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A further decline in battery storage costs can pave the way for a solar PV-dominated Indian power system

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A B S T R A C T

India, mainly powered by coal, has adopted ambitious renewable energy targets and currently considers a climate neutrality target for 2050. The rapid growth of solar PV power faces challenges due to its variable generation resulting in a decline in its economic value. In this paper, we evaluate the potential of battery storage to stabilize the market value of solar PV for three scenarios of further battery costs decrease. We estimate optimal battery storage and power generating capacities and their hourly operation in a 2040 Indian wholesale electricity market using an open-source power sector model. We find that battery storage increases the optimal solar PV shares from ~40-50 % (without batteries) to ~65 % (90%) in our central (optimistic) battery cost scenarios, while they hardly increase in our pessimistic battery cost scenario. We conclude that if battery cost drop to below ~200 USD/kWh (including balance-of-system costs) they could become essential in a transition to a solar PV-dominant Indian energy system.

1. Introduction

In 2019, India was the third largest market for solar PV in Asia after China and Japan and the fifth largest globally [1]. Annual capacity additions of ~10 GW led to ~43 GW, by the end of 2019, with an additional 24 GW in the pipeline, keeping India on track for achieving its target of 100 GW solar PV by the end of 2022. Indian government officials are currently debating a 2050 net-zero green-house-gas emissions target [2]. Several scenario analyses [3–6] including a very recent IEA study [7] demonstrate that solar PV electricity is the most prominent low-carbon option for India.

However, as solar PV is a variable renewable energy source (VRE), there are well-researched challenges related to the temporal variability of its electricity output, specifically its mismatch with electricity demand [8–12]. This could become a potential barrier to the further expansion of solar PV. These physical challenges translate into a decrease of the market value of solar PV generation, which in functioning power markets corresponds to a decrease of the average income (i.e. market value) and competitiveness of a PV plant.

One major option for the provision of flexibility to better accommodate solar PV electricity is short-term storage [13,14]. Li-Ion batteries are one of the most prominent short-term storage technology largely due to their plummeting costs and high potential [15–17]. Costs are expected to decrease even further, although to what extent remains uncertain. While today batteries typically act as a short-term operational reserve and provide ancillary services [18], with increasing VRE shares, in particular solar PV, they generate income through arbitrage in intraday markets [19–22] and thus provide diurnal balancing of load and VRE supply, and reduce curtailment (at high solar shares) [23].

Flexible demand from temporally shifting electricity demand (in e.g. households or industry) can also provide short-term flexibility at lower costs [24]. However, demand-side measures are constrained in flexibility and potential. Not all end-use services (or their associated electricity input) can be shifted in time, consumers have limits in accepting for example a delay in end-use services and implementation is often challenging. Hence, it seems likely that both low-cost demand-side management with limited potential and higher-cost scalable batteries will be part of the solution.

While the majority of research on high-renewable energy systems has been conducted for industrialized economies (e.g. compare country distribution of studies in this review: [25]), there are three recent scenario studies that point to the potential of an immense scale-up of solar PV together with battery storage in India. Gulagi et al. (2017) [3] show batteries together with solar PV to be the low-cost backbone

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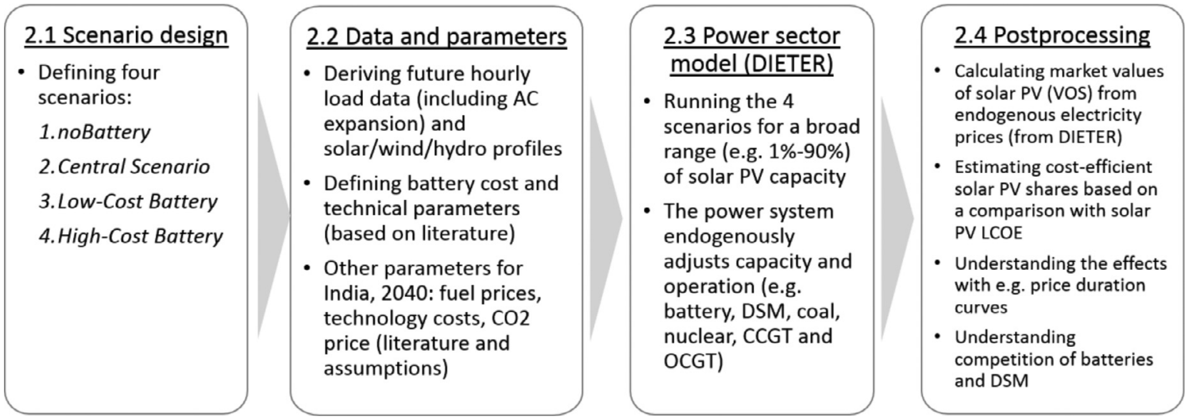

Fig. 1. Workflow of the analysis.

of a 100% renewable energy system in India by 2050. Spencer et al. (2020) [4] models pathways to 32% VRE in India by 2030, in which battery capacity was scaled up exogenously to 60 GW (120 GWh, 2h storage). Finally, Rose et al. (2020) [5] analyse the long-term power system transition in India (2017-2047) and include a high solar PV scenario, endogenous battery capacities (with fixed storage duration of 4h) increase from low levels in 2034 (~35% VRE share) up to 650 GW in 2047 (~70% VRE share).

In this paper, we want to investigate the underlying techno-economic interactions of solar PV, batteries, and increasing AC demand (and associated demand-side management options) that drive such solar-heavy scenario results for India. We model a wide range of system configurations from low up to very high shares of solar PV combined with three scenarios for future battery cost developments. This structured approach allows us to consistently explore the underlying drivers of solar PV and (endogenous) battery deployment and dispatch. We analyze hourly electricity prices and the increase of the market value of solar PV generation due to increased battery deployment (depending on their costs decline). This then determines optimal shares of solar PV in India. As air-conditioning is growing rapidly in India, we consider the competition of batteries with two demand-side management technologies using cool thermal energy storage (CTES) connected to the increasing AC electricity demand.

We focus the time horizon of our analysis on 2040, which allows us to explore a broad range of potential futures of the dynamic Indian power sector, while some existing capacity will still be standing (brown field approach). We use the power sector model DIETER [26] which is an open-source investment and dispatch model and that is well established for analyzing VRE and flexibility options for Germany [27]. We do not account for seasonal storage options such as hydrogen storage or power-to-liquids/gases as there is hardly seasonal mismatch in solar PV supply and Indian electricity demand, in particular with rising AC demand. Many input parameters of our modeling are uncertain such that we do not seek to derive exact numbers, but rather want to estimate the type and magnitude of effects that batteries can have on solar PV in a future Indian power system.

2. Methodology

We take the following four steps (Fig. 1) to estimate the effect of battery storage on the market value and the optimal share of solar PV. First, we develop four scenarios - three battery scenarios with different battery investment costs (*Central, Low-Cost Battery, and High-Cost Battery*) and one reference scenario with no batteries (*noBattery*) (section 2.1). Second, we adjust the DIETER model to the electricity system and market in India in 2040 under various exogenous solar PV shares and our above battery storage scenarios (section 2.2). We assume a well-functioning Indian electricity system which is fully inter-connected e.g. no transmission constraints. Key inputs to the model include hourly supply (solar, wind and hydro) and electricity demand profiles, assumptions concerning long-term policy constraints to mitigate climate change and fuel prices. Third, we run the DIETER model for each of our four scenarios to optimize battery investment and dispatch for our range of solar PV shares and extract the resulting wholesale electricity prices. We explain in detail the battery storage model in section 2.3. Finally, we estimate optimal solar PV shares using endogenous electricity prices and solar PV generation and an exogenous range of solar PV levelized cost of electricity (LCOE) (section 2.4). Optimal solar PV shares could also be derived by allowing for an endogenous investment in solar PV capacity. The main purpose of estimating market values and then comparing them with LCOE is to show the shapes of the economic supply (LCOE) and demand curve (market value) and how these are impacted by batteries (and their costs). With this approach we derive understanding behind the competitiveness and optimal shares of solar PV.

2.1. Battery cost scenarios

We explore four electricity supply scenarios with and without Li-Ion batteries in a highly air-conditioned Indian electricity system in 2040 over different shares of solar PV generation in the total electricity generation.

First, in our **No Battery** scenario, we explore how the market value of solar PV changes with different solar PV shares and determine the optimal solar PV share without batteries. Next, in our **Central Scenario**, we allow investment in batteries at a battery reservoir cost of 137 USD/kWh and battery capacity cost of 117 USD/kW as shown in Table 1 derived from total battery cost estimates given in Schmidt et al. 2018 [28]. Here, battery capacity refers to the rated capacity of the power conversion unit and battery reservoir refers to the battery system's rated energy capacity. For a 2-hour storage system in Schmidt et al. 2018 [28], these costs add up to 196 USD/kWh (storage duration is endogenous in our modeling). In the DIETER modeling the energy-to-power ratios are endogenously determined in each model run based on the capacity and reservoir cost components shown in Table 1.

The battery investment cost is one of the most important properties of storage technologies [9,24]. For example, Arcos-Vargas et al. [15] studied the impact of improving three battery characteristics namely round-trip efficiency, life cycles, and investment costs on the net present value of storage investments and found that past investment cost reduction contributes the most to the improvement of net present value. Hittinger et al. [29], in their pursuit of understanding what properties of grid energy storage are most valuable, also found that capital cost of storage was consistently important for combinations of application and storage type.

Table 1
Main scenario assumptions concerning battery investment cost

Battery parameter	Scenarios				Unit
	noBattery scenario (reference scenario: no flexibility from batteries)	*Central Scenario*	*Low-Cost Battery scenario*	*High-Cost Battery scenario*	
Battery reservoir cost	/	137	82	266	USD/kWh
Battery capacity cost	/	117	70	228	USD/kW

To explore the impact of battery investment costs and account for their uncertainty, we add two further scenarios with different battery investment costs also derived from uncertainties shown in Schmidt et al. 2018 [28]. In our **Low-Cost Battery** scenario, we assume a battery reservoir cost of 82 USD/kWh and battery capacity cost of 70 USD/kW, a 40 % reduction compared to the costs in our Central Scenario. In our **High-Cost Battery** scenario, we assume a battery reservoir cost of 266 USD/kWh and battery capacity cost of 228 USD/kW, double the cost in our Central Scenario.

To adjust their design to the electricity system needs, investments in battery reservoir and battery capacity are independent in our model (Section 2.3). This requires independent projections of battery reservoir and capacity costs. Schmidt et al. 2018 [28] provide long-term cost projections for different storage systems. However, they project only total battery investment costs. For the purpose of our analysis in this paper, we referred to Schmidt et al. 2018 [28] for 2040 total battery cost scenarios. We then disaggregated the assumed total battery cost given in USD per kWh for each scenario into the part scaling with reservoir in USD per kWh and the part scaling with capacity in USD per kW as required by the model. According to Mongird et al. [30], the reservoir cost for a Li-Ion battery system comes from the cost of electrodes, electrolytes and the separators and the capacity cost comes from the cost of the power conversion system (e.g. inverters, packaging, containers and inverter controls), the balance of the plant (e.g. site wiring and interconnecting transformers) and construction and commissioning.

Schmidt et al. [28] project costs of utility-scale Li-Ion battery systems for 2040 using modelled cumulative installed capacity and three different experience rates, i.e. cost reduction for each doubling of installed capacity in %, scenarios namely central, high, and low (12%, 15%, and 9%). Cumulative installed capacity for a given year in the future is modelled using sigmoid functions (S-curves) used to derive annual market growth projections. It is assumed that utility-scale storage systems reach market maturity by 2050 at an annual installed capacity of ~200 GWh.

As a result, 2020 costs for utility-scale Li-Ion batteries were 548 USD/kWh (high experience rate), 625 USD/kWh (central experience rate), and 790 USD/kWh (low experience rate). 2040 costs used in our paper show a decrease of 85% (high experience rate called low-cost scenario in our paper), 75% (central experience rate called central scenario in our paper) and 50% (low experience rate called high-cost scenario in our paper) compared to actual 2017 battery cost. Compared to 2020 costs for the same battery systems, we see a decrease of 80%, 70%, and 50% in the same scenarios. Our assumed 2040 costs for utility-scale Li-Ion battery systems resemble current costs for Li-Ion battery packs used in electric vehicles.

To give a point of comparison: Actual 2017 cost of utility-scale Li-Ion battery systems (>100 kWh systems with energy-to-power ratios >1) was 775 USD/kWh with a price reduction of ~16 % for each doubling of installed capacity. Global installed capacity of stationary utility-scale Li-Ion battery systems reach ~2 GWh. Current costs of utility-scale Li-Ion battery systems are cheaper than Li-Ion battery systems used for residential applications (<30 kWh systems with energy-to-power ratios >1) and much more expensive than Li-Ion battery packs used in electric vehicles for transport applications (>25 kWh packs with energy-to-power ratios <1).

For our **Central Scenario,** we assume a total battery cost of 195 USD per kWh as projected by Schmidt et al. 2018 [28] in their *Central Experience Rate* scenario. Cost projections are for a utility-scale Li-Ion battery of more than 100 kWh capacity with an indicative battery energy-to-power capacity ratio of ~2. Battery investment cost data in Schmidt et al. 2018 [28] is not differentiated across regions. Costs include transportation, installation, and commissioning. For our **Low-Cost Scenario**, we assume a total battery cost of 117 USD per kWh as projected by Schmidt et al. in their *High Experience Rate* scenario, a 40 % reduction compared to the cost in our Central Scenario. For our **High-Cost Battery** scenario, we assume a battery cost of 380 USD per kWh, double the cost in our Central Scenario, as in Schmidt et al.'s *Low Experience Rate* scenario.

Table 2
Li-Ion battery technical and cost assumptions

Parameter	Li-Ion Batteries	Unit
Annual fixed costs	10	USD/kW
Interest rate	7	%
Technical lifetime	20	Years
Efficiency	92	%

There is substantial uncertainty regarding reservoir and capacity cost shares in the total battery cost as it depends on the energy-to-power ratio of the battery system under consideration. For this study, using reservoir and capacity cost data for Li-Ion battery systems reported in Schmidt et al. [17] and assuming an energy-to-power ratio of 2 to be consistent with our total battery cost assumptions taken from Schmidt et al. 2018 [28] in terms of storage durations, we estimate the reservoir cost share in the total battery cost to be 70%. Based on a brief review of the literature [9,11,25,26] that report separately on the reservoir cost and the capacity cost of a wide range of Li-Ion battery systems, we find that the share of the reservoir cost in USD per kWh in the total battery cost to be in the range of 10-77 % (35 % average) for $\frac{1}{2}$ hour storage duration, 30-93 % (58 % average) for 2 hours of storage duration, and 52-97 % (74% average) for 5 hours of storage duration.

Even though we are overestimating the share of reservoir cost for a 2-hour battery system, it is consistent with the literature on the share of reservoir cost for battery systems with relatively long storage durations. Giving a higher weight to the reservoir cost share is a valid assumption as we anticipate future utility-scale battery systems to have higher energy-to-power ratios to be able to balance day and night fluctuations of VRE instead of short-term fluctuations. Next, we convert the capacity cost estimated previously in terms of USD per kWh to USD per kW. Other Li-Ion battery technical and cost assumptions are given in Table 2. Assumptions other than those shown in Table 1 are the same across all scenarios.

2.2. Further data and parameters

Apart from battery costs and scenario design, we use the same data and assumptions as in an early DSM-focused publication [31]. Total electricity demand reaches 3,535 TWh out of which around 23% is demanded by air conditioners in 2040 in India showing a significant increase compared to the current share of AC demand [31]. The impact of an increase in AC demand with its unique temporal profile that is expected to peak around 6 PM on the total electricity demand profile in India will be significant in many aspects. First, it will change the temporal profile of total electricity demand by advancing the overall peak demand by a few hours. Next, it will reduce the overall load factor to ~67% which is much lower than the load factors observed now. This is mainly due to the increase in peak demand induced by increased use of air conditioners early in the evening.

As the analysis at hand partly focuses on the interaction of batteries and DSM, we briefly summarize the DSM parameterization and other key assumptions. With the help of the DSM module in the DIETER model, we allow for the provision of flexibility by air conditioners using CTES which can directly respond to the wholesale electricity prices. Facilitating technologies include either programmable thermostats that manage storing the cooling energy in the building thermal mass during times of low prices and release it when prices increase, here called Precooling, or chilled water storage (CWS) tanks. We assume maximum total DSM installed capacity to be 2/3 of maximum hourly AC demand (2/3 of 350 GW), split evenly between two DSM measures to account for thermal comfort constraints in the case of precooling and space constraints in the case of chilled water tanks. In terms of power capacity provision, each technology can provide up to 116 GWs of power.

Electricity supply technologies modelled in our current analysis include solar PV, wind, coal, combined cycle gas, open cycle gas, and nuclear power plants. We assume a carbon tax of 50 USD/tCO_2 to capture the likely implementation of a climate policy to mitigate global climate change. We take a brownfield approach that allows us to combine the high detail of the DIETER model, which requires to limit the temporal horizon and to focus on one future year (2040), while considering plausible aspects of the energy transition until 2040. This comes with the challenge of reflecting intertemporal aspects such that the focus year can be regarded as a plausible part of a broader energy transition. For this purpose, the model optimization of investment and operation is constrained by a few limits and fixes reflecting the legacy of the today's system (especially for coal power), plausible developments (pumped hydro storage, hydro and wind power) and scaling constraints (nuclear power). More detailed explanations can be found in [31].

- A fixed capacity of 20GW of pumped hydro storage with a modest energy-to-power ratio of 4.
- A fixed capacity of 40 GW of hydro power with a capacity factor of 35 %
- A fixed capacity of 209 GW of wind which is equivalent to ~11% of total electricity demand.
- At least 147 GW of coal capacity to be standing by 2040.
- At most 47 GW of nuclear capacity.

The purpose of this paper is to add to the understanding of how batteries impact the economics of solar PV in India. We focus on deriving insights into the underlying economic mechanics rather than deriving exact numbers or future projections.

2.3. Battery storage modelling in DIETER

The power sector model DIETER [26] which is an open-source investment and dispatch model DIETER minimizes total system costs over 8760 hours of an entire year ensuring that all costs are recovered from the electricity sales. Total system cost comprises annualized fixed costs (e.g. capital and fixed operation, and maintenance costs), and variable costs of dispatchable power generators (e.g. fuel, CO2 and load change costs), variable renewables, storage, and demand-side management (DSM) technologies. Some key constraints of the optimization include the balancing of energy and generation, DSM and storage capacity restrictions. Key inputs to the model include hourly supply (solar, wind and hydro) and electricity demand profiles, assumptions concerning long-term policy constraints to mitigate climate change and fuel prices. Key outputs of the model include total system costs, investment into generation, DSM and battery storage capacity, their optimal hourly dispatch to meet the electricity demand, and the resulting wholesale electricity prices.

We use the battery model in DIETER Version 1.0.2 to simulate battery investments and energy arbitrage in an energy-only market with scarcity pricing. Wholesale electricity prices in DIETER come from the marginal of demand balance equation. In other words, it is the cost of meeting one additional unit of electricity demand. The following equations show how battery charging and discharging are formulated in DIETER. Battery round-trip efficiency (ε_{sto}) losses in the battery dynamics equations 1 and 2 and are attributed equally to battery charging and discharging.

$$STO^{l}_{sto,1} = \varphi^{ini}_{sto} * N^{E}_{sto} + STO^{in}_{sto,1}\frac{\left(1+\varepsilon_{sto}\right)}{2} - STO^{out}_{sto,1}\frac{2}{\left(1+\varepsilon_{sto}\right)} \tag{1}$$

$$STO^{l}_{sto,h} = STO^{l}_{sto,h-1} + STO^{in}_{sto,h}\frac{\left(1+\varepsilon_{sto}\right)}{2} - STO^{out}_{sto,h}\frac{2}{\left(1+\varepsilon_{sto}\right)} \tag{2}$$

Where $STO^{l}_{sto,h}$ is the storage level in GWh, φ^{ini}_{sto} is the initial storage level as a fraction of storage energy installed, N^{E}_{sto} is the battery reservoir installed capacity in GWh, $STO^{in}_{sto,h}$ is the hourly battery charging in GW, and $STO^{out}_{sto,h}$ is the hourly battery discharging in GW. The model also assures that energy stored after the last hour must equal the initial level.

Investments into battery reservoir or energy and power capacities occur independently and power investments are assumed symmetric between battery charging and discharging Equations 3-(5). The energy-to-power ratios are endogenously determined by the DIETER model and can change across model runs.

$$STO^{l}_{sto,h} \le N^{E}_{sto} \tag{3}$$

$$STO^{in}_{sto,h} \le N^{P}_{sto} \tag{4}$$

$$STO^{out}_{sto,h} \le N^{P}_{sto} \tag{5}$$

Where N^{P}_{sto} is the battery power/ inverter installed capacity in GW. Equations 6 and 7 restrict power flows in and out of batteries to the available energy in the battery reservoirs.

$$STO^{out}_{sto,h}\frac{2}{\left(1+\varepsilon_{sto}\right)} \le STO^{l}_{sto,h-1} \tag{6}$$

$$STO^{in}_{sto,h}\frac{\left(1+\varepsilon_{sto}\right)}{2} \le N^{E}_{sto} - STO^{l}_{sto,h-1} \tag{7}$$

2.4. Postprocessing

We define market value of solar PV here as the ratio of total wholesale revenues of solar plants and the total gross solar generation (i.e., potential generation before curtailment) (Equation 8).

$$Market\ value = \frac{\sum_{h=1}^{8760} P_h G_{PV}}{\left(\sum_{h=1}^{8760} G_{PV} + \sum_{h=1}^{8760} CU_{PV}\right)} \tag{8}$$

where P_h is the price of electricity, G_{PV} the solar PV feed-in to the system, and CU_{PV} is the solar PV curtailment.

The optimal solar PV share is then the solar PV share at which solar PV's market value equals its expected levelized cost of electricity (LCOE). For further assumptions on solar PV generation revenues and costs, refer to [31]. We follow a method similar to [32] where we first quantify the decrease in the market value of solar PV and the optimal solar PV share without batteries. We then allow investment in batteries and quantify the change in the market value of solar PV. In addition to showing optimal solar PV shares with and without batteries, we also show the underlying physical and economic reasons behind the changes in the market value of solar PV with batteries and the interaction of batteries with flexible air conditioning electricity demand.

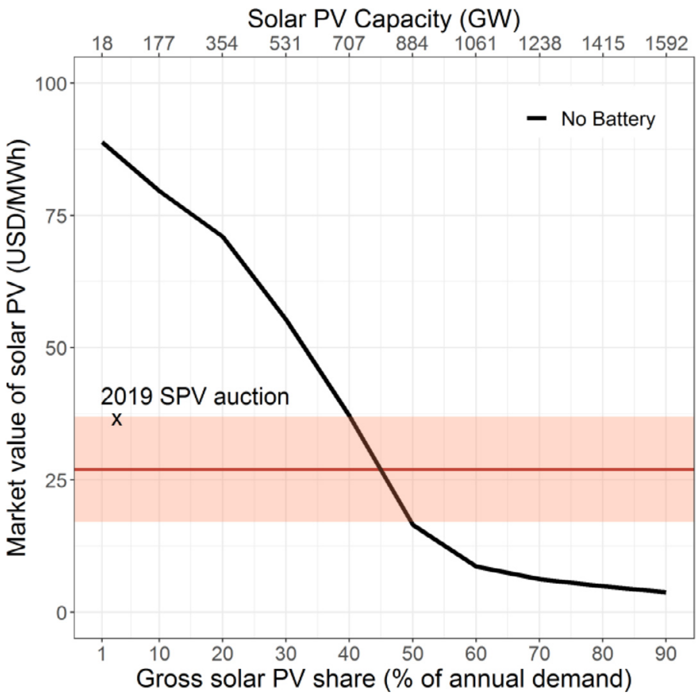

Fig. 2. The drop in the market value of solar PV and the optimal solar PV share in the No Battery scenario.

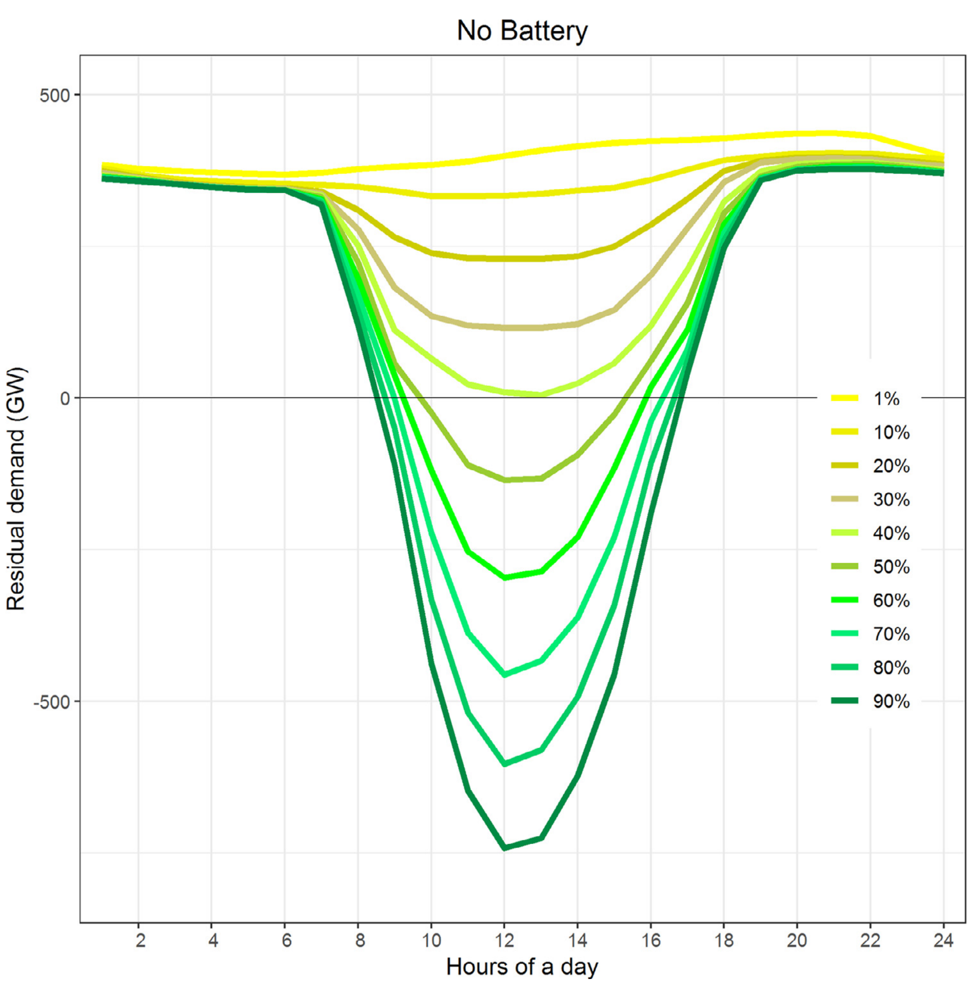

Fig. 3. Annual average hourly total residual demand of one day for the No Battery scenario with increasing solar PV generation shares. Residual demand is the difference between gross solar PV generation and electricity demand. Note that CTES provides some demand flexibility such that the evening demand peak can be shaved.

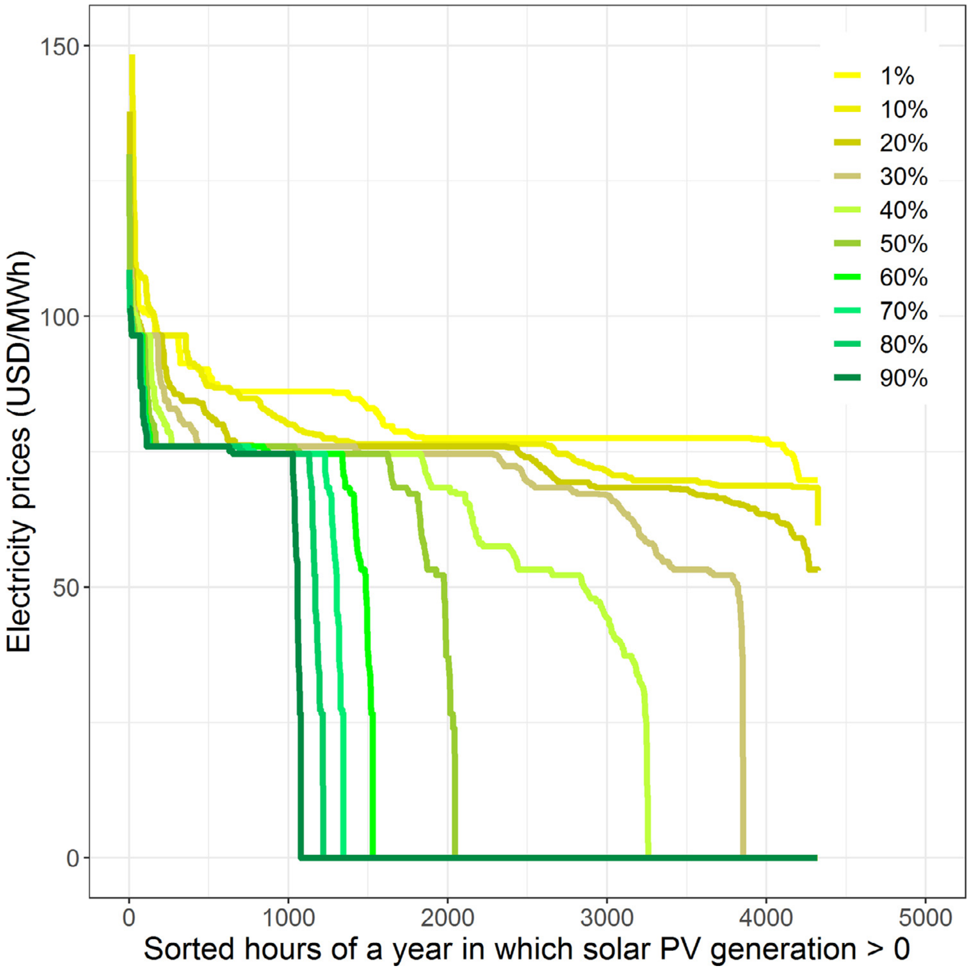

Fig. 4. Electricity price duration curves (No Battery scenario). The number of zero-price hours increase with solar PV generation share. Low solar PV generation also occurs a few times during scarcity price hours (>1000 USD/MWh) that cannot be displayed here.

3. Results

3.1. Optimal solar PV shares without batteries

In our *No Battery* scenario (Fig. 2), we find optimal solar PV shares to be ~40-50 % assuming a wide range of solar PV LCOE (17-37 USD/MWh) in India in 2040. Note that optimal solar PV shares are defined by the intersection of the market value and the levelized cost of energy (LCOE) of solar PV.

The market value of solar PV sharply declines from ~90 USD/MWh at 1 % solar PV share to less than 4 USD/MWh at 90 %. This decline is caused by the mismatch between temporal supply and demand profiles as well as by the self-correlation of additional solar PV generation, as captured in the residual demand curves of an average day in Fig. 3. With increasing PV share in the *No Battery* scenario, the residual electricity demand drops significantly as all solar PV plants in aggregate generate electricity at the same time. Beyond 40 % solar PV share, average solar PV generation starts exceeding average electricity demand around noon.

Already at low PV shares, there is a mismatch of solar PV supply and average daily peak demand, which occurs in the evening at around 8 pm. Some of this peak demand can be indirectly shaved by solar PV through moving demand forward in time via flexible cold thermal energy storage CTES, which is available already in the *No Battery* scenario. Moving demand forward in time is somewhat equivalent to moving generation backward in time via battery storage. However, CTES flexibility is limited by the temporal profile and overall electricity demand of air conditioning such that most of the solar-CTES synergies are realized already at low solar PV shares (~10%).

Average curtailment rates (also see Fig. 12 in section 3.4.) are ~2 % at 30 % solar PV share, ~16% at 50 % and ~35 % at 70 % solar PV share. Marginal curtailment, in contrast to average values, is defined here as the additional system-wide curtailment when adding one unit of solar PV and tend to be higher than average curtailment rates.

Fig. 4 shows the price duration for hours of the years in which solar PV plants are generating, i.e. revenues as seen by solar PV operators. At 30 % solar PV share, in the *No Battery* scenario, ~11% of the solar-PV generating hours face zero prices while this number reaches ~53 % at 50 % solar PV share and 70% at 70 % solar PV share. Electricity prices become zero when solar PV generation with very low or zero operating cost exceeds demand and sets the price of electricity. The more the number of hours with solar PV overgeneration, the more the number of hours with zero prices. The increase in the number of zero-price hours is very pronounced during 30-50 % because the minimum of the residual load curves cross the x-axis in Fig. 2. The decline in the market value of solar PV is thus steeper at 30-50 % solar PV shares (Fig. 2).

3.2. Deployment of batteries

When allowing for battery investments in the model, we find that their deployment grows with increasing solar PV shares. Fig. 5A to D display this optimal deployment from different angles for a range of battery cost assumptions. Investments in battery power capacity and energy reservoir (Fig. 5-A and C) start at 20-40 % solar PV share depending on battery costs and increase to high values of 525 GW and ~3500 GWh at 90 % solar PV for the *central scenario*. While the *central* and *low-cost scenario* results are similar, battery deployments remain at lower levels when assuming high battery costs. Battery deployment also

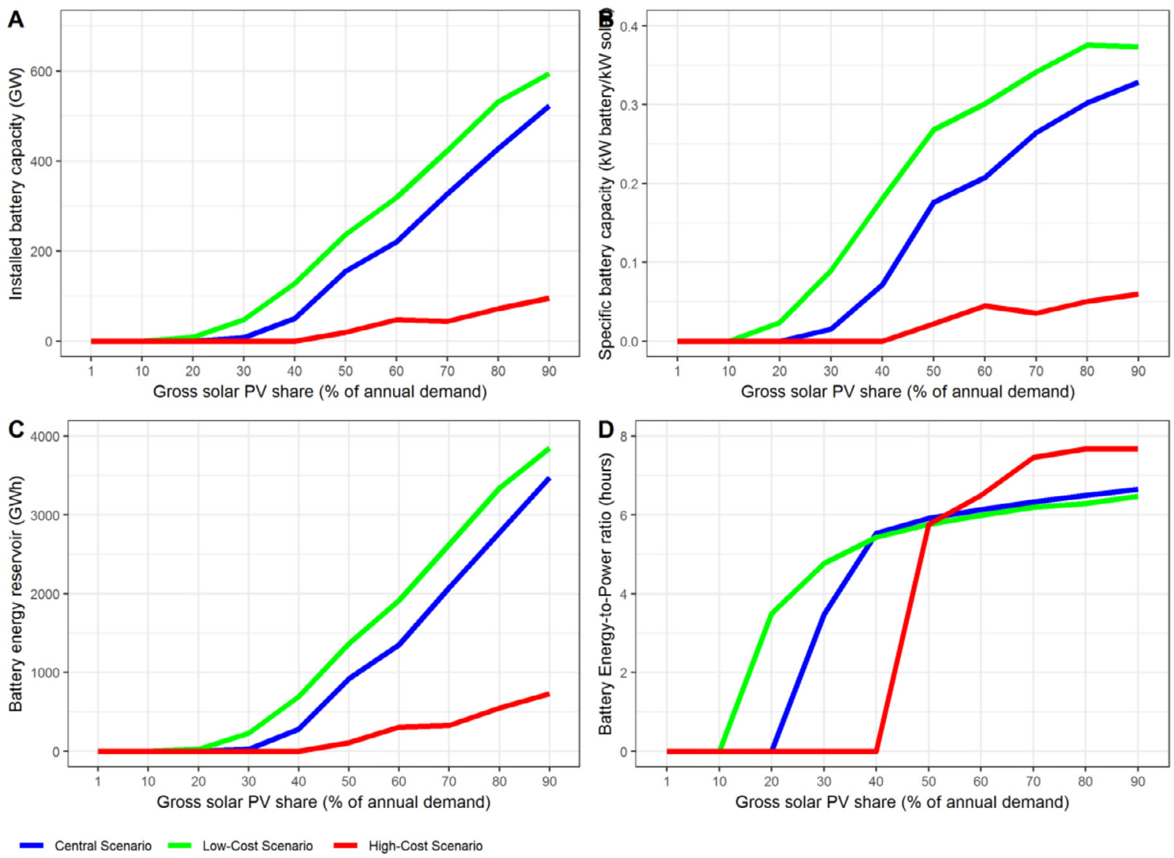

Fig. 5. Battery investments at different solar PV shares. A) Total battery inverter capacity in GW, B) Battery specific capacity in kW battery per kW solar PV, C) Total battery reservoir capacity and D) Optimal battery inverter to reservoir capacity ratio.

increases in specific terms, i.e. in relation to solar PV investments for all scenarios. In the *central scenario*, specific installed battery capacity per capacity of solar PV is ~0.02 kW battery/kW solar PV at 30% solar PV, increases to 0.26 kW battery/kW solar PV at 70% solar PV share and reaches 0.33 kW battery/kW solar PV at 90 % solar PV share (Fig. 5-B). We also find that optimal energy-to-power ratios are in the range of 4-8 hours of storage with a tendency of longer storage durations at higher solar PV shares for all three battery cost assumptions (Fig. 5-D).

Fig. 6 shows battery deployment results in terms of short-term storage reservoir in relation to total annual demand as a function of VRE share that is solar PV share in addition to 11% wind. For comparison purposes, we added results from modeling studies and reviews, partially for other regions: India [3,4,33], EU [14], Germany [27], the US [34] and Texas [35]. These studies explore different short-term storage such as Li-Ion batteries, redox flow batteries, PHS, and compressed air energy storage (CAES) with storage durations less than 24 hours for different solar-wind mixes of VRE. For a broader review of storage requirements as a function of the share of VRE sources, see Zerrahn & Schill [36] or Cebulla [37].

The comparison shows that our short-term storage deployment results in the Central and Low-Cost scenario are in the range of those in the literature. The difference in storage deployment levels at any given gross VRE share can be explained by 1) storage investment costs, 2) the degree of solar PV curtailment reduction, and 3) other competing flexibility options such as transmission, flexible generation or load and 4) the wind-solar mix of VRE. Only one scenario from Schill & Zerrahn [27] is in the range of our significantly lower battery deployment results of the High-Cost scenario; however, this is a wind-heavy scenario which does not benefit much from diurnal battery operation.

We find that the deployment of batteries increases dramatically at PV shares greater than 30-40%, because at those shares, a) other (cheap) sources of flexibility, like demand response from air conditioning, reach their maximum use, b) the amount of days in which solar PV generates as much as or even more than demand during midday - and thus allows batteries to charge at low or zero electricity prices - increases substantially, leading to a high number of charge/discharge cycles.

3.3. Interaction of batteries and DSM

Batteries and DSM technologies (here two types of CTES) can provide flexibility on similar time scales, i.e. shift electricity supply and demand within hours. The model endogenously decides on the investment and operation of both competing flexibility options based on costs, flexibility, efficiency, and overall potential (which is not limited to batteries). The investment costs for the power capacity of CTES are four (CWS) or thirteen (precooling) times lower than those of batteries (*central scenario)*. Low-cost CTES capacities require relatively small price spreads or differences in electricity price when shifting load from early evening to mid-day and are thus scaled up irrespective of battery costs already at low solar PV shares (<30%) (Fig. 7, left). By contrast, more capital-intensive batteries require higher price spreads, which they can achieve at high solar PV shares while making use of their higher flexibility (Fig. 7, right).

Note that the CTES investment cost advantages outweigh their limited flexibility and lower efficiencies. Precooling and CWS can shift demand by a maximum of 4 and 8 hours respectively and have efficiencies of 70-90 % (precooling 70 % and CWS 90 %) compared to 92 % of batteries. CWS reaches its full potential of 116 GW already at 1 % solar PV share in all the scenarios. Precooling, however, reaches its full potential of 116 GW at 20 % solar PV share in all the scenarios. At higher solar PV shares, CTES are complemented with batteries, which reach installed ca-

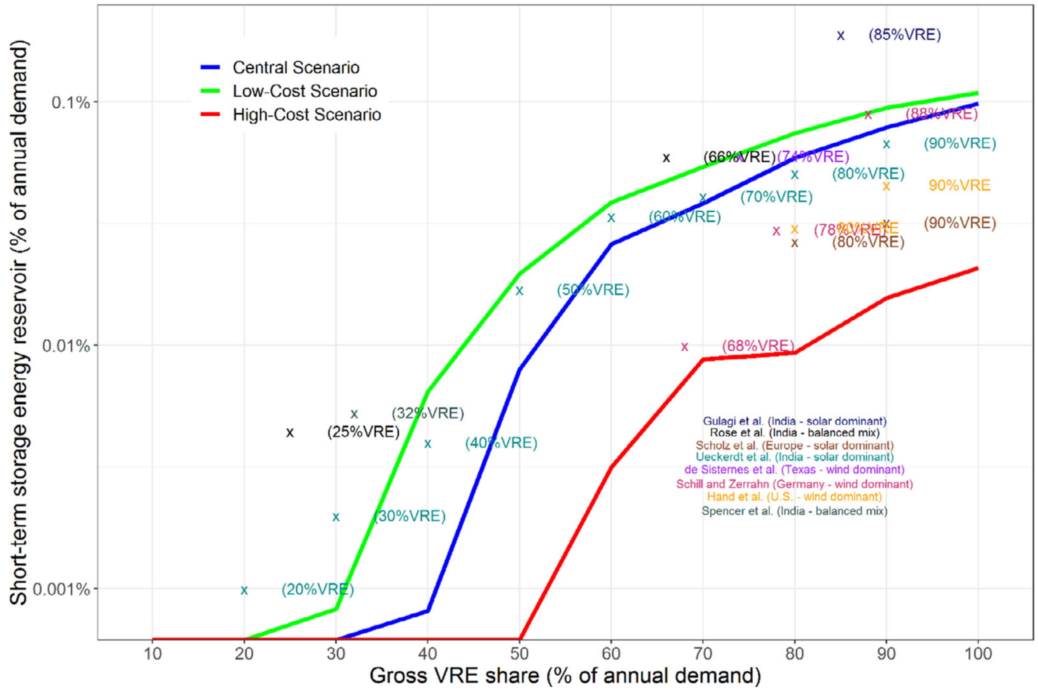

Fig. 6. Short-term storage energy reservoir (% of annual demand). VRE shares for our study are always gross solar PV share plus 11 % gross wind share.

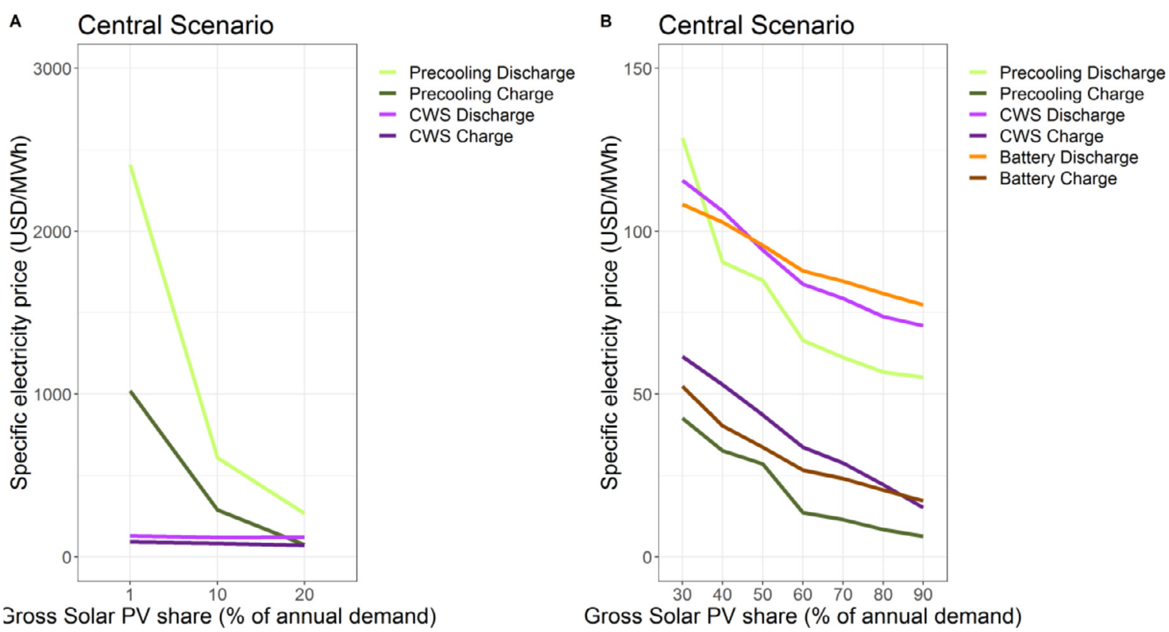

Fig. 7. Specific electricity price for charging and discharging of batteries and CTES. The results shown here are from the Central Scenario only.

pacities levels that are 2-4 times as high as the exploited CTES capacity potential.

The cost-efficiency and profitability of batteries (and CTES) is determined not only by price spreads (Fig. 7), but also by the annual utilization (Fig. 8). While the endogenous CTES capacities remain the same throughout battery cost scenarios, the utilization of CTES, in particular for *precooling*, decreases with increasing battery deployment. Due to its low specific capacity costs, CTES can recover its costs already at low levels of annual utilization. This can also be seen in a detailed example in Fig. 9, which shows the dispatch of generation technologies, CTES, and batteries for three days in August for 70 % solar PV shares across all four scenarios. Batteries store all curtailment on moderately sunny day one, while CTES operate on sunnier days two and three to utilize solar curtailment that cannot be stored as all battery reservoirs are filled up. As described above, batteries are more flexible and efficient and are thus dispatched before CTES.

3.4. Optimal solar PV shares with batteries

Our results show that battery investments increase optimal solar PV shares. According to Fig. 10, optimal solar PV shares in our Central Scenario increase to ~65 % (50-90 % for the assumed solar PV LCOE range) up from 45 % in our No Battery Scenario. If battery costs decrease further (Low-Cost scenario), the optimal solar PV share is pushed even higher to ~90 %. Interestingly, if battery costs stay as high as 380 $/kWh

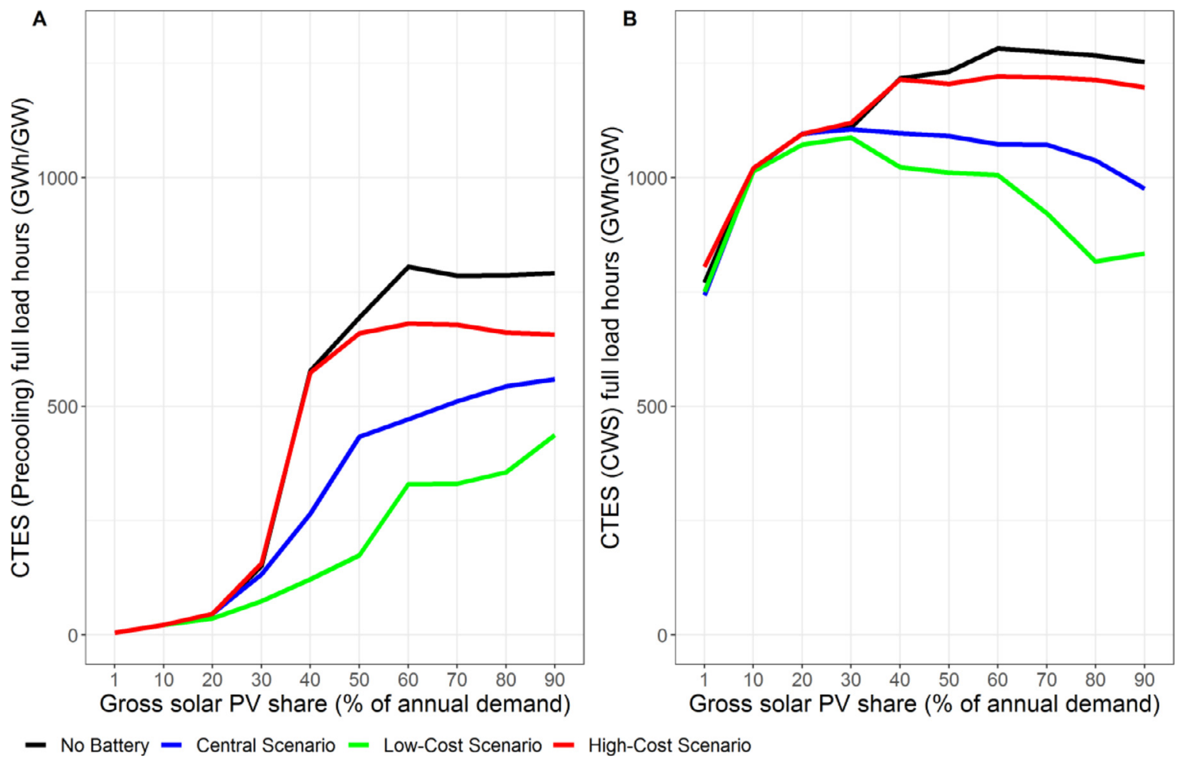

Fig. 8. Operation of CTES technologies in terms of full load hours (FLH).

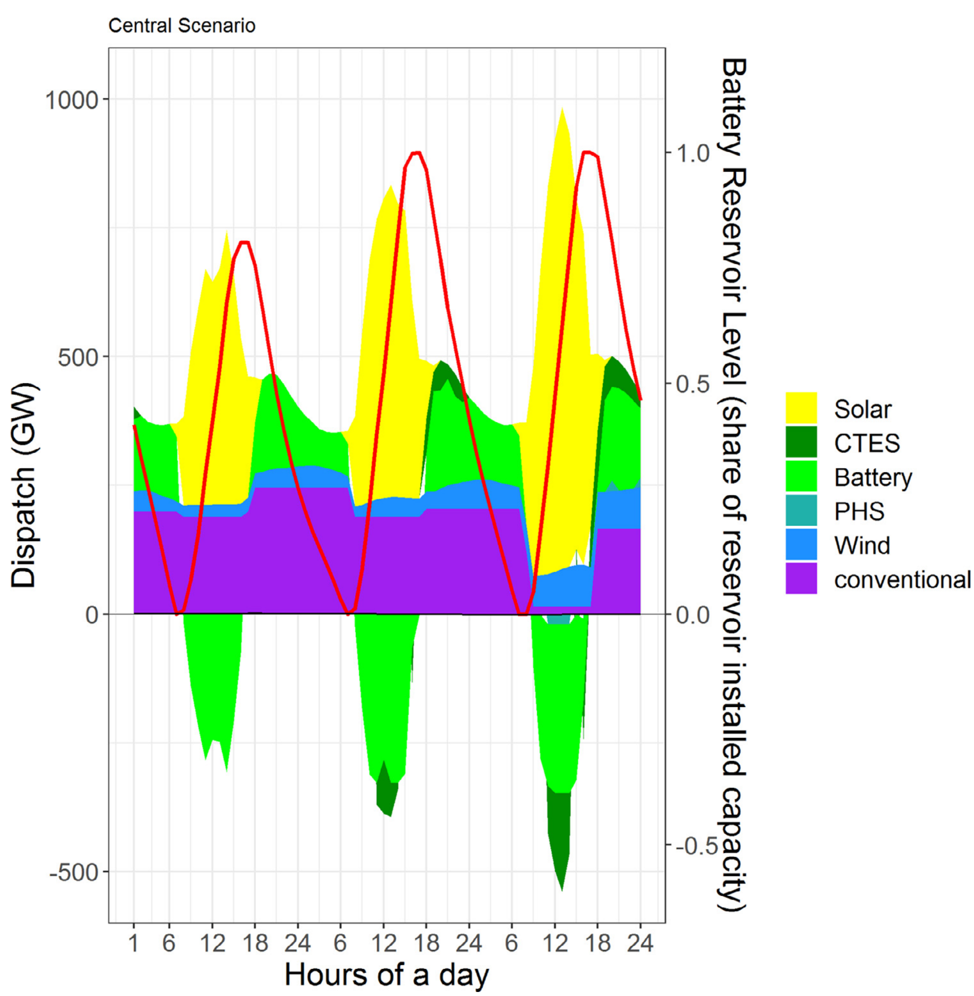

Fig. 9. Hourly dispatch of solar PV, CTES, batteries, wind, and conventional technologies for three consecutive days in August for 70 % solar PV share.

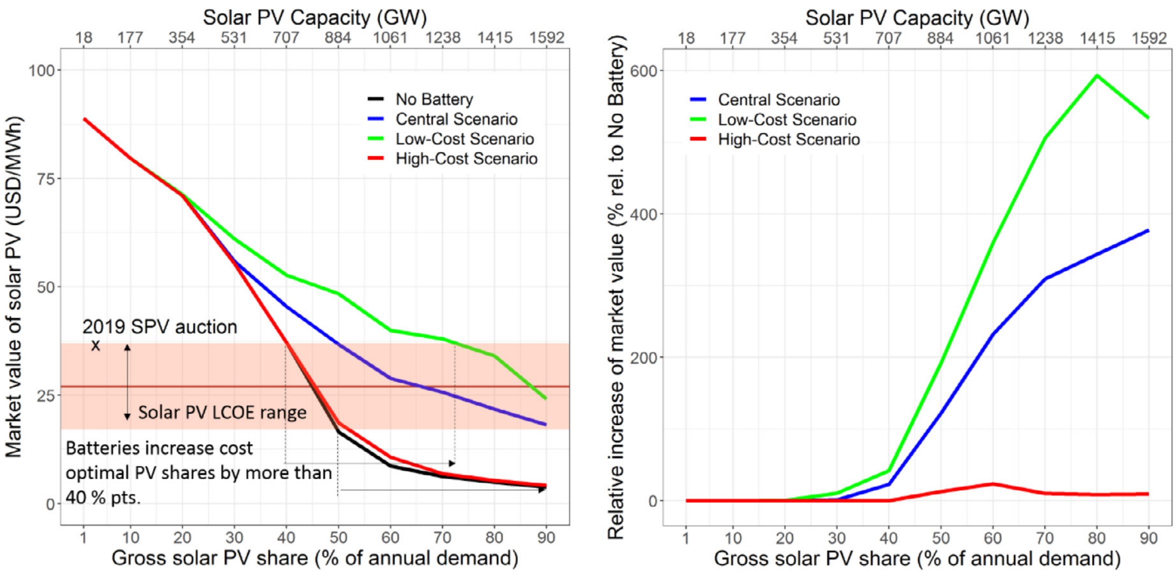

Fig. 10. The change in the market value of solar PV across gross solar PV shares in the battery scenarios with different investment costs and in the No Battery scenario (left) and the relative increase in the market value of solar PV compared to the No Battery scenario (Right).

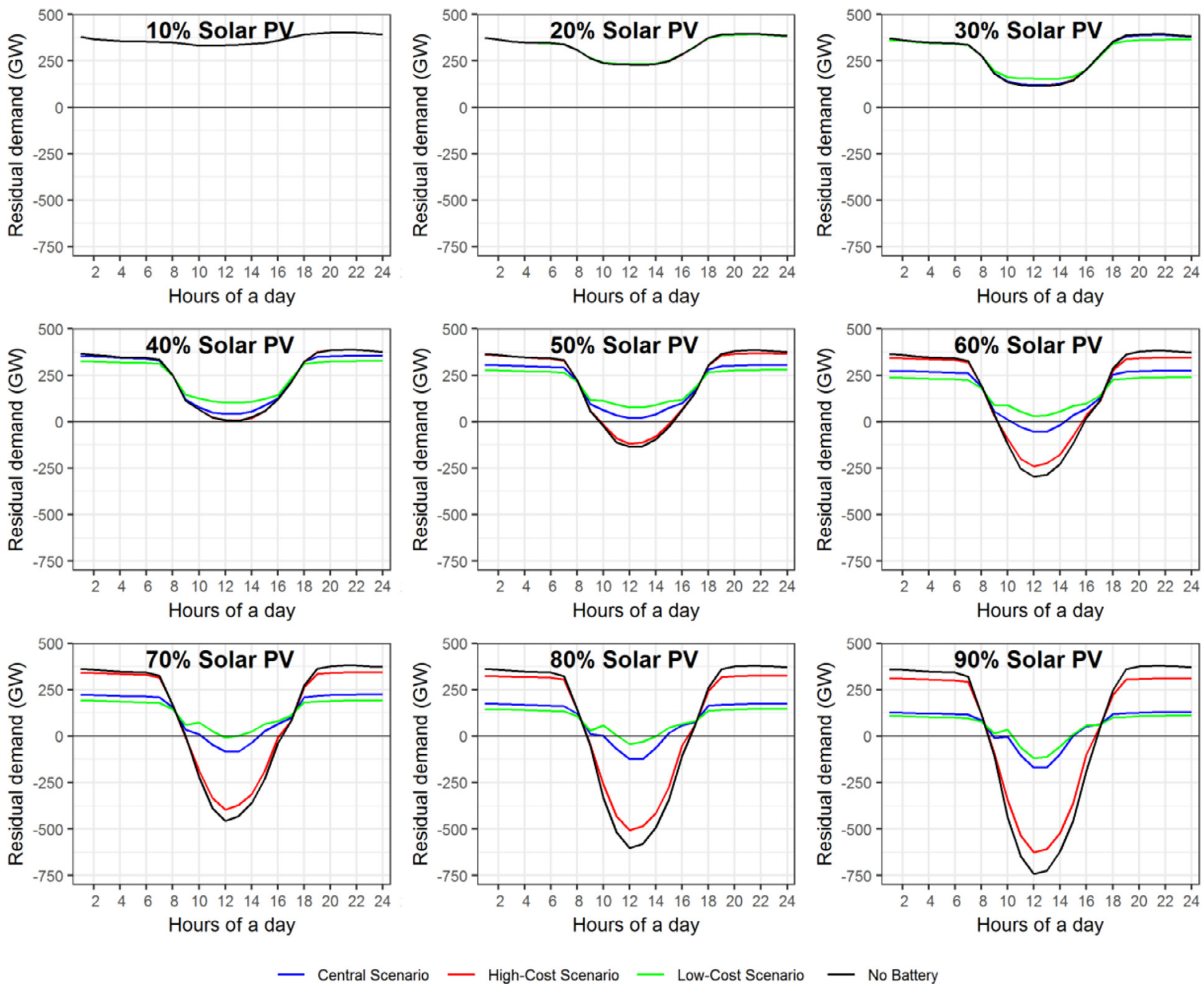

Fig. 11. Hourly residual demand of one day, averaged over all days of one year, for various solar PV shares.

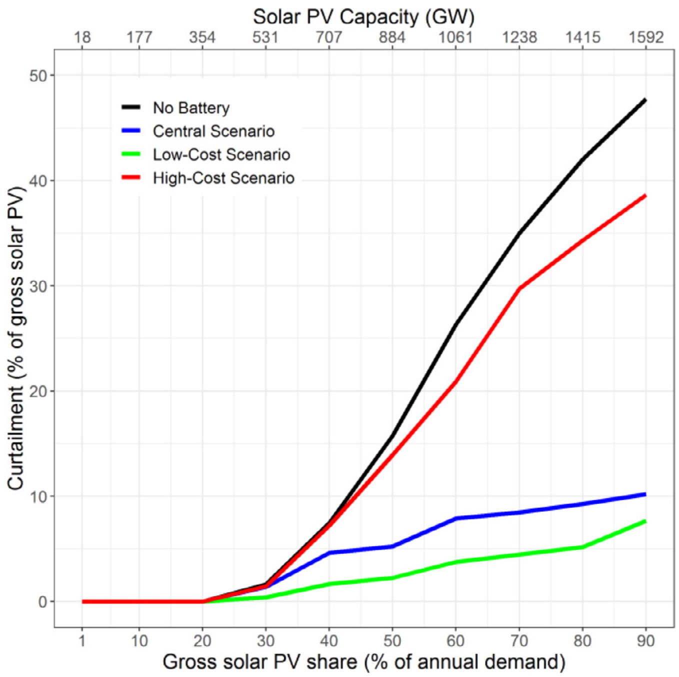

Fig. 12. Solar PV average curtailment rates as a share of gross solar PV generation.

(High-Cost Battery scenario), we find battery deployment of ~50GW at 60% PV share, but negligible increase in optimal solar PV shares.

In our Central Scenario, batteries are deployed starting at 30% solar PV share. The impact of battery deployment on the market value of solar PV is negligible at this share. However, the market value can be roughly doubled (an increase of 20 USD/MWh in absolute terms) at 50% solar PV share and increases by a factor of five (an increase of 14 USD/MWh) at 90 % solar PV share relative to the No Battery scenario. Further battery cost decrease in our Low-Cost Battery scenario improves the market value of solar PV further. The market value can now be roughly tripled (an increase of 32 USD/MWh in absolute terms) at 50% solar PV share and increased by ~seven times (an increase of 20 USD/MWh) at 90 % solar PV share relative to the No Battery scenario.

Fig. 11 shows hourly residual demand of one day, averaged over all days of one year for all four scenarios for a wide range of solar PV shares. It shows how batteries shift solar electricity supply from midday to the evening peak. The resulting reduction in solar PV curtailment is shown in Fig. 12. Average curtailment rates in the Central Scenario, for example, drop to less than 9 % compared to ~35 % in the No Battery scenario at 70 % solar PV share.

Fig. 13 shows the electricity price duration curves for those hours in which PV plants generation is greater than zero. We distinguish for different battery cost scenarios and solar PV shares. Below 30 % solar PV share, no significant amount of batteries are economical, as price spreads are too small. At 30 % solar PV share, solar revenues experience a minor improvement only in our Low-Cost Battery scenario. At this share in the Low-Cost Battery scenario, the number of zero-price hours as seen by solar PV plants is roughly halved. At 40 % solar PV share and beyond, solar revenues are significantly increased during zero-price hours not only in the Low-Cost Battery scenario but also in the Central scenario by reducing solar PV curtailment. For example, at 50 % solar PV share, the percentage of solar PV generating zero-price hours are reduced from 53 % in the No Battery scenario down to 26 % and 18 % in the Central and Low-Cost Battery scenarios respectively. The improvement of solar revenues in our High-Cost Battery scenario is negligible.

4. Discussion and conclusion

In this study, we investigate the techno-economic interactions of solar PV and battery storage in a future Indian electricity system (~2040), while also considering the increasing AC demand and associated demand-side management options. The purpose is to contribute to the understanding of the underlying drivers of solar-heavy scenario results for India.

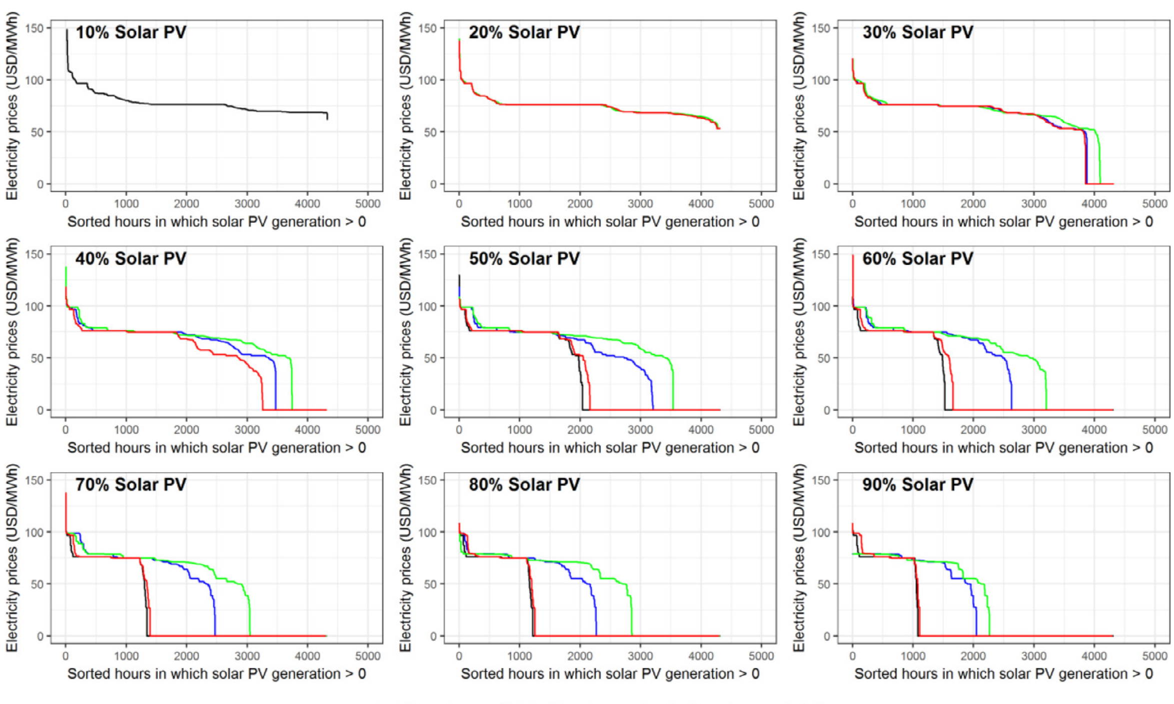

Fig. 13. Electricity price duration curves at different solar PV shares across all four scenarios. Only electricity prices that solar PV plants see are shown in the plots.

Without battery storage (as a reference), we estimate optimal solar PV shares in India in 2040 to be in the range of ~40-50 % (for future solar PV LCOE of 17-37 USD/MWh). Demand response from AC load (up to 230 GW) does not provide enough flexibility to somewhat smoothen residual demand or electricity prices. Instead, the market value of solar PV significantly drops as electricity prices and residual electricity demand sharply decline in hours with high solar PV generation. With solar PV generation above ~30%, curtailment rates significantly increase up to ~50% at very high solar shares (~90%).

The role of battery storage in securing the market value of solar PV depends on their further cost decline. If battery costs stay above 380 USD/kWh (high-cost scenario, costs including balance-of-system costs such as the converter), only little battery capacity is installed (<0.1 kW_battery/kW_solar) and optimal solar PV shares thus hardly increase. With future battery costs falling to below ~200 USD/kWh (central scenario), significant synergies with solar PV deployment unfold. Battery investments become optimal at >30 % solar PV shares and strongly increase to ~500 GW at 90% PV share (>0.3 kW_battery/kW_solar). Optimal solar shares increase to about 60-70%. A further battery cost decline to 117 USD/kWh pushes solar shares to even ~90 % supporting the economic viability of 100% renewable electricity supply scenarios shown for mostly industrialized countries [25], even at a rather low CO2 price of 50 USD/tCO_2 assumed here for 2040 in India.

Battery storage competes with other flexibility options. AC-related cold thermal energy storage (CTES) is cheap and a no-regret option. Battery storage deployment hardly affects related CTES investments. However, CTES capacity is utilized less with more battery deployment as CTES is less energy-efficient. An even faster and deeper uptake of AC, CTES and other electrification options would likely reduce the role of battery storage. However, we demonstrate that the long-term potential for batteries in India is huge (~300-400 GW at 70% PV share, if costs further decline) such that even with an accelerated uptake of electrification (other than AC) the role for batteries would likely remain significant.

While battery cost reductions determine their future role, high battery costs are no fundamental show stopper for solar PV. With increasing AC demand and some related flexibility, optimal solar PV shares increase to ~45% even without any battery storage. This likely increases when considering additional flexibility from electric vehicles and other newly electrified end-uses (which has been out of scope for our study). In addition, higher carbon prices (here: 50 USD/tCO_2) can significantly increase revenues for solar PV plants especially in co-existence with coal power plants (for example, during a transition period).

Our findings are relevant to most power systems and countries, which can expect larger electricity shares from solar PV. While today's battery storage is mainly competitive in niche markets such as reserve markets, further growth in solar PV investments will likely expand their revenues to new markets such as intra-day energy arbitrage. With further battery cost reductions, significant synergies with solar PV can help paving the way for a solar PV-heavy global energy supply.

Author Contributions

AME, FU, RP, and GL designed the study. AME conducted the modeling work, post-processing, and created the figures. AG supported the modeling work, post-processing, and creation of figures. FU and RP supported interpreting the results and deriving conclusions. AME wrote the main part of the paper. FU, RP, and AG supported the writing. All authors have read and agreed to the published version of the manuscript.

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Declaration of competing interest

The authors declare no conflict of interest.

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Data availability

Data related to this article can be provided upon request.

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