Evaluating Battery Storage in High Renewable Energy Scenarios for India

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***Abstract*—Declining costs of Lithium-based batteries can enable grid-scale storage to provide peaking capacity and energy balancing services, especially to systems with high variable renewable energy shares. Using a new capacity expansion model with high spatial and temporal resolution, we examine cost-optimal investments in generation and storage capacity for high renewable energy scenarios in India. While energy generation from both wind and solar photovoltaic technologies is becoming increasingly cost-competitive with India's traditionally dominant coal-based generation, low-cost battery storage will be key to a cost-effective transition towards deep decarbonization.**

I. Introduction

Building on its renewable energy target of 175 GW by 2022, India is poised to pursue much higher targets by 2030, mainly to take advantage of the low costs of solar PV and wind technologies. The Government of India's (GoI) Central Electricity Authority (CEA) projected the variable renewable energy (VRE - wind and solar) capacity to reach 440 GW by 2030 [1]. Higher penetration of VRE generation will increase the variability of net demand, which is defined as demand minus wind minus solar generation. Increased variability leads to greater curtailment of renewable energy and increased system costs caused by constraints on conventional generators such as minimum generation levels and limited ramp rates. Studies examining the impacts of high shares of VRE generation have shown the benefits of various strategies including larger balancing areas, greater flexibility of conventional generators, demand response, and optimal VRE capacity mixes [2], [3], [4]. The limited availability of natural gas and hydropower for providing peaking capacity and balancing resources coupled with the dramatic fall in international prices of battery storage systems [5], specifically Li-ion batteries, has triggered a significant interest in battery storage systems to help integrate VRE generation.

Many studies, mainly focused on the U.S. or European regions have employed capacity expansion models to examine the impacts of high VRE penetration and strategies including battery storage to reduce those impacts [6], [7], [8]. Other studies have analyzed the effect of storage on the value of wind and solar [9] and the storage duration required to reduce VRE curtailment [10]. Very few studies have focused on high VRE penetration in India and the role of storage [1]. In this study, we explore the impacts of different cost trajectories of wind, solar PV, and Lithium-based battery storage on generation and storage capacity investments while meeting different VRE generation targets of up to 70% by 2030. Insights from our analysis can inform capacity investments in conventional generation, renewable energy, and battery storage in India.

II. Methods

A. Model

We modeled India's electricity system using GridPath, a production cost and capacity expansion modeling platform. In this analysis we used GridPath's capacity expansion functionality to co-optimize power system operations costs and investments in new system infrastructure including generation and storage while meeting load, reliability, and policy goals. For details on the GridPath model, see [11], [12].

We simulated India's electricity system over 4 investment periods - 2018, 2022, 2026, and 2030. Each investment period represents four years. Within each period, we sampled demand, wind, and solar data for one day per month and 24 hours per day, giving 288 time points for each of the 4 investment periods. By minimizing total operations (variable) costs and investment (capital) costs across all investment periods, the model chose the most cost-effective deployment of conventional and renewable generation as well as storage to meet demand during all sampled time points. In this version of the model, we did not include transmission or demand response constraints or investments.

B. Data

We created hourly demand time series for the four investment periods by linearly extrapolating India's hourly demand data for 2014 [13] to meet future annual demand as projected by the 19th Electric Power Survey [14]. To simultaneously meet annual peak demand projections, we adjusted the shape of the demand duration curves by uniformly increasing or decreasing the load in peak hours and correspondingly decreasing or increasing the load in off-peak hours. For each month, we then chose one day for which daily electricity demand most closely matched the average daily demand for that month. Only days between the 11th and 20th days in a month were considered to ensure adequate temporal distance between subsequent sampled days.

Installed generation capacities for conventional generators were adopted from [3]. We assumed zero variable costs for hydro power plants. Variable costs for other existing conventional generators including coal, natural gas, diesel, and biomass power plants were adopted from [3].

For new candidate conventional generators, we considered only combustion turbine (CT or peaker) plants, combined cycle gas generators (CCGT), and super-critical coal power plants. We assumed both CT and CCGT new power plants will consume imported liquefied natural gas (LNG) because of limited domestic natural gas availability in India. We excluded new nuclear and hydro plants because of the uncertainty in their development. However, including these technologies in new capacity build-outs is unlikely to change the main conclusions of this study. We did not consider any retirements of power plants during the investment periods.

Cost and other parameter assumptions for new conventional plants are presented in I. We assumed that the real costs of both existing and new conventional generation plants remain constant across all investment periods.

For system operations, we captured the main constraints on conventional generation plants. We assumed average minimum generation levels of coal plants to be 60%, five percentage points above the Central Electricity Regulatory Commission's recommended level of 55%, because of the inability of some older power plants to comply with the lower level (Fig. I). We assumed minimum generation levels for natural gas generators to be lower than coal, a reflection of their greater flexibility. Because of the hourly resolution of the model, we did not include ramp rate constraints of conventional generators. The least flexible conventional generator – a coal generator unit – can have a ramp rate of 1 % of rated capacity per minute, which allows it to ramp from 60% to 100% of rated capacity in 40 minutes, less than the hourly time step of our model. Hydro storage was dispatched under energy generation constraints derived from monthly energy generation in 2014. Hydro run-of-river and pondage power plants were dispatched as non-curtailable variable generators with the same generation outputs from 2014. Nuclear and biomass generators were dispatched as must run generators.

TABLE I
PARAMETERS FOR NEW CONVENTIONAL GENERATION

	Coal	**CCGT**	**CT**
Capital cost [USD/kW] [15][1]	1,140	775	678
Annualized fixed cost [USD/kW-y]	140	78	65
Fixed annual O&M costs [USD/kW] [16]	42	11	7
Variable annual O&M costs [USD/MWh] [16]	5	4	11
Start up and Shutdown costs [USD/MW]	69	289	58
Discount Rate (real)	7%	7%	7%
Plant life [years]	25	25	25
Minimum generation level [% of rated capacity]	60%	50%	40%
Fuel cost [USD/GJ] [17] [18]	2.6	9.5	9.5
Heat rate [MJ/kWh] [19]	10.3	8.7	12.1

Capital costs from source are adjusted to 2018 US Dollars and include additional costs for environmental compliance.
Costs are in 2018 US Dollars.

We adopted wind and solar sites selected in [20]. The site suitability and site selection analysis followed the methodology outlined in [21], [4]. Wind and solar PV sites or potential project areas were selected using annual average wind speeds from [22] and annual average global horizontal irradiance (GHI) from [23] after excluding protected areas, water bodies, and certain land use land cover types (e.g. agricultural land in the case of solar, forested land for both technologies). For wind, we associated 100 locations with hourly modeled wind speeds [22] with the nearest potential project areas to estimate the capacity potential associated with each time series point assuming a land use factor of 2.25 MW per km^2. We then converted the wind speeds to hourly power generation by applying wind power curves as outlined in [4]. Similarly, for solar, we calculated the power generation [24] for over 600 locations with hourly modeled GHI [23] assuming fixed-tilt systems. We then associated these locations with the nearest potential project areas to estimate the capacity potential for each location using a land use factor of 7.5 MW per km^2. Because variability of solar generation reduces significantly after aggregation across large geographical areas, we aggregated the solar generation profiles for each state by taking capacity-weighted means of hourly generation. This aggregation reduced the number of candidate solar sites from over 600 to 17 and thus, reduced the size of our optimization problem. To maintain the temporal correlation between wind and solar generation and demand, we selected wind and solar hourly generation data from the same sampled days as demand data.

For 2018, we derived capital costs of wind and solar PV from India's 2017-18 renewable energy auctions (II). For battery storage, we considered only Lithium Ion (Li-Ion) batteries given their increasing cost competitiveness and widespread adoption [5]. We assumed costs of battery storage provided by NREL's Annual Technology Baseline [25]. Cost parameters with capital costs for 2018 are presented in II. All costs were assumed in constant 2018 US Dollars.

TABLE II
COST PARAMETERS (2018) FOR WIND AND SOLAR PV TECHNOLOGIES

	Wind	**Solar PV**	**Li-ion Battery**
Capital cost [USD/kW]	1,250	850	668
Capital cost [USD/kWh]			204
Fixed annual O&M costs [USD/kW]	15	10	37
Discount Rate	7%	7%	7%
Plant life [years]	25	25	15

Capital costs of wind and solar PV are adjusted for LCOE costs to match 2018-19 auction prices.
O&M costs and plant life of wind and solar PV are from [26].
Li-ion battery cost parameters are from [25].
Costs are in 2018 US Dollars.

C. Scenarios

For future cost trajectories, we assumed two scenarios each for renewable energy technologies and battery storage (Fig. 1). In the 'High Cost' scenario for VRE, we assumed that real capital costs of wind and solar PV would remain constant across all investment periods until 2030. In the 'Low Cost' scenario for VRE, we assumed capital costs of wind and solar PV power plants would fall at annual rates of 3% and 5% respectively. These annual cost declination rates are similar to those assumed in [25]. For the 'High Cost' and 'Low Cost' scenarios for battery storage, we assumed the 'Battery storage - Low' and 'Battery storage - High' projected cost trajectories for capital costs per energy and power capacity from [25]. Battery storage costs are projected to reduce from USD 1,484 per kW in 2018 to USD 1,314 per kW (USD 329 per kWh) in 2030 for the 'High Cost' scenario and to USD 486 per kW (USD 121 per kWh) for the 'Low Cost' scenario. Although we have shown costs of 4h Li-Ion battery storage in Fig. 1, we allowed the model to choose the optimal power and energy capacity for the new storage build-out.

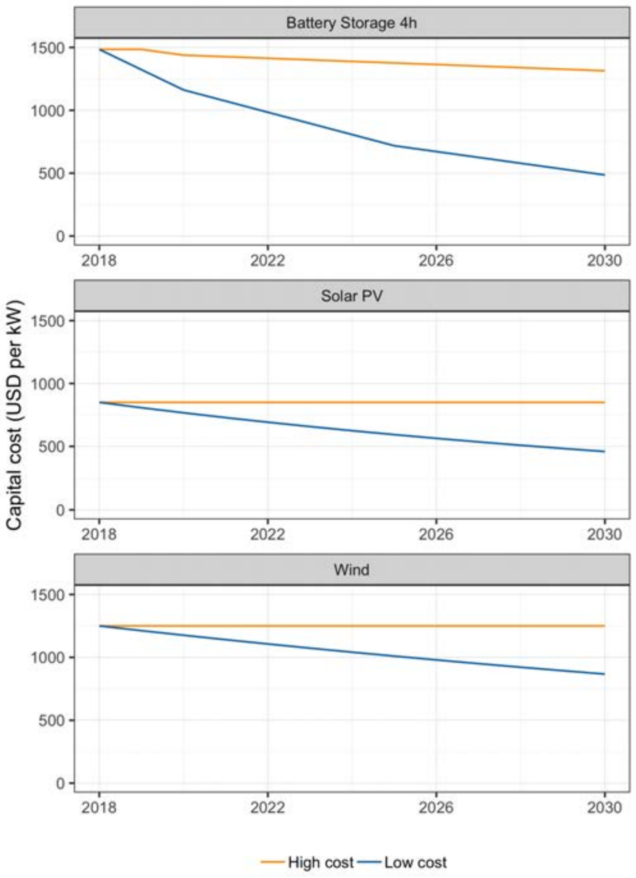

Fig. 1. Battery storage, solar PV, and wind costs.

In addition to the four combinations of 'High Cost' and 'Low Cost' scenarios for renewable energy and battery storage, we modeled four targets for renewable portfolio standards (RPS) or Renewable Portfolio Obligations (RPO) – 10%, 30%, 50%, and 70% – to be met by 2030. These targets are for only wind and solar generation and not other renewable energy technologies such as small hydro and biomass. Including the other renewable energy technologies would increase the share of renewable energy beyond the targets assumed in these scenarios. The 10% target approximately represents the 2018 share of wind and solar energy in India's power system and the scenario assumes that this share remains the same across all investment periods. In each of the higher renewable energy target scenarios, the annual targets increase linearly until 2030.

By varying the costs of wind, solar PV, and battery storage for different renewable energy targets, we aimed to understand the optimal balance between investments in new generation and storage capacities.

III. Results and Discussion

A. *New generation and storage capacity*

The GridPath India model selected the cost optimal new generation and storage capacities for each scenario subject to constraints on conventional generator operations, variable renewable energy generation including wind, solar PV, and hydro run-of-river, and hydro and battery storage energy and power availability. The optimal capacity build-outs change with variable renewable energy targets as well as costs of wind, solar PV, and battery storage.

With increasing RPS targets, naturally more wind and solar PV capacity is built (Fig. 2). When VRE costs are low, 400-440 GW of total wind and solar PV capacity is built cost-effectively, with VRE generation surpassing both the lower RPS targets of 10% and 30% (Fig. 3). In other words, if VRE costs follow the low-cost trajectory, wind and solar PV can cost-effectively meet approximately 40% of energy generation in 2030. However, when VRE costs are high, these lower RPS target constraints are binding. For higher RPS targets of 50% and 70%, the requirement for total VRE capacity is 540-560 GW and 850-950 GW, respectively.

If VRE costs remain constant until 2030 ('High Cost' VRE scenario), 34 GW and 16 GW of new coal capacity is built for the 10% and 30% RPS targets. If VRE costs follow the low-cost trajectory, new coal capacity is limited to zero or less than 1 GW in all RPS-target scenarios. For higher RPS targets of 50% and 70%, no coal power plants are built regardless of VRE or storage cost trajectories.

When RPS targets are low (10% and 30%), battery storage is built only when both VRE and battery costs are low. In these scenarios, low-cost battery storage of 22 GW helps offset 9 GW of conventional capacity that is built when storage costs are high. For the higher RPS target of 50%, battery storage is built only when its costs are low, resulting in approximately 50 GW of battery storage offsetting 17 GW of natural gas capacity built when storage costs are high. For the highest target of 70%, battery storage is required across all VRE and storage cost scenarios to balance the increased net-demand variability due to high shares of VRE generation. Thus, greater shares of VRE generation increases the value of energy storage in the electricity system, a finding which is in line with previous studies [27].

Except for the highest RPS target of 70%, all RPS targets result in investments in more wind capacity than solar capacity. When the 2030 RPS target is raised from 50% to 70%, approximately all additional VRE capacity is from solar PV. When greater battery storage capacity is installed, as a result of low battery storage costs, the share of solar generation in total VRE generation increases. Battery storage helps to balance increased diurnal variability in net-demand caused by solar generation. Hence, storage incentivizes new capacity of solar more than wind, the latter's variability being more inter-seasonal. Similar results were reported by other studies where storage increased the relative value of solar PV more than that of wind [9], [28].

Fig. 2. New generation and storage capacity build-out. Wind, solar PV, and battery storage capacities are total installed capacities in the 2030 electricity system. Conventional generation capacity is new capacity built from 2018 to 2030. Renewable Portfolio Standard targets (RPS) are for 2030 and include only wind and solar generation.

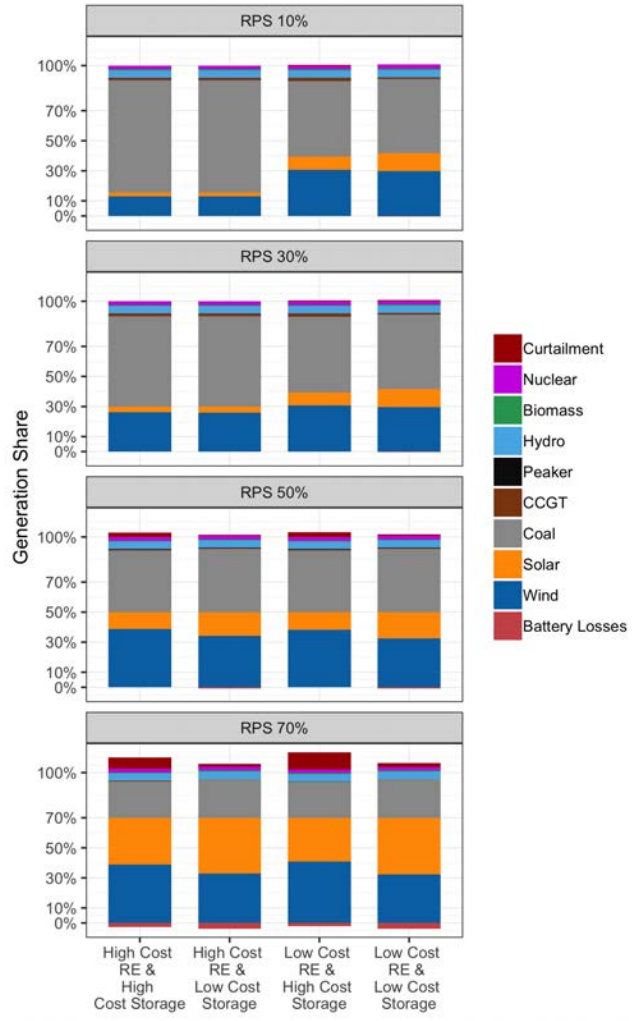

Fig. 3. Electricity generation, variable renewable energy curtailment, and battery losses as share of annual 2030 demand. Renewable Portfolio Standard (RPS) targets are for 2030 and include only wind and solar generation.

B. Electricity generation share

Greater shares of wind and solar generation forced by higher RPS targets displace mainly coal generation (Fig. 3). Shares of peaker and CCGT generation are small. Because of both greater installed capacities and higher capacity factors, shares of wind generation exceed those of solar generation across all RPS targets and cost scenarios except for the 70% RPS target scenarios with low-cost storage.

Renewable energy curtailment increases with higher renewable energy generation shares. Higher storage build-out enabled by low cost of batteries reduce curtailment of renewable energy. In the 70% RPS target scenario, the additional battery capacity in low-cost storage scenarios reduce renewable energy curtailment to a quarter of that resulting in the 'High Cost' storage scenarios. However, battery storage losses of 15% during the charge-discharge cycles requires generation to exceed demand. Note that the economic costs of these losses are included in the optimization problem.

C. Battery storage power and energy capacity

In this analysis, we allowed the model to choose the required power and energy capacity for battery storage instead of specifying a fixed charge-discharge duration. The ratio of energy to power capacity of the battery storage required by the system depends on the variability of its net-demand and the relative costs per kW (power) and kWh (energy) of the storage technology. For all low-cost storage scenarios, the energy-to-power ratio varies from 5 to 7 i.e. the duration of battery storage required is between 5 to 7 hours (Fig. 4). As the renewable energy shares increase, the duration of battery storage requirement reduces, potentially because of the increased diurnal variability of net-demand, which favors shorter duration batteries. Across all VRE and battery cost scenarios of the 70% RPS target, the duration of battery storage requirement is approximately 5 hours.

Our assumption of battery storage balancing across a horizon of a single day likely affects the required energy-to-power ratio. Balancing across longer timescales may change this requirement.

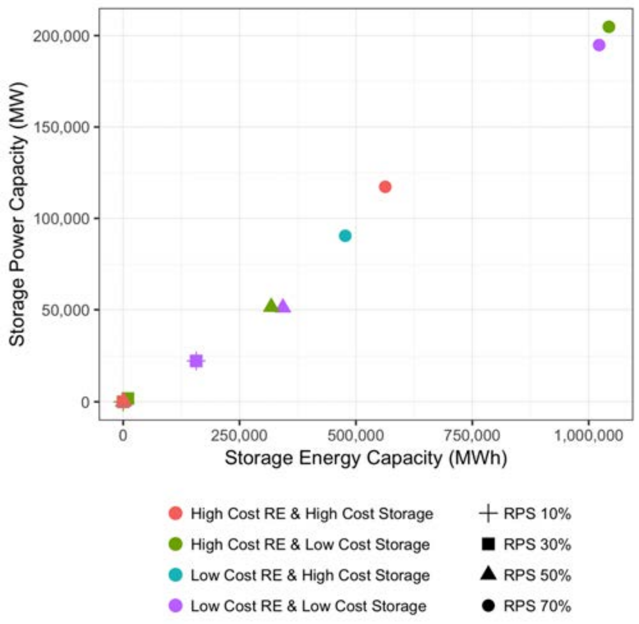

Fig. 4. New storage energy versus power capacity requirements. Renewable Portfolio Standard (RPS) targets are for 2030 and include only wind and solar generation.

D. Future work

The results presented in this analysis are preliminary. They illustrate the capabilities of the model under development. For reliability requirements, we intend to add planning reserve margin and primary, secondary, and regulation reserves to the model. The value of battery storage will increase because of its ability to provide ancillary services. We will also add project availability constraints to reflect low availability of certain power plants due to historical fuel shortages and forced outages. These constraints will lead to additional new generation and storage capacity, likely from coal and natural gas generators and battery storage. Additional renewable energy capacity may also be built but will likely be limited because of the low capacity value of both wind and solar in India.

The model presented here is a single node model without any transmission constraints. A future version of the model will include a higher spatial resolution of the transmission infrastructure, with multiple nodes each representing either a state load balancing area or a 400 kV substation with transmission transfer capacities specified between nodes. The model will then be able to optimize new transmission capacity in conjunction with new generation and storage capacity to meet future demand at least cost. Inclusion of transmission constraints will also lead to higher generation and storage capacity requirements, result in greater system costs, and may increase the value of storage during congested periods.

IV. Conclusion

In this study, we explored the effects of different cost trajectories for solar PV, wind, and battery storage and multiple renewable energy generation targets on new capacity investments in India's electricity system until 2030. Co-optimizing capital investments and operations costs enabled the selection of cost-optimal generation and storage capacities to meet India's future demand.

When costs of solar PV and wind decline from average auction winning bids in 2017-18 at annual rates of 5% and 3% per year until 2030, almost no new coal generation is built. If storage costs remain high i.e. 2018 real costs remain constant until 2030, storage is cost-effective only when the share of wind and solar generation is increased to 70% of demand in 2030. But if costs of storage follow a low-cost trajectory, investments in energy storage are cost-effective at VRE shares of 40% and above. Greater storage capacity reduces renewable energy curtailment and enables an increase in the share of solar PV in total VRE installed capacity.

We intend to improve the representation of India's present and future electricity system in the GridPath model. This modeling platform will be made open-source within the next year to aid in improving electricity system planning and operations.

Low-cost battery storage will be crucial to cost-effectively transition India towards deep decarbonization, especially in the absence of low-cost natural gas and limited hydro capacity. The GoI's "Transformative Mobility and Battery Storage" mission with its focus on battery manufacturing, electric vehicles, and stationary storage is a step in the right direction. Detailed electricity systems modeling can enable cost-effective planning of storage capacity in conjunction with investments in renewable and conventional generation.

Acknowledgment

The authors would like to thank the Power Systems Operation Corporation (POSOCO) for system operation and load data.

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