly time resolution and evaluate the implications of such outcomes for power system operations.

Figure 8A shows the system dispatch on the peak net load day (October 16) of a stringent CO₂ emissions limit scenario with high VRE penetration. The peak load reaches 422 GW at 8p.m. While the contribution of VRE is limited during peak load (zero solar generation, 8% wind capacity factor), dispatchable sources, including storage and backup generators, are operating at full capacity. Owing to the variability of VRE generation, over 338 GW of non-VRE capacity is required to ramp up during 4 h (4p.m.–8p.m.) to meet the increase in net load while solar PV generation winds down. Half of this ramping comes from storage discharging. (As a point of reference, the 3-h ramping need in the California ISO system, which has a peak load of about 1/10th of the simulated India system for 2040, was on the order of 15 GW in 2018 and 2019 (California ISO, 2020).) The storage capacity also mitigates solar curtailment (which amounts to 171 GWh from 11a.m. to 3p.m.) by absorbing 1943 GWh during daytime hours (8a.m.–4p.m.).
Figure 6. Electricity generation by technology, system emissions, and system cost in 2040 when assuming CO₂ emissions limit of 1,146 Mton/year versus a corresponding RPS

The percent generation from coal, natural gas, VRE, and other generation sources, in addition to the system emissions of CO₂, SO₂, and NOₓ and total system cost, are reported for the 1,146 Mton/year (and corresponding RPS) scenarios.

Figure 8B illustrates the system dispatch on the minimum net load day (March 29) for the same expansion scenario. In this case, load peaks at 396 GW at 8p.m., when, without solar generation, wind covers 25% of the load. Less ramping capacity is needed when the sun sets, and this is primarily supplied by storage discharging (167 GW). The maximum renewable generation of more than 700 GW is reached at 1p.m., surpassing load by 89% in that hour. Energy curtailment is much higher on this day due to higher VRE generation and lower load; over 477 GWh of energy is curtailed from 1p.m. to 6p.m. Here again, storage is a key resource to help accommodate high shares of VRE, chiefly solar.

In contrast, Figure 8C shows the system dispatch during the peak net load day (October 16) under a moderate CO₂ emissions limit scenario with low VRE and high deployment of natural gas power plants. While during daytime hours renewable energy curtailment reaches 34 GW, the installed generation capacity is not sufficient to satisfy all the load at peak hours in the evening, activating diesel backup generation and load shedding. A total of 7.5 GW (1.6% of total load) in load shedding is observed at 8p.m. Wind only operates at 8% capacity factor during that hour. About 270 GW is required in ramping capacity within a 7-hour period, mainly covered by CCGT plants instead of storage. The latter plays a less prominent role when VRE penetration is lower.

Finally, Figure 8D shows the day (April 28) with the highest level of coal ramping across all scenarios. In this RPS scenario, coal plants ramp more than 117 GW within 3 hours. During this day, total coal power output must increase from 58% to 100% to meet the rise in net load as the sun sets. RPS policies generally produce a generation mix rich in VRE and coal generation (see Figure 5), which places more operational stress on coal power plants than when natural gas or storage provides more of the system flexibility.

DISCUSSION

Over the next several decades, India will face the dual challenge of increasing the supply of electricity to meet rapidly growing demand while mitigating air pollution and CO₂ emissions. Under a policy that imposes CO₂ emissions limits on the system, our results indicate that solar PV will become the largest renewable source of electricity, while the potential for wind power assumed in this study will be fully exploited. The resulting renewable penetration in 2040 ranges between 40% and 65% of total electricity generation, which increases the need for power system flexibility. Hydro represents about 7%, while wind varies between 10% and 18% and solar generation between 17% and 40%. These penetration levels imply as much as 300 GW of
wind and 721 GW of solar capacity by 2040. Although India has sufficient VRE resource potential to realize such capacity (Gulagi et al., 2017), deploying large amounts of VRE needs to be considered in the context of land acquisition challenges (Mohan, 2017), the societal and political implications of which are outside the scope of this study. Energy storage and natural gas power plants deliver most of the flexibility in the scenarios with emissions limits. While ramping the coal fleet could, in principle, provide additional flexibility, coal is rendered less economic in these scenarios due to the relatively high carbon intensity of coal generation. In contrast, under RPS policies, the existing coal fleet (assumed to be retrofitted with air pollution controls) is typically a lower-cost flexibility solution that provides substantial ramping capacity. Detailed operational results show that one-quarter of the coal power plants may need to start up within 3 h to accommodate the largest fluctuations in VRE under RPS policies.

When comparing tradable CO₂ emissions limits and RPS policies, the former is more cost-effective as a means to reduce CO₂ emissions. The difference in the CO₂ abatement cost between the two policies is substantial under several of the technology combinations, particularly under high energy storage costs. This observation, which is particularly important for a coal-dominated power system such as India’s, is due to the technology flexibility enabled by a CO₂ emissions limit, which allows natural gas to compete as a mitigation option. A limit on CO₂ emissions is also more effective at reducing air pollution emissions because these policies provide a more explicit incentive to reduce the use of coal. In contrast, RPS policies do not create an incentive to shift from coal to natural gas, as CO₂ emissions are not explicitly penalized. At the recently concluded 2021 COP26 climate summit, India committed to increasing its non-fossil fuel energy capacity to 500 GW and that 50% of its electricity generation capacity should come from renewable energy by 2030 (Sinha, 2021). These goals suggest that renewables-oriented policies continue to be favored in India.

Our investigation of a tradable CO₂ emissions limit is not meant to suggest that it is the policy instrument that we expect the Indian government to select. Rather, we use this instrument in a capacity expansion...
framework as a means of studying the most cost-effective CO₂ reduction strategy. In the real world, other policies and measures could be used to promote similar outcomes. While it is beyond the scope of this work to address the political feasibility and social acceptance of various instruments, modeling an explicit CO₂ emissions limit provides insight about the type of technology deployment actions that would be consistent with the least-cost CO₂ reduction strategy.

In addition to discussing a number of barriers to gas growth, (Malyan et al., 2021) also point out that multi-billion dollar investment and low gas prices are creating a favorable ecosystem for gas adoption in India. While increasing imports of natural gas could raise issues of energy security, (Das et al., 2021) note that, under certain IEA-projected scenarios, India’s energy security by 2030 could increase as natural gas imports from countries outside the Middle East become cost competitive. In addition, domestic sources of natural gas would not raise similar issues. To reiterate, while policy will play a critical role in determining whether the government’s overall objective of gas growth in India is realized, a detailed discussion on the economic, political, and social feasibility of gas demand and infrastructure expansion is beyond the scope of the current study.

In summary, India’s large and rapidly growing power sector plays a key role in its overall objective to achieve net zero emissions by 2070 (Sinha, 2021). Our results indicate that future power system solutions with greater technology diversity, including contributions from renewables, natural gas, and energy storage, would generally be more cost-effective at meeting future carbon emissions goals than solutions
that primarily pair renewables and energy storage with incumbent sources, namely coal generation. The former approach also tends to yield significantly lower SO\textsubscript{2} and NO\textsubscript{x} emissions. Noting the possible socio-political advantages to relying more on incumbent sources, we recognize that a variety of different factors ultimately need to be considered. Our results provide a scenario-based, techno-economic perspective to the power sector expansion challenge, which can be used alongside other types of analysis to inform future power system planning efforts.

The conclusions from this study could be refined in future work by explicitly considering the time path of the generation mix over 20 years, as well as energy-environmental objectives beyond 2040. Furthermore, additional information about electricity demand from different sectors, including transportation, and how this might evolve in the future could further inform modeling of the electricity system. It is also important to consider system resilience to climate change and extreme weather (Perera et al., 2020) when assessing different supply options. Nevertheless, we believe that our study contributes to the current discussion on how India could meet its environmental objectives and transition to a lower-emission power system while reliably meeting growing national electricity demand.

Limitations of the study

The model takes the vantage point of a centralized planner seeking to determine least-cost generation and storage to meet hourly load for a single future year, disregarding some market dynamics (e.g., risk aversion). The model is solved as a relaxed mixed-integer linear programming (MILP) problem that does not fully take into account the unit commitment constraints, which may be a substantial simplification, especially when modeling power systems with high VRE generation (Mallapragada et al., 2018). Nevertheless, we compared the results from the MILP and relaxed LP variants of the model in (Rudnick, 2019), and found relatively small differences in expansion results.

Another potential limitation is the lack of inter-annual resolution. In the optimization lexicon, our model is known as a “two-stage” planning model as it considers only two distinct stages of the power grid’s evolution. The first stage represents the 2020 grid infrastructure, while the second stage represents the year 2040, including the load profiles and techno-economic parameters for that year. In contrast, the ReEDS-India model (Rose et al., 2020) and the ORDENA model (Central Electricity Authority, 2020) formulate the capacity expansion problem as a “multi-stage” planning problem as they allow for capacity to be built sequentially over multiple years (but at the expense of lower intra-annual resolution). As costs decline over time, a multi-stage least-cost optimization model may, for example, choose to invest in fewer VRE and storage options in early stages when costs are higher, leading to less VRE capacity in later stages. Meanwhile, a two-stage model could potentially overestimate the capacity and generation of cheaper future options because these options appear to have low costs in the single future period for which investment is optimized. We believe that our scenario-based approach provides some immunization against this potential overestimation as the scenarios themselves have substantially different cost structures. Furthermore, we only considered one year of time series data for load and VRE. Other studies, e.g. (Mallapragada et al., 2018) and (Jafari et al., 2020), illustrate the advantage of using multiple years of such data for capacity expansion. However, we did not have access to such data for India.

A “pipe-and-bubble” transmission representation is considered to model hourly flows between major regions in India subject to transmission limits (Figure 1). While such an approximation is commonly used in capacity expansion models, it means that reactive power and Kirchhoff’s laws to enforce AC optimal power flow are neglected. In addition, in order to reduce computational complexity, we assume no explicit losses from the transmission of electricity between zones. However, transmission losses are already included implicitly as the regional peak load projections taken from (Central Electricity Authority, 2017b) consider losses in the transmission and distribution systems.

We did not consider transmission expansion endogenously, mainly due to computational challenges involved in jointly solving a generation expansion and transmission expansion problem. Instead, we assumed a transmission system forecasted by (Central Electricity Authority, 2016a, 2016b) that can accommodate the forecasted imports and exports between regions by that year. However, we did conduct sensitivity analyses which revealed that additional transmission capacity accommodates additional solar PV capacity, and thus, a higher solar PV share in the generation mix.
We do not consider cross-border power trade with neighboring countries. According to CEA’s forecast, 2021–2022 imports would represent only 1% of total generation (Central Electricity Authority, 2021). Looking ahead, CEA forecasts 6 GW of imported hydro power capacity out of 817 GW of total capacity (i.e., <1% on a capacity basis) in its report for 2029–30 (Central Electricity Authority, 2020). In stark contrast, while simulating a hypothetical 100% renewables-based electricity grid in 2030 for the South Asian Association for Regional Cooperation (SAARC), (Gulagi et al., 2017) found that cross-border electricity trade could play a more prominent role and ultimately reduce total costs. (Timilsina and Toman, 2016) also investigated the potential gains from cross-border electricity exchange in South Asia from 2015–2040 and found that it could reduce aggregate power grid spending and CO2 emissions.

We consider all major generation technologies except open-cycle gas turbines, utility-scale diesel engines, offshore wind, or carbon capture and sequestration technologies. CEA does not include these technologies in their national electricity plan. For example, operating diesel plants are expected to be retired by 2022 (Central Electricity Authority, 2018a). In addition, we aggregate coal, natural gas, and nuclear plants into technology clusters. Each cluster is assumed to have the same operational and technical characteristics, such as heat rate, ramp rates, and minimum power output. The incurred error of this clustering approach in practical applications is described in (Palmintier and Webster, 2016).

We do not consider methane emissions in this study. (Mallapragada et al., 2019) have developed life cycle analysis (LCA) approaches to calculate overall GHG emissions for natural gas and coal-fired power generation in India. According to their study, fugitive methane emissions from domestic coal mining are estimated to be 38.6 kg CO2eq/MWh, while the total methane emissions associated with the imported LNG life cycle amount to 46 kg CO2eq/MWh. These values are similar, and a relatively small fraction (~4%–8%) of the overall CO2eq emissions associated with either technology. Hence, we expect that contributions from methane emissions will have a limited impact on overall greenhouse gas projections from the power sector, as determined within this study.

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

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  - Operating reserves
  - Load and renewable energy profiles

Supplemental Information
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D.J.P., M.R.H.; Writing – Review & Editing, B.K.M., S.R., K.G.; Supervision, A.B. and D.J.P.; Project Administration, A.B.

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STAR METHODS

KEY RESOURCES TABLE

| REAGENT or RESOURCE | SOURCE | IDENTIFIER |
|---------------------|--------|------------|
| Deposited data      |        |            |
| India 2040 dataset  | Zenodo | https://zenodo.org/record/5946990 |
| Software and algorithms | GenX model | GitHub | https://github.com/GenXProject/GenX |

RESOURCE AVAILABILITY

Lead contact
Further information and requests for resources should be directed to and will be fulfilled by the lead contact, Pablo Duenas-Martinez (pduenas@mit.edu).

Materials availability
The study did not generate new unique reagents.

Data and code availability
All original code and data have been deposited at GitHub and Zenodo and is publicly available as of the date of publication. Links are listed in the key resources table.

METHOD DETAILS

Least-cost capacity expansion model
We find the least-cost mix of generation resources to meet the projected electricity demand in 2040 using the GenX capacity expansion model, which finds the optimal expansion plan for a future year considering unit commitment, transmission, and other operational constraints (Jenkins and Sepulveda, 2017).

The model takes the vantage point of a centralized planner seeking to determine least-cost generation, storage, and demand-side resources to meet hourly load for a single future year—in this case 2040. By treating 8,760 consecutive hours in this future year, GenX has a high intra-annual temporal resolution for operational requirements including: unit commitment (e.g. binary start/stop decisions and minimum up and down time constraints for thermal generators), hourly ramping constraints, and operating reserves as a function of the level of VRE in the system. Modeling consecutive hours chronologically, rather than using “time slices” as done in many other capacity expansion models, e.g (Rose et al., 2020), allows for a more faithful representation of electricity system dispatch, including energy storage. GenX formulates a deterministic mixed-integer linear programming (MILP) optimization model with perfect foresight of hourly loads and renewable capacity factors. The model can also be solved under a linear programming (LP) relaxation approach that relaxes the integer and binary variables to be continuous. Using an LP relaxation reduces the complexity of the optimization problem and, as a consequence, the computational requirement.

Scenarios
We develop 40 scenarios, accounting for uncertainty in future natural gas prices and costs for energy storage and VRE technologies, as well as different policy approaches for limiting CO2 emissions, as illustrated in Figure 2. Future technology costs are based on projections in (International Energy Agency, 2019) (Chaturvedi et al., 2018), (Cole and Frazier, 2019), (World Bank, 2019). The policy options include a tradable emissions limit (implemented as a constraint on CO2 emissions in the capacity expansion model, with two different limits considered) and an RPS (implemented as a lower limit on the annual VRE generation). The moderate CO2 emissions limit of 1,146 Mton/year is set to the same level as the historical emissions from the electricity sector in India in 2018, as reported in (International Energy Agency, 2019). The low limit of 486 Mton/year is in line with IEA’s SDS, as reported in (International Energy Agency, 2019), which was developed to be consistent with the aims of the Paris Agreement (The Paris Agreement, 2015). Furthermore, we consider two versions of the RPS, with the levels of the standard chosen to match VRE penetration...
levels projected in the two emissions limit scenarios. Finally, we also include an unconstrained scenario with no limit on CO2 emissions (or any other policy) as a benchmark for comparison.

**Transmission network**

A five-zone “pipe-and-bubble” transmission representation is considered to model hourly flows between major regions in India subject to transmission limits. We set the capacity for each interregional transmission link exogenously (before running GenX) based on the peak import and export requirements estimated by the CEA for the fiscal year 2035–36 in (Central Electricity Authority, 2016b, 2016c). Although GenX has the capability to treat transmission expansion decisions endogenously, we chose not to use this feature in our final experiments. Transmission (and distribution) losses are included in the regional peak load projections taken from (Central Electricity Authority, 2017b).

**Generation and storage technologies**

We consider all major generation technologies currently deployed in India such as thermal plants with unit commitment decisions (e.g. coal, natural gas combined cycle, and nuclear plants), VRE sources (e.g. solar PV, onshore wind farms and run-of-river hydro plants), storage plants (e.g. reservoir hydro and pumped-storage hydro plants) and other sources (e.g. biomass plants and behind-the-meter small-scale diesel generators). We also consider lithium-ion batteries with 4-h storage duration, although currently not deployed at a large scale in India. We do not consider open-cycle gas turbines, utility-scale diesel engines, or carbon capture and sequestration technologies. CEA does not include these technologies in their national electricity plan. The installed capacities for all considered technologies are summarized in supplemental information, Table S1.

Dispatchable technologies include coal-based plants, natural gas combined cycle units, nuclear plants, biomass-fired plants and behind-the-meter diesel generation sets. The power output from these plants can be controlled by their operators. The model allows defining unit commitment constraints for these technologies, such as ramping rates, startup costs, and minimum output levels, among others (Jenkins and Sepulveda, 2017). We aggregate coal, natural gas and nuclear plants into clusters. Each cluster is assumed to have the same operational and technical characteristics. We assume (forced and planned) outages for coal and nuclear plants based on the historical performance of both fleets in India, by de-rating plant capacities accordingly. Additionally, nuclear plants are considered baseload and not allowed to operate at output levels below 100% of de-rated nameplate capacity. Finally, we assume no technical constraints for behind-the-meter diesel generators, as they are considered fully flexible assets owned and operated by residential, commercial and industrial customers, as a backup source when facing blackouts in the main grid.

VRE resources include onshore wind plants, solar PV plants (behind-the-meter rooftop solar and utility scale solar plant, although we do not consider any different modeling assumptions between the two) and run-of-river hydro plants. Maximum generation from VRE is limited by hourly availability factors derived from (General Electric, 2018). VRE generation can be curtailed during surplus conditions. We aggregate 2022 state VRE availability factors into regional production profiles and use them as a proxy for the 2040 production profiles. Note that investments in wind and solar PV capacity are continuous decision variables, as opposed to investments in thermal capacity, which are discrete. Regarding hydro plants, we assume monthly capacity factors and water inflows of run of river plants, and reservoir hydro plants, respectively.

We define installations limits per zone for solar PV, wind and biomass sources, as summarized in supplemental information (Table S2). Solar PV and biomass installation limits are set according to (Central Electricity Authority, 2018a) while wind installation limits follow the potential defined in (Jethani, 2017). Nuclear, run of river, hydro, pumped-storage hydro and reservoir hydro plants follow predetermined expansion path (Central Electricity Authority, 2020), while no additional capacity expansion is allowed for behind-the-meter small-scale diesel generators. Finally, unlimited expansion is allowed for coal- and gas-fired plants and lithium-ion batteries.

Storage technologies include reservoir hydro, pumped-storage hydro plants and 4-h lithium-ion batteries. These technologies can either generate now or store energy for later. Pumped hydro plants and batteries can either charge by withdrawing energy from the grid, or discharge by injecting energy into the grid. Reservoir hydro plans, although usually classified as renewable sources, are represented in the model as...
energy storage plants that cannot charge but receive exogenous inflows to their storage reservoirs. We consider as reservoir hydro plants only those units considered as major reservoirs in (Central Electricity Authority, 2018).

Technical, fuel cost, and emissions assumptions for generation plants
Table S3 through Table S5 (supplemental information) summarize the technical assumptions per type of generation technology considered in the analysis. We assume forced and planned outages for coal and nuclear plants consistent with the historic performance of both fleets in India. The forced and planned outage for each technology is spread uniformly across the 8,760 h. (Considering that we are modeling clusters representing a fleet of several plants, spreading the outage uniformly along the year is equivalent to modeling that, on average, a specific percentage of plants are not available in every hour. This de-rating approach is commonly used in generation expansion studies.) We also de-rate the minimum output per plant by its availability. In contrast, we assume no technical constraints for backup diesel generators, as we include these sources as a type of demand response. Finally, we did not allow nuclear plants to operate at output levels below 100% of de-rated nameplate capacity.

We allow any continuous amount of VRE sources to be deployed into the grid, i.e. continuous investment variables. Solar and wind plants generation profiles and capacity factors are taken from (General Electric, 2018) while run-of-river hydro generation profiles are based on our own assumptions considering (Central Electricity Authority, 2018a) (Central Electricity Authority, 2018c), and (National Power Portal, 2018a). VRE plants can be dispatched down (i.e. curtailed) during surplus conditions.

We model storage technologies as continuous and fully flexible. Hydro reservoir assumptions are mostly taken from official CEA statistics (Central Electricity Authority, 2018b), adjusted to reflect the historical operations taken from (National Power Portal, 2018b). (Reservoir water inflows are modeled as a percentage of the maximum energy that can be stored in reservoir hydro plants per region. Hourly inflows modeled only present monthly variation, no daily or hourly variation is considered. The months with higher water inflows are July and August.) Table S6 (supplemental information) details the fuel and emissions assumptions undertaken in the analysis. Emissions considered in this study are CO₂, SO₂, and NOx. Gas prices are specified in Figure 2 of the main text and depend on the scenario simulated. The high price of $11/MMBtu is based on an assumed $7.50/MMBtu LNG delivered ex-ship price (consistent with publicly-available projections, e.g (World Bank, 2019)), plus a number of auxiliary costs: $1.80/MMBtu for regasification, $0.60/MMBtu for transmission, and $1.10/MMBtu tax (i.e., a mix of LNG import taxes and VAT, which varies by state). Meanwhile, the low price of $8/MMBtu allows for several possible outcomes to take place: an increase of cheap domestic gas is available for power; abundant global gas supply and reduced auxiliary costs lead to an overall cost reduction for LNG imports; or a combination of the two.

Operating reserves
We assume similar regulating and spinning reserves requirements to those defined in (Cole et al., 2018). We assume that regulating reserves must always be met, while the penalty cost of not meeting spinning reserves is set at 1,000 $/MWh. Regulating reserves depend on the amount of energy injected by VRE sources, 0.5%, into the grid plus the demand, 1%. Spinning reserves are defined as 3% of the demand plus 3,000 MW. The reserves contribution per technology are also mostly obtained from (Cole et al., 2018). Storage technologies may provide up to 100% of reserves, while coal and biomass may provide 20% of their capacity for regulating and 40% for spinning reserves. In a similar fashion, gas may provide up to 25 and 50%, respectively. As a conservative assumption, VRE and backup diesel generators are assumed to be unable to provide reserves.

Finally, we set the cost of load shedding at 9,000 $/MWh (Potomac Economics, 2018). We did not impose an explicit planning reserves requirement. We observed that by imposing operating reserves only, there is an adequate level of capacity in the system: 14 of the 40 scenarios do not show any load shedding. In the remaining scenarios, the average non-supplied energy is lower than 0.0005% of the total annual energy demand. Moreover, the maximum hourly load shedding observed in all 40 runs represents less than 4.5% of the total load.
Load and renewable energy profiles

We assemble a 2015 base load profile for each region by aggregating the load profiles available for every state in that region. State load profiles from 2015 are derived from (General Electric, 2018). We did not have access to load profiles from some states and union territories, such as Chandigarh (Northern Region), Puducherry (Southern Region) and all states in the Northeastern region. We assume that the load profile in the Northeastern region would be the same as in the Eastern region. Due to the lack of available data in some states and considering the approximations made in some state load profiles, there are differences in the maximum demand and total annual demand obtained by summing the state load profiles, between our assumptions and those reported by the CEA in (Central Electricity Authority, 2015) (Central Electricity Authority, 2016b). We use CEA’s 2037 regional peak load projections (Central Electricity Authority, 2017b) and then apply the average peak load growth rate from 2026–27 to 2036–37 to estimate regional 2040 peak loads. Then, we estimate the load profiles in the target year, by scaling up the load of each hour per region:

\[ \text{Load}_{r,t,2040} = \text{Load}_{r,t,2015} \times \frac{\text{Peak load}_{r,2040}}{\text{Peak load}_{r,2015}} \text{ for each region } r \text{ and hour } t \]

Note that little to no vehicle electrification is assumed in these profiles.

We derive solar and wind production profiles from (General Electric, 2018). We aggregate 2022 state production profiles into regional production profiles and use them as a proxy for the 2040 production profiles. The solar profiles do not have any distinction between rooftop and ground-mounted PV, while only onshore wind plants were modeled (General Electric, 2018). The generation profiles have an hourly resolution.