

The Role Of Repurposing Coal Plants to Thermal Energy Storage in the Context of India

by

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ABSTRACT

Substantial coal phase out initiatives have been growing as the world mobilizes to meet the Paris climate goals. However, the stranded asset risk associated with this critical transition could fall disproportionately on Asian economies with younger coal fleets, like India. Here, we use a bottom-up and top-down techno-economic modeling approach to explore the value of installing commercially available, molten-salt thermal energy storage (TES) systems for repurposing existing coal power plants in the Indian context. We combine thermodynamic simulation and an economic optimization model to evaluate design and operations of TES systems for a variety of technology assumptions, coal plant archetypes, and electricity price scenarios. Key drivers of economic viability identified include longer remaining plant lifetime, increasing peak TES temperature, lower TES energy capacity cost, co-production of waste heat for end-uses, and increasing temporal variability of electricity prices. The plant-level analysis was then extended to screen for the potential for TES retrofits for the coal power fleet in Uttar Pradesh, the most populous Indian state with amongst the largest coal capacity. Analysis for a single electricity price scenario indicates that over 89% of the coal capacity in the state can be retrofitted and recover the costs of TES retrofits. Under the top-down, capacity expansion modeling approach, we find TES retrofits can save 3-6% in system costs in zero emission scenarios and operate as long-duration energy storage, complementing shorter-duration Li-ion based energy storage. Our results justify further investigation into articulating the value of repurposing coal plants from the interests and positions of different just energy transition stakeholders.

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Contents

Title page	1
Abstract	3
Acknowledgments	5
List of Figures	9
List of Tables	13
1 Introduction	15
1.1 Background	16
1.1.1 Thermal Energy Storage	16
1.1.2 Regulatory Environment	17
1.1.3 Contract Structures	19
1.2 Research Contributions	21
2 Plant-level evaluation of repurposing coal plants to TES in India	22
2.1 Introduction	22
2.2 Methods and Data	22
2.2.1 Thermodynamic plant-level simulation	23
2.2.2 Economic evaluation via Integrated Design and Scheduling (IDS) Optimization	24
2.2.3 Electricity price scenarios	26
2.2.4 Modeling co-production of heat and electricity	27
2.2.5 Coal power plant archetypes evaluated	27
2.2.6 Fleet-level analysis: case study of Uttar Pradesh	27
2.2.7 Plant-level metrics of interest	29
2.3 Results	30
2.3.1 Base Case coal power plant analysis	30
2.3.2 Impact of TES technology parameters	32
2.3.3 Impact of Electricity Price Volatility	33
2.3.4 Impact of Co-production Industrial Process Heat	35
2.3.5 Fleet-level analysis - case study of Uttar Pradesh	36
2.4 Discussion	38

3	System-level evaluation of repurposing coal plants to TES in India	39
3.1	Introduction	39
3.2	Case Study	40
3.2.1	Data	40
3.2.2	Capacity Expansion Model Formulation	41
3.2.3	Scenarios	41
3.2.4	Metrics	42
3.3	Results	42
3.3.1	Effect of Emission Constraints	42
3.3.2	Effect of Age, Energy storage cost, and Efficiency	47
3.3.3	In the Context of Electricity Contracts	50
3.4	Discussion	51
4	Relation to the Just Energy Transition	53
4.1	Introduction	53
4.2	Energy Justice	53
4.2.1	Existing Methods and their distributive justice implications	54
4.3	Discussion	58
5	Discussion and Conclusion	60
5.1	Limitations and Future Work	60
5.2	Conclusions	61
A	Model Description	62
A.1	Nomenclature and Data Inputs	62
A.2	Integrated Dispatch and Sizing (IDS) Model Formulation	70
A.2.1	Objective Function	70
A.2.2	Constraints	71
A.2.3	Metrics	75
A.3	Capacity Expansion Model (CEM) Formulation	75
A.3.1	Objective Function	76
A.3.2	Constraints	76
A.3.3	Metrics	78
A.4	Aspen Modeling	78
A.5	Note on Land-Use	79
A.6	Notes on Price Scenarios	79
A.7	Supporting Figures	79
	References	87

List of Figures

2.1	Overall approach for plant-level and fleet-level analysis of TES retrofits of coal power plants in the Indian context. Each of plant-level thermodynamic simulations are calibrated to match available performance data for the existing coal plant archetypes. With the relevant techno-economic data and design characteristics of archetype coal plants, we evaluate fleet-level impacts by mapping the plants in the fleet to one of the coal plant archetypes modelled in detail.	23
2.2	a. Steady-state process simulation of TES retrofit of a coal power plant steam cycle. The solar salt stream flow on the primary side of the heat exchanger is sized to deliver 500 MW power from the steam cycle. The process diagram with local industrial process heat supplied is indicated by the slipstream (dashed line) before the low pressure turbine where a percentage of the main steam flow is diverted to the industrial heat load. b. (left) We use the operating power output, auxiliary power consumption, efficiency, main steam temperature, pressure, and flowrate from the NETL baseline [43] and a dataset of 85 CFPP units across India to calibrate 85 TES conversions and generate 7 technical plant archetypes representative of the fleet. This shows the coal power plant steam-turbine efficiency vs. the steam-turbine efficiency of the retrofit system, both calculated from the simulation. c.(right) The peak salt flow rate estimated to achieve the peak power output for the different CFPP archetypes. For reference, typical salt flow rates used in TES systems for concentrated solar power (CSP) plants are on the order of 380 kg/s [44].	25
2.3	a. Capacity (MW) and age (year) distribution from 194 GW of the coal fleet in India compared to just Uttar Pradesh (22.4 GW of total coal capacity) [30], visually underscoring that Uttar Pradesh has a representative coal fleet by age and capacity. b. The number of coal fired power plant units per state in the dataset [30]. Uttar Pradesh has a high number of units to consider, serving as a good case study.	29
2.4	a. Optimal dispatch over two representative weeks for the retrofitted TES system for base case 500 MW unit CFPP underscores the baseline interweek variability. The plots above show the hourly electricity price over two selected weeks and the plots below display the resulting charging and discharging salt flows with the subsequent energy storage state of charge in a select week. b. The estimated TES state of charge over every hour in the year, which showcases daily and multi-day cycling patterns and a small degree of seasonality.	31

2.5	<p>a. Impact of increasing the storage medium peak temperatures on the heat exchanger network sizing decision and the overall TES annual loss. b. The impact of reducing or increasing the storage per-unit cost on the annual profit or loss from the TES is shown in the top graph, and the bottom graph shows the resulting storage capacity, which is a decision variable in the optimization model. Below storage unit costs of \$10 per kWh, the TES system becomes profitable, and above \$25 per kWh the model builds the minimum enforced storage requirement indicating it is uneconomical to deploy storage.</p>	32
2.6	<p>The top plot shows a summary of the electricity price distribution by price scenario. These are the inputs to the TES optimization model and the 23 representative weeks drawn from the year-long profiles from [9]. The bottom plot shows annualized revenues and components of annualized cost categories per MWh of discharged electricity for a 500 MW coal-fired unit under the different representative electricity price scenarios considered. The black circle indicate the annual profit for the retrofitted TES system.</p>	34
2.7	<p>The base TES system supplying different amounts of industrial process heat, defined as a percentage of the facility interconnection capacity under three price scenarios shows favorability toward co-located industrial process heat. The minimum industrial process heat price is calculated from the perspective of an industrial customer and reflects the minimum price (\$/MWh) that industrial customers would pay their local TES facility for the industrial process heat so that the TES facility earns the same annual profit as the case where they are only selling electricity. These are compared to the reference price that the industrial customer would pay to supply their constant heat needs under the equivalent wholesale electricity price scenario (dotted lines). We consider three states with higher amounts of industrial process heat needs at the temperature being modeled.</p>	36
2.8	<p>Annual profit from IDS for each CFPP in Uttar Pradesh, based on the 26 representative units classified by age and capacity. In this case, the annual fixed operating and maintenance (FOM) costs of the original coal plant are excluded in the profits calculation. The unprofitable units that should be retired are to the left of the zero marker, and are typically in the older age-bands groups.</p>	37
3.1	<p>a. Installed Capacity Breakdown and b. Annual Generation Breakdown for scenarios with emissions constraints. Installed Capacity Breakdown is the installed capacity (MW) by technology, normalized by the total installed capacity. Annual Generation Breakdown is the annual generation from each resource (MWh) normalized by the total annual generation. With more stringent emissions constraints, the coal plant capacity factor decreases (as seen in the annual generation plot) and the amount of VRE + storage capacity installed increases. TES retrofits are optimal to deploy in the zero emissions case. Both zero emissions cases do not have any installed coal capacity. . . .</p>	44

3.2	Dispatch profile for Representative Week 4 under a. the base case, with no emissions constraint and b. the zero emissions case with TES dispatch shown in green. In the base case, the coal dispatch does not serve base load.	45
3.3	System cost normalized by the base case, for scenarios with various emissions constraints. With more stringent emissions constraints, the system cost generally increases from the base case. TES retrofits is optimal to deploy in the zero emissions case, and results in lower system costs than the zero emissions case without TES that simply retires coal.	46
3.4	a. Shows the demand profile of the representative week, an input to the model. b. Compares the State of Charge (SOC) of the Li-ion batteries and TES. TES generally operates on a longer, weekly cycle whereas Li-ion batteries operate on a daily cycle.	47
3.5	For the zero-emissions cases, this figure compares the a. total system curtailment and b. system cost relative to the zero-emissions case with no option to deploy TES retrofits (full coal retirement is the only option). The sensitivities compared exhibit similar trends to the plant-level modeling sensitivities and include: TES storage capacity cost, years remaining, and steam-turbine efficiency, with the storage and efficiency causing the largest range of impacts on system cost.	48
3.6	These show the State of Charge (SOC) of the TES throughout the year for a. the base case and b. the case with 0.2x storage capacity cost (lower cost storage). Both exhibit a small degree of seasonality, with the lower storage cost resulting in decreased throughput.	49
3.7	Dispatch profile for a flat demand profile, Representative Week 4 under a. the base case, with no emissions constraint and b. the zero emissions case with TES dispatch shown in green.	50
A.1	Diagram describing the decision variables and some parameters in the integrated sizing and dispatch optimization model.	62
A.2	The remaining lifetime of the coal plant affects the annual profit. In this base case and price scenario, and without FOM, the break-even point occurs (e.g. annual profit = 0) when the remaining lifetime is 22 years.	80
A.3	The TES dispatch is more sensitive to electricity price profile and exhibits more cycling under the TES design with 350 MW_t co-located industrial process heat supplied at a constant 180°C compared to the the base stand-alone TES system design under the 2030 Gujarat price scenario. TES could technically serve lower industrial heat demands and assist in industrial decarbonization efforts particularly in industrial parks with high percentages of captive coal units. It is an economically viable method when compared to using electric resistive heaters to supply the heat load, but the ultimate economic viability of such a system depends on site-specific decisions.	80
A.4	The TES dispatch is sensitive to storage costs. The lowest cost storage (\$4/kWh) cycles more often than the reference cost (\$21/kWh) and high cost (\$41/kWh).	81

A.5	Li-ion dispatch shows more cycling and sensitivity to the price profile compared to TES dispatch which exhibits a longer, weekly cycle. Li-ion assumptions include: investment costs (\$49/kW per year and \$17/kWh per year), FOM (\$6/MW/year), OPEX (\$0.1/MWh), charging and discharging efficiency (0.95). In this result with a 2 hour minimum build enforced, the Li-ion cost is \$110/MWh and TES is \$242/MWh.	81
A.6	The left plot shows that the coal plant model in Aspen is calibrated to the input design efficiency of the steam turbine as reported, but the model often does not reach the same design steam turbine efficiency under the practical design limits imposed. This serves as a lower bounded value for efficiency. The right plot shows the coal model steam turbine efficiency calibrating. the thermal energy storage retrofit discharge efficiency for the same units. . . .	82
A.7	Levelized Cost of Storage (LCOS) values for each representative group of CFPP unit in Uttar Pradesh. These groups were determined by grouping capacity and age of each unit and assigning them to the appropriate cluster. This LCOS graphic shows main drivers of cost, namely the charging costs, capital costs, and the Fixed O&M costs. Revenue per dispatch is also plotted, and overlaid with annual profit per dispatch (which is the the simple difference between the LCOS and revenue). Under this assumed Fixed O&M, 0% of the fleet is profitable under the 2030 Uttar Pradesh electricity price scenario. . .	82
A.8	Annual profit or loss from IDS for each CFPP in Uttar Pradesh, based on the 26 representative units classified by age and capacity. Under this assumed Fixed O&M, 0% of the fleet is profitable under the 2030 Uttar Pradesh electricity price scenario.	83
A.9	This plot shows the top 4% of electricity prices per price profile. The bands are grouped into bins of above \$200/MWh and between \$50 and \$200/MWh. The price profiles are the input to the integrated dispatch and optimization model and are made of 23 representative weeks derived from a k-means clustering analysis from the original year-long hourly profile per state.	83
A.10	System emissions and system cost trade-off	84
A.11	a. Annual Generation (MWh), b. Installed Capacity (MW), and c. System Cost Difference for Scenarios with emissions constraints. With more stringent emissions constraints, the coal plant capacity factor decreases (as seen in the annual generation plot), the amount of VRE + storage capacity installed increases, and the system cost generally increases from the base case. TES retrofits is optimal to deploy in the zero emissions case, and results in lower system costs than the zero emissions case without TES that simply retires coal. Both zero emissions cases do not have any installed coal capacity. . . .	85
A.12	For the zero-emissions cases, this figure compares the percentage reduction in a. curtailment and b. system cost from the zero-emissions case with no option to deploy TES retrofits and full coal retirement is the only option. The sensitivities compared exhibit similar trends to the plant-level modeling sensitivities and include: TES storage capacity cost, years remaining, and steam-turbine efficiency, with the storage and efficiency causing the largest range of impacts on system cost.	86

List of Tables

2.1	Major cost and performance assumptions used in integrated design and optimization model formulated for evaluating thermal energy storage (TES) retrofits of a coal power plant. All financial data in 2020 USD.	28
2.2	Optimal size of components for the base case 500 MW coal power plant unit under 2030 price scenario from Maharashtra	30
3.1	CEM Scenario Table	42
A.1	Sets and Indices	63
A.2	Time-independent Variables	63
A.3	Time-dependent Variables	64
A.4	Modeling Parameters	65
A.5	Economic Parameters	66
A.6	Additional Economic Parameters for CEM	67
A.7	Technical Parameters	68
A.8	Thermal Energy Storage Characteristics	69
A.9	Price Scenario Characteristics	79

Chapter 1

Introduction

Despite the recent growth of solar and wind based energy generation, from 3% in 2015 to 10% in 2021, coal remains a dominant share of electricity generation in India (76% in 2015 to 70% in 2021) and contributes to the country's standing as the world's 3rd largest greenhouse gas emitter [1]. On a per capita basis, however, India's annual GHG emissions are a fraction of the world's average, ranking at 130th among countries [2]. Moreover, demand projections from multiple sources [1],[3] indicate rapid growth in energy consumption over the next 2-3 decades to support development, which would require substantial low-carbon energy deployment in order to be compatible with the country's net-zero goal by 2070. Previous studies analyzing multi-decade evolution of India's electricity system have found that variable renewable energy (VRE) dominates new capacity installations. These studies also generally conclude that coal remains part of India's generation mix in the long term without policy interventions or steep reductions in energy storage costs, peaking in either 2030 or 2040 in many technology and policy scenarios [4],[5],[6],[7],[8],[9].

The continued role of coal generation in the Indian electricity generation mix across these studies stems from two major factors: a) growth in electricity demand, which grew by 13% from 2015 to 2020, a trend that is expected to continue, b) the relatively young age of the Indian coal fleet, with an average age of 13 years as of 2020, as compared to over 30 years in Europe, Russia and U.S. [10]. A younger coal plant fleet implies greater stranded asset risk associated with early retirements in the absence of any targeted policy incentives. A key gap in the analysis to date is the potential and value of repurposing or retrofitting existing fossil-fuel based generation in the long-term evolution of the grid. While repurposing could alleviate stranded asset risk associated with fossil fuel assets, it could also support economic diversification and the preservation of livelihoods in communities dependent on the fossil fuel industry for employment, supporting calls for equitable energy transition strategies [11], [12]. Inclusion of a comprehensive repurposing plan within the country's overall coal retirement strategy has potential to increase participation by affected and dependent communities, while mitigating potential harms. [13], [14], [15],[16].

The value of a solution such as retrofitting or repurposing coal plants will differ among involved stakeholders. This work aims to quantify and contextualize the technical and economic value of using thermal energy storage (TES) systems within existing coal generating stations to absorb electrical energy from the grid in times of low demand and return it to the grid when needed. The following section provides background on TES technology and In-

dia’s regulatory environment with relevant energy contract structures and polices. Following this, Chapter 2 introduces a plant-level analysis of TES retrofits and identifies key drivers of techno-economic viability, and Chapter 3 extends this model to identify system-level values of TES in zero emission grids. Chapter 4 discusses the relevance of TES retrofits within just energy transition frameworks by offering perspectives in energy justice and state-level political economies, providing a basis for the ways in which the suggested technical solution prioritizes different values among just energy transition practitioners. Chapter 5 discusses limitations of the models, suggested future work, and concludes.

1.1 Background

1.1.1 Thermal Energy Storage

The term TES denotes a family of technologies that can be used to store thermal energy from hours to months and subsequently deliver it to a thermal load. They differ from conventional Li-ion batteries in many ways including: a) having lower energy capacity costs for commercial systems, b) allowing for independent sizing of charging power and discharging power components, and c) operating with lower energy storage round-trip efficiencies [17],[18]. TES systems may utilize a wide variety of low-cost or abundant materials including oil, molten salt, fire brick, and crushed rock, and consequently can cost an order of magnitude less than Li-ion battery systems per unit of energy [19]. Depending on the approach taken, a substantial part of the plant’s thermal and electrical infrastructure (e.g., transformers, boilers, heat exchangers and steam turbines, cooling towers and pumps) may be reused, thereby creating the functional equivalent of a large battery at very low cost [4].

To date, TES systems using molten salts (referred to as Solar Salt, a eutectic mixture of 60% sodium nitrate, NaNO_3 and 40% potassium nitrate, KNO_3) have been commercially deployed in concentrated solar power (CSP) plants to enable such plants to shift solar thermal energy supplied during the day to meet night-time demand [20]. Instead of solar energy, the stand-alone TES systems under consideration would use resistive heaters or electric heat pumps to supply heat to molten salts stored in large tanks. Resistive heaters or heat pumps draw electricity from the grid to charge the thermal storage medium, which will store the thermal energy until used for discharge. A heat exchanger replaces the combustion boiler to produce steam that drives the existing power cycle in periods of discharge. Steam Rankine cycles have peak temperatures around 600°C and operational round-trip thermal efficiency of 30-45%. Solar Salt can supply heat at a maximum temperature of 565°C . Emerging TES system innovations are directed toward the use of alternative storage media, heat pumps based on Joule-Brayton cycle for charging that can supply heat at higher temperatures than feasible with commercially available heat pumps, as well as multi-tank system configurations to improve overall system round-trip efficiency [21],[22].

Very few studies have investigated molten salt based TES retrofits of existing coal plants to examine both technical and economic viability. Among studies on this topic, the general focus has been on using thermal energy storage to improve flexibility of the coal power plant rather than replacing the coal boiler [23]. For the handful of studies focused on displacing coal boilers with TES, the emphasis has been on technical performance of the process and

use of simplified economic assessments that do not account for plant dynamic interactions with the grid [24]. While TES based retrofits is being contemplated in the U.S.[25] and other countries such as Chile [26], most studies lack situational relevance within younger coal fleets like India. The few plant-level studies that evaluate repurposing in the context of India focus on re-use of land rights or interconnection equipment, and do not account for technologies such as molten salt based TES that re-use existing coal plant infrastructure [27],[28],[26],[16].

1.1.2 Regulatory Environment

The state governments control generation, transmission, distribution, policy making, budgetary support and regulatory functions within state boundaries, through the state energy department, generation, distribution and transmission companies, load dispatch center, and the electricity regulatory commission. These companies may be owned by the central government or privately owned. Distribution companies (discoms) are often sub-contracted to franchisees. The central government is responsible for preparing national legal and policy frameworks, safety guidelines, implementing centrally sponsored programs, country-wide planning, multi-state generation projects, and interstate transmission systems which is generally carried out under the Ministry of Power, the Ministry of New and Renewable Energy, and the Central Electricity Authority as well as other companies. Central generating companies include the National Thermal Power Corporation (NTPC), the Solar Energy Corporation of India (SECI), and the National Hydro Power Corporation (NHPC). POWERGRID is the transmission company and Power System Operation Corporation Limited (POSOCO) is the load dispatch operator. The Central Electricity Regulatory Commission has a key regulator role. The State Energy Boards (SEB) formed in the 1950s historically served as the state government owned vertically integrated monopoly, handling generation, transmission, and distribution.

The SEBs deterioration of performance in the 1980s spurred reforms that identified privatization as the solution to inadequate financial performance of the state utilities. These "market oriented reforms" led to the formation of the Electricity Act in 2003 and developments toward this goal are still taking place today. The first round of reforms from 1990 to 2003 privatized generation (unbundling generation) and restructured State Electricity Boards. Though there was enormous response to generation projects, the power purchase agreements (PPA) and Memorandum of Understandings (MoUs) were confidential and these projects were not subject to any open or transparent bidding processes causing many of these projects to fail. In the restructuring, the state's vertically integrated monopolies were unbundled into generation, transmission, distribution, and an independent electricity regulator. Generation and distribution were to be managed by private companies and transmission would be managed by a state owned company. The implementation and success of the reforms varied by state [29].

The Electricity Act of 2003 had wide impacts. With the same market-oriented goals in mind, it aimed to increase competition through delicensing generation, facilitating open access, and introducing power trading. This allowed for private generators to build and industries to set up captive power suppliers [29]. Open access refers to the non-discriminatory provision for use of the network (transmission or distribution) by consumers or any entity

engaged in generation. This allowed electricity consumers to have the right to procure power from a supplier of choice and not be forced to buy from the distribution company. They could use the existing network and only needed to pay appropriate charges. With unreliable supply and high industrial tariffs, industries decided to generate power themselves, or purchase it from dedicated generators because of open access (78 GW or 18% of install capacity is captive power [3]).

Despite the unbundling and restructuring, the distribution companies are not fully independent. They are typically managed by state power secretaries without independent directors and are subject to financial issues [29]. On paper, the generation, transmission, and distribution is unbundled; but in practice, the level of liberalization has nuances.

Because electricity consumption is expected to grow with economic development, many power distribution companies signed power purchase agreements (PPAs) based on high predicted electricity demand for India, which has yet to be realized. These PPAs force distribution companies (discoms) to honor fixed cost payments even if they don't supply power, which pushes up costs for these discoms. This underlies the primary challenge of India's power sector: the operating expenses of discoms are not covered by the revenue. However, the central regulator has proposed moves toward a market-based system for dispatch that does not rely on bilateral scheduling between generators and discoms which will have different implications for moving from a state-based energy regulation regime to a nationwide regime [30], [31].

Power plant operators often have long term contracts to recover their entire fixed charge if they declare their capacity available to their contracted state system operator (the State Load Dispatch Center) for at least 85% of the time in a month. 87% of India's electricity is transacted through these long-term 25 year fixed contracts of power procurement between discoms and generators, a widely used mechanism to reduce risk and lower cost for stakeholders by ensuring the power purchasers buy electricity at a pre-negotiated price. Although, the share of power under long term contracts is expected to decrease to 50-60% by 2025. Discoms self-schedule generation from the portfolio of generators they hold these long term contracts with. The remaining power is traded through bilateral transactions between utilities through power exchanges and traders. This process is opaque and does not allow discoms to choose from cheaper generators outside of their portfolios. Furthermore, without this visibility, discoms cannot accurately anticipate or adjust for demand, future demand, variable generation, or renewable energy curtailment [32].

The dispatch is based off of the plant's variable charge, which includes delivered cost of fuel, taxes, and regulated transmission charges. These are updated monthly, so the prices do not have hourly variability. This structure renders new, more efficient plants to remain underutilized if they enter this market without any long term contracts, generating a short term misallocation in dispatch. Each state operates the grid within its boundaries and self schedules contracted power plants once they declare their day ahead availability. Any residual demand is met through short term bilateral contracts, or through a power exchange. The fixed charges under a long term PPA are paid on the basis of power plant availability, not their generation. Therefore, the marginal cost of one unit of contracted power is much lower than one unit of uncontracted power. The real electricity market in this case is the competition for contractual access. Bidding is basically for the power plants, a one time process, not for power. Fuel supply agreements are also laden with long term contracts, where coal suppliers

sell coal to power generation utilities. 50% of this coal is transported by rail, exposing interlinkages between the coal industry and transportation. Coal freight charges subsidize passenger rates within India Railways and also account for the large disparity in coal costs across the country. Pithead plants have the cost advantage of not needing to pay these high transport costs. Additionally, coal plants owned by the state government often only contract within their own state distribution system due to the history of India’s power system build-out. Market based policies may exacerbate the underlying misallocation of pricing out the newer more efficient plants that lack contracts. Though the market based economic dispatch and greater regional integration can reduce costs, facilitate more competition, and unlock more environmental benefits, the state-level political economy poses nuanced challenges in moving to a centralized dispatch [33].

Most recently, India has introduced a Real Time Market based on double-sided closed auction with uniform price in addition to a Green Term-Ahead Market for VRE targets. They have also piloted a Security Constrained Economic Dispatch with 3 generating stations representing 1600 MW of capacity as well as an algorithm for dispatching ancillary services in tandem. POSOCO acts as the System Operator ensuring power balance in interconnected systems in real-time for reliable, secure, economic, efficient dispatch of the power system through the National Load Dispatch Centre (NLDC) and 5 Regional Load Dispatch Centres (RLDCs). They facilitate interstate transmission and administer India’s wholesale electricity market every 15 minutes [34].

1.1.3 Contract Structures

Even though renewable-based PPAs are cheaper than coal-based PPAs, taxpayers and utility customers end up paying more for electricity if the management of VRE in the system is not managed, undermining the opportunity for clean energy development.

Despite widespread consensus to transition away from coal and develop cleaner, more affordable grids, breaking or changing a coal-PPA might cause regulatory instability, which is not incentivized in the risk-averse energy regulator paradigm. However, India’s central power regulator allowed BSES (Delhi’s largest distribution company) to exit a 25 year old power purchase agreement with NTPC’s Dadri-I power plant. This sets a precedent to allow distribution companies (discoms) to terminate PPAs that have completed 25-year tenures [35]

With this precedent, discoms could procure cheaper power and fulfill Renewable Purchase Obligations (RPOs). Furthermore, these thermal power plants could be candidates for thermal energy storage conversion. Without PPAs, these older power plants would compete on a variable cost basis with other sources of generation. While some may compete, especially with expected demand growth, some could be mothballed (not in operation but still capable of being used).

The transaction costs of breaking coal contracts and supporting clean energy and energy storage still remains a daunting challenge. To accelerate this transition, the Asian Development Bank has developed the Energy Transition Mechanism (ETM), with the most advanced stage of implementation occurring in Indonesia. The ETM uses concessional and commercial capital to “retire or repurpose coal and other fossil fuel plants” before their technical end-of-life, as well as direct investments toward reliable, affordable clean energy. So far, the

announced, non-binding, early closure (15 years early) of the Ciberon-1 plant in Indonesia is the first announcement of ETM implementation, indicating there is still a lack of precedent or standardization on costs of early coal plant retirement [36].

Energy Storage Contracts and Policies

PPAs will generally cover 100% of the project output (including dispatch and charging control). For stand-alone energy storage contracts, there is generally a fixed monthly capacity payment plus a variable cost per MWh of throughput. Combined renewable-plus-storage contracts often have an energy-only price instead of a fixed monthly capacity payment. Some energy storage contracts might be structured as capacity-only contracts, in which case the developer maintains responsibilities for the sale of energy (and the costs of procurement from the utility). Another contract structure is a virtual power purchase agreement, where oftentimes companies looking to offset carbon emissions acquire the rights to the renewable energy. A shared savings contract structure could also be used, generally for behind-the-meter projects. In these, the customer shares the savings with the developer of the energy storage unit. These will generally be for high energy customers. Finally, the utility may solicit contracts for new storage that would be owned by the utility, in different Engineering, Procurement, and Construction (EPC) contracts [37]. Longer term strategies for LDES have longer planning horizons. They include utility resource planning, transmission and distribution deferral (avoiding expensive, long-term asset upgrades), and energy market participation (including system stability compensation such as inertia and frequency regulation). These longer term strategies have large potential but rely on many more stakeholders for planning, approval, and integration [38].

Currently, India's Central Electricity Authority predicts at least 27 GW and 108 GWh of grid-scale Battery Energy Storage Systems (ESS) along with 10GW of pumped hydro storage, to meet peak electricity demand in 2030. To support these ambitious goals, the government has 1) waived Inter-state transmission system (ISTS) charges for ESS projects commissioned before June 2025, 2) issued a standard bidding guideline for BESS (as of March 2022), and 3) is working toward a National Energy Storage Policy [39],[40].

Though standalone storage tenders in India is relatively low at the moment, there have been some interesting tender types that display progress in the EPC process. Solar+BESS EPC is the most common types, but these are not flexible tenders. The second is a peak power supply tender. In this tender, the ESS charges during off-peak hours and supplies power at the high peak tariff. There are no PPAs with this tender that have been signed. Round-the-Clock (RTC) supply tender describes the case where the developer fulfills an annual minimum capacity utilization factor of 80% and monthly requirement of 70%. These are typically renewable energy hybrid projects with some amount of storage capacity as to meet base load without any external balancing or strategy. Renew Power won one project with an RTC PPA and PSA signed, and is currently under construction. Finally, there are Standalone ESS tenders, or ESS-as-a-Service. There are 2 tenders so far, from NTPC and SECI, which will set the tone of future ESS tenders in India. Stakeholders predict that the ESS-as-a-Service tendering experience will inform and facilitate future standalone storage tenders. Based on international experience with utility-scale battery business models, there should be business models for storage that encompass multiple revenue streams [39]. In the

future, regulations that provide incentives for domestic content requirements will likely be implemented in India. Some other regulatory challenges that might hinder storage in India could come from the Indian Electricity Act of 2003, which does not consider energy storage as a standalone asset, and therefore can lead to tax issues [39],[40].

1.2 Research Contributions

We contribute to the nascent literature on coal power plant retrofits with TES by developing a configurable, plant-level optimal sizing and dispatch model that can be used to evaluate the potential for TES retrofits for different coal plant designs and grid contexts as well as TES technology scenarios. We develop a mixed integer linear programming model (MILP) capable of accounting for dynamic plant-grid interactions, plant-specific operating characteristics as well as TES technology assumptions to determine the least-cost operation and investment in TES system components. We apply the model to study the economic viability of TES retrofit, based on Solar Salt, of various coal plant designs/archetypes operating in the Indian context under alternative plant configurations and grid electricity price scenarios. In summary, the aim of our work is to determine the technical and economic drivers that incentivize CFPPs to be retrofitted into TES facilities.

We find that TES retrofits of coal power plants can be economical for certain plant-level and grid contexts. Generally when economical to deploy they are sized to storage durations between 4-6 hours and even longer (12-24 hours) when competing with shorter-duration storage. Secondly, we determine factors that improve the economic viability of TES retrofits include: availability of lower energy capacity cost TES media, higher peak salt temperatures, longer remaining lifetime of coal power plant, higher steam cycle heat to power conversion efficiency as well as potential to sell heat directly for end-uses (e.g. industrial use case). We apply our methods to the coal fleet in the populous state of Uttar Pradesh; the case study illustrates the scale of the available retrofit opportunity, notably among younger plants owned primarily by Central government and private sector entities. The analysis leverages detailed plant-level data, serving as the starting point for further investigation of the plant-level impacts of retrofits, and lays the groundwork for evaluating grid-level impacts that such retrofits will have on grid dispatch and within capacity expansion models.

We explore the system value of TES retrofits by comparing the results from capacity expansion model framework to the plant-level model, revealing modest differences in TES dispatch, larger differences in optimal design, and similar trends regarding the difference in the remaining lifetime of the coal plant, higher steam cycle heat to power conversion efficiency, and lower energy capacity costs of TES media. We also quantify the emissions reductions and system cost tradeoff along with modest curtailment reduction by retrofitting coal plants to TES rather than retiring them.

Finally, we offer a critical political economy perspective that investigates the elements of energy justice embedded in different modeling decisions and metrics within decarbonization plans, demonstrating the ways in which the modeling frameworks and case studies chosen in this study appeal to different stakeholders and states.

Chapter 2

Plant-level evaluation of repurposing coal plants to TES in India

2.1 Introduction

In this chapter, we develop and apply an optimization model at the scale of a power plant to study the economic viability of TES retrofit, based on Solar Salt, of various coal plant designs/archetypes operating in the Indian context under alternative plant configurations and grid electricity price scenarios. The aim of our work is to determine the technical and economic drivers that incentivize CFPPs to be retrofitted into TES facilities. This chapter introduces our methods and data for the plant-level analysis. This is followed by a discussion of results at the plant-level under various scenarios and an assessment of the potential at the fleet-level – focusing on a single Indian state with highest proportion of the existing coal plants. Finally, we discuss the implications of these results and conclude.

2.2 Methods and Data

We rely on a combination of analytical approaches and data sets that are summarized in Figure 2.1. The plant-level analysis is based on two models: 1) steady-state thermodynamic simulations of the coal plant and the TES retrofitted coal plant in Aspen Plus v11 [41] that evaluate technical performance of the proposed concept and generate parameters for the subsequent techno-economic optimization of the concept; and 2) an integrated design and scheduling (IDS) optimization framework that evaluates the cost-optimal sizing and dispatch of the TES components while adhering to a range of operational constraints and parameter inputs characterizing technical performance of the system derived from the Aspen simulations in step 1. The fleet-level analysis scales up the outputs of the plant-level simulations for different coal plant archetypes, based on mapping individual plants in the fleet to one of the modeled plant archetypes.

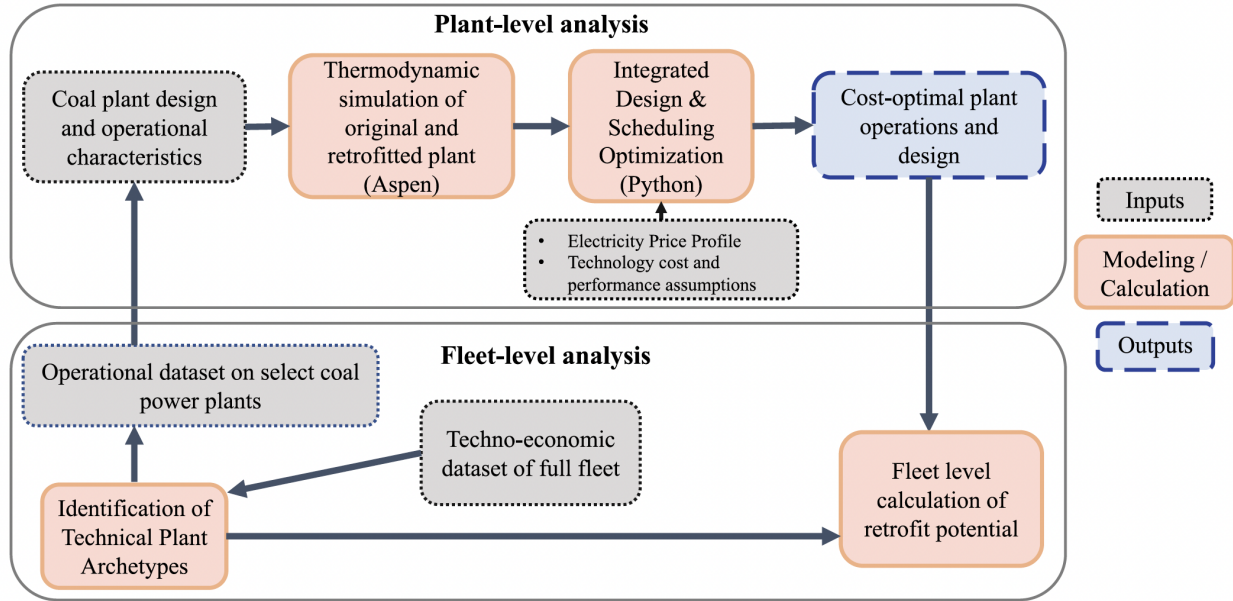


Figure 2.1: Overall approach for plant-level and fleet-level analysis of TES retrofits of coal power plants in the Indian context. Each of plant-level thermodynamic simulations are calibrated to match available performance data for the existing coal plant archetypes. With the relevant techno-economic data and design characteristics of archetype coal plants, we evaluate fleet-level impacts by mapping the plants in the fleet to one of the coal plant archetypes modelled in detail.

2.2.1 Thermodynamic plant-level simulation

We developed thermodynamic process simulations in Aspen Plus version 11 [41] for each envisioned CFPP archetype and its corresponding retrofit system. The process simulation is based on the standard design of the steam-turbine cycle of CFPPs differentiated by boiler type (sub-critical and super-critical), as well as design and operational data (steam temperature, pressure, and flow rate at the high pressure, intermediate pressure, and low-pressure turbines) [42],[43]. This first step aims to account for the heterogeneity of the Indian coal fleet, which consists of plants with different operating parameters, like efficiencies and steam flow rates, that directly impact the corresponding retrofit system parameters, as highlighted in Figure 2.2. For each coal plant archetype, the process simulation was calibrated to closely approximate the reported data for steam cycle efficiency and gross power output (not including plant auxiliary consumption) while maintaining practical design limits: a) low pressure turbine outlet temperature of 35°C, b) isentropic efficiencies of 90% for each turbine, and c) steam flow rates that are within 10% of the reported steam flow rate. Through this calibration exercise, we find that the difference between model predicted power output and design data is relatively low (up to 2.5 MW), but the differences in efficiency persist because the minimum standard outlet temperature and pressure of the low pressure turbine constrains the maximum efficiency achievable in our modeling framework (See Appendix Figure A.6). However, this framework still captures the heterogeneity of the coal fleet (as seen in Figure 2.2b.) in a manner that does not violate the practical design limits mentioned above.

Under the TES retrofit design, a heat exchanger network replaces the boiler (Figure 2.2a.), and the steam flowing through the steam-turbine cycle is heated using the molten salt. The molten salt serves as the heat transfer fluid and flows through the primary side of the heat exchanger, cooling from 565°C to 290°C as it heats up the steam on the secondary side of the heat exchanger. As indicated in Figure 2.2a, we approximate the heat exchange process using a single multi-stream heat exchanger in the Aspen model. In a more detailed engineering design, there will likely be multiple heat exchangers that cover the heat exchange across the entire temperature range of streams involved. For example, a typical coal power plant involves three heat exchangers: an economizer for heating liquid water, an evaporator for producing saturated steam from the saturated liquid feed, and a superheater to produce superheated steam. Optimizing the heat exchanger network design was out of scope for this techno-economic study. Instead, we used the Aspen simulation to quantify the temperature approach of hot and cold streams across different temperature segments of the multi-stream heat exchanger and subsequently used this information to approximate the cost of the three different heat exchangers (superheater, evaporator, and economizer) within the economic optimization model (see next section).

In the process model, we used a design spec to adjust the total molten salt flow rate such that the final temperature is 290°C and power output is as close as possible to the steam turbine capacity of the coal power plant while adhering to a 5°C minimum temperature difference in the heat exchanger. Figure 2.2b, shows how this ensures that when the design peak steam temperature for the original coal power plant is higher than the peak steam temperature achievable with a solar salt TES (565°C), then the heat-to-electricity efficiency of the retrofitted system drops as compared to the original coal power plant. This behavior is typically observed in super-critical coal plants with peak steam temperatures above 565°C. Otherwise, when the coal boiler steam temperature is less than 565°C, the TES can obtain the same steam-cycle efficiency.

2.2.2 Economic evaluation via Integrated Design and Scheduling (IDS) Optimization

We formulate the IDS optimization model to evaluate the cost-optimal design and operation of the TES retrofitted coal power plant under dynamic grid electricity prices. The objective function of the model is the annualized profit of the facility, defined as the annual revenue earned from sale of electricity throughout the year minus annual operating costs (including charging costs) and annualized capital costs associated with the TES (see Eq. A.1-A.5 in Appendix). This objective function is maximized while adhering to constraints governing plant operation including: a) ramp rates and minimum stable power output of steam turbines, b) capacity constraints that limit operating variables to not exceed design values (e.g. maximum salt flow rate, storage capacity), c) constraints defining energy balance around heat exchanger and heat to power electrical conversion efficiency, d) TES energy storage inventory over time. The key investment decision variables in the model include the sizing of the heat exchangers (economizer, evaporator, superheater), pipes and valves associated with the TES system, molten salt pumps, storage medium and tanks, electric resistive heater (for charging), and, if applicable, the industrial process heater.

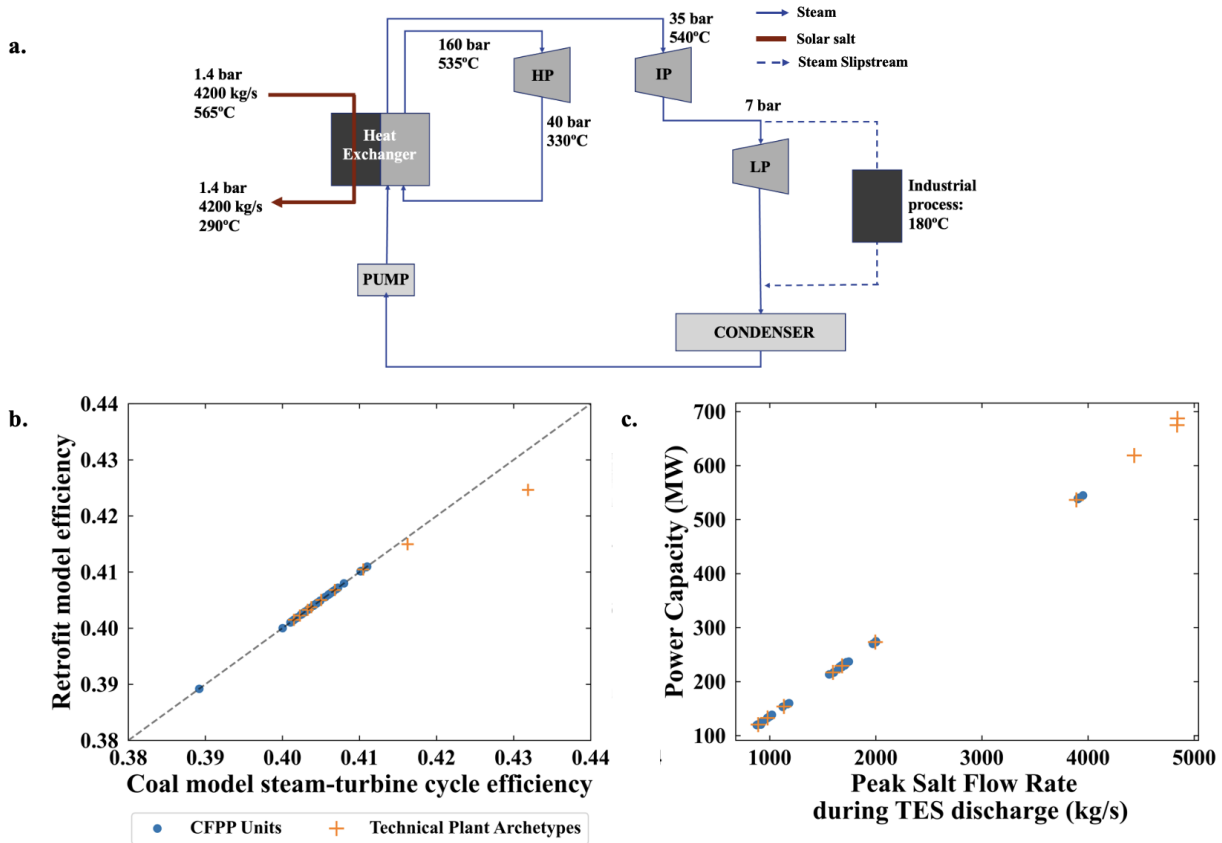


Figure 2.2: **a.** Steady-state process simulation of TES retrofit of a coal power plant steam cycle. The solar salt stream flow on the primary side of the heat exchanger is sized to deliver 500 MW power from the steam cycle. The process diagram with local industrial process heat supplied is indicated by the slipstream (dashed line) before the low pressure turbine where a percentage of the main steam flow is diverted to the industrial heat load. **b. (left)** We use the operating power output, auxiliary power consumption, efficiency, main steam temperature, pressure, and flowrate from the NETL baseline [43] and a dataset of 85 CFPP units across India to calibrate 85 TES conversions and generate 7 technical plant archetypes representative of the fleet. This shows the coal power plant steam-turbine efficiency vs. the steam-turbine efficiency of the retrofit system, both calculated from the simulation. **c. (right)** The peak salt flow rate estimated to achieve the peak power output for the different CFPP archetypes. For reference, typical salt flow rates used in TES systems for concentrated solar power (CSP) plants are on the order of 380 kg/s [44].

The key techno-economic parameter inputs to the IDS model are summarized in Table 2.1, with remaining parameter inputs summarized in Table A.5 and A.7 in the Appendix. In addition to these parameters, for each coal plant archetype, we use the following outputs of the process simulation as parameter inputs for the IDS model: a) log-mean temperature difference (LMTD) for hot and cold composite streams for each heat exchanger, b) steam-cycle heat to power efficiency, and c) maximum salt flow rate. Section A.2.2 of the Model Formulation section of the Appendix. further details the three components of the heat exchanger network that are optimized following the design assumptions for a molten salt shell-and-tube heat exchanger network for steam-turbines that consists of a superheater, evaporator, and economizer [45],[46].

A key input to the model is the electricity price scenario throughout the year, which characterizes the hourly variations in wholesale electricity prices from the perspective of the TES facility and ultimately determines its economic profitability. Rather than modeling plant operations over the entire year, which is computationally expensive, we model plant operations over 23 representative weeks across the year that captures fluctuations in electricity price patterns throughout the year. For each price scenario, the representative weeks are chosen by segmenting the electricity price data in weekly time series and subsequently applying k-means clustering to group the weeks into one of 23 groups. Then each group of weekly prices are represented by the weekly price series closest to the centroid of that group and its weight, which quantifies how many and which weeks in a year will be represented by this centroid.

The full optimization model with parameters and sources are further detailed in the Appendix. Further constraints are included if the retrofit also supplies industrial process heat (See Eq A.43 - A.46 in Appendix). The overall optimization problem is a mixed-integer linear program (MILP) and is formulated in Julia (1.7.3) and solved using Gurobi (9.5.1). Each optimization is run on the MIT supercloud using 48 Intel Xeon Platinum 8,260 cores. The model has 3,864 quadratic constraints and 3 SOS II constraints. There are 54,970 continuous variables and 7,729 integer variables, 7,729 of which are binary variables. The presolved model consists of 104,047 rows, 36,400 columns, and 313,688 nonzeros.

2.2.3 Electricity price scenarios

We evaluated the economic viability across a range of electricity price scenarios obtained from outputs of other grid-based capacity expansion studies for the Indian grid. We use state-level hourly electricity price scenarios from the Reference 2030 scenario of recent grid evolution analysis carried out by NREL using the ReEDS capacity expansion model [9]. The electricity price scenarios represent a future grid with greater amounts of VRE penetration than the current system, which increases the frequency of high and low price periods compared to the current power exchanges in India (See Table A.9). The range of each electricity price scenario ultimately reflects the variability of the marginal cost of electricity over the year due to changes in load, demand, network congestion, and increasing VRE deployment, which broadly affects the value of purchasing or selling electricity in each area.

2.2.4 Modeling co-production of heat and electricity

Many industrial customers in India and other regions rely on local CFPPs, also called captive coal power plants, that provide reliable, less expensive power for industrial processes and may sell power on the Power Exchange occasionally¹. According to India’s National Electricity Plan 2023, there are 78 GW of captive power plants above 1 MW as of 2021 [3]. Here, we evaluate the techno-economic potential for TES retrofits of captive power plants that export electricity to the grid and also meet low-temperature process heat (180°C) for co-located industrial processes. To model co-production of process heat, we expand the the IDS model to consider a constant supply of industrial process heat, that is met either by the TES system through the low pressure steam slip taken from the steam cycle (as shown in Figure 2.2a.), or by a grid-powered industrial heater. In other words, the TES system owner can either supply this industrial process heat using heat stored in the TES system, or purchase electricity from the grid at the marginal cost of electricity at that timestep to power the industrial heater. From the TES system owner perspective, there is trade-off in revenues earned from selling heat, albeit with much higher efficiencies, as compared to selling electricity to the grid with much lower efficiencies. From the industrial process heat customer, the use of TES based heat supply allows for hedging against the electricity price volatility and associated cost impacts of electrification of heating powered by grid electricity. At low price periods, the customer’s heat supply is met via electric resistive heater, while at high price periods, the TES can both supply heat for the industrial process, offsetting the need for high-cost electricity purchases, as well heat for power generation.

2.2.5 Coal power plant archetypes evaluated

The above simulation and optimization models are first applied to a single, privately operated, 500 MW coal fired power plant unit in Maharashtra, with an estimated 25 years of remaining life. We refer to this plant as the base case coal power plant in the rest of the paper. Key cost and performance assumptions and the sensitivities for this baseline study are documented in Table 2.1. Sensitivity analyses were conducted on this single plant to understand robustness to uncertainties and uncover trade-offs in efficiency, higher temperature storage mediums, local industrial process heat end uses, and spatial variability in electricity price scenarios. Then, the plant-level method is applied to the 12 coal plant archetypes that represent the coal power fleet in Uttar Pradesh (see fleet-level portion in Figure 2.1), a state with the highest proportion of existing coal power plants by unit as of 2020 and second highest by capacity as of 2023.

2.2.6 Fleet-level analysis: case study of Uttar Pradesh

Uttar Pradesh (UP) serves as a suitable state for evaluating potential for CFPP-TES conversion for several reasons including: a) a relatively high capacity of subcritical, high-cost, aging CFPP units exhibiting low capacity utilization in 2019, b) comparatively lower per-capita energy consumption vs. other Indian states, and c) most populated state which also

¹In contrast to regions like the U.S, industrial electricity tariffs in India are generally higher than residential tariffs which motivates self-generation.

Parameter	Baseline Values	Values considered for sensitivity analysis	Source
Remaining plant Lifetime	25	data for UP coal fleet (3 - 42 years)	[47] [30]
Steam-turbine Efficiency	0.41	data for UP coal fleet (40 to 41.5 %)	[30],[42]
Steam turbine capacity	500 MW	data for UP coal fleet (45 to 660 MW)	[30]
Discount Rate	0.09	-	[48]
TES Self-Discharge Rate	1% per day	-	[49]
Electric Heater electricity to heat efficiency	95%	-	[4]
Minimum stable power fraction for steam cycle	17%	-	[50]
TES maximum temperature	565 C	565 to 965 C	[47],[51]
TES minimum temperature	290 C	-	[47]
Start-up cost for steam cycle	10.15 \$/MW	-	[52],[53],[54]
TES Fixed Operating & Maintenance Cost	13.5 \$/kW/year	-	[43],[55]
Electric Heater capital cost	3.3 \$/kW	-	[4]
Storage Medium and Tank capital cost	\$21/kWh	\$5 to \$40 / kWh	[47],[56]
Percentage to 180 C Industrial Load	0%	0 to 70%	-
Electricity price scenario	Maharashtra price scenario for 2030	price scenarios from other states	[9]

Table 2.1: Major cost and performance assumptions used in integrated design and optimization model formulated for evaluating thermal energy storage (TES) retrofits of a coal power plant. All financial data in 2020 USD.

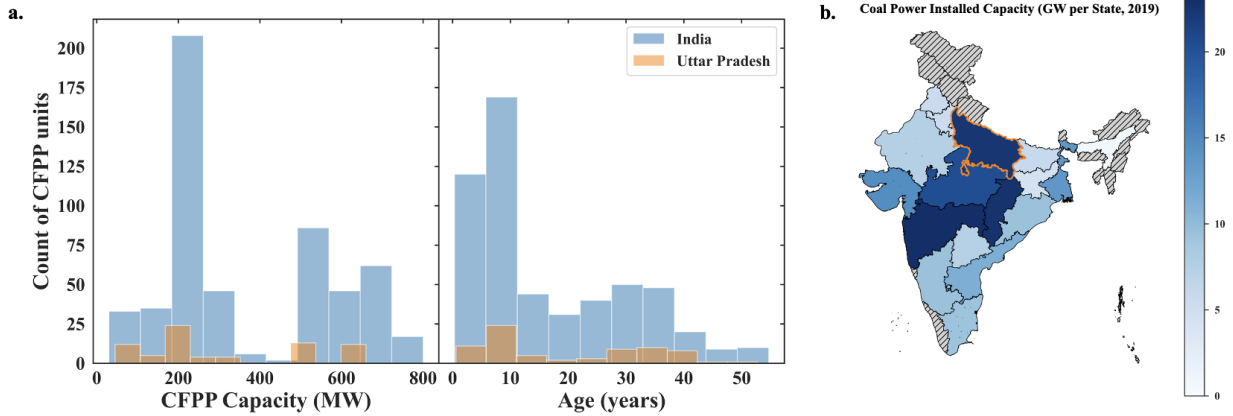


Figure 2.3: **a.** Capacity (MW) and age (year) distribution from 194 GW of the coal fleet in India compared to just Uttar Pradesh (22.4 GW of total coal capacity) [30], visually underscoring that Uttar Pradesh has a representative coal fleet by age and capacity. **b.** The number of coal fired power plant units per state in the dataset [30]. Uttar Pradesh has a high number of units to consider, serving as a good case study.

has the amongst the largest share of the national fleet in terms of MW [57]. These reasons underscore how the UP fleet serves as an ideal candidate state and representative sample of the national coal fleet, which is further visualized in Figure 2.3.

We mapped 26 types of operational coal-fired power stations in Uttar Pradesh to the 12 simulated archetypes using the following approach. We developed a process simulation for each of the 12 archetypes based on plant level technical characteristics available from a publicly available data set on India CFPP [42]. This was complemented by data from [30], which tracked 194 GW of coal power capacity over 30 months prior to the COVID-19 pandemic in India. In parallel, the UP coal plant fleet, summarized in Figure 2.3, was grouped by age and capacity which resulted in 26 representative coal units. The technical outputs from the thermodynamic models of the archetypes were assigned as inputs for the economic optimization model for each of the 26 units. Outputs from the optimization layer includes optimal dispatch and sizing under the electricity price scenarios associated with Uttar Pradesh in 2030 sourced from the NREL analysis for each CFPP-TES conversion [9]. This process is visualized in Figure 2.1.

2.2.7 Plant-level metrics of interest

We use the following metrics to characterize the scope and potential for coal power plants retrofit via TES for the evaluated case studies (see for Section 2.4 in the Appendix for further details).

- The annual profit from the retrofit is effectively the value of the objective function in the IDS optimization model described above
- The levelized cost of storage summarizes the net present cost of the system relative to its annual dispatch and is often used as metric by plant operators and stakeholders

Component	Optimal Size
Energy Storage	2372 MWh _t
Discharge Capacity	500 MW
Charger Capacity	500 MW
Superheater Heat Exchanger (A_1)	4238 m ²
Evaporator Heat Exchanger (A_2)	2180 m ²
Economizer Heat Exchanger (A_3)	2693 m ²
Hot Salt Pump Size	548 kW
Cold Salt Pump Size	216 kW
Peak Charging Salt Flow rate	1100 kg/s
Peak Discharging Salt Flow rate	2909 kg/s
Annual Profit	-6.7 million USD/year
Annual Profit without plant FOM	228,000 USD/year
Levelized Cost of Storage	\$238/MWh

Table 2.2: Optimal size of components for the base case 500 MW coal power plant unit under 2030 price scenario from Maharashtra

to evaluate the potential of such retrofits. For example, the LCOS of storage can be compared against the operating cost of the existing coal power plant as a measure of economic viability of the proposed concept².

- Energy storage duration defined as the ratio of energy storage capacity derated by discharge efficiency and the rated discharge power output.
- We quantify the benefit of industrial process heat on enabling electricity storage via TES by finding the relative break-even price, or the minimum price of industrial process heat that would make it an economical for a TES operator to co-produce heat. This is calculated by taking the difference between the annual profits of the stand-alone TES and the annual profits (or net loss) of the TES with co-production, and scaling by the total industrial heat supplied by the TES dispatch. This gives a break-even price that allows us to economically compare the two designs under varying percentages of industrial process heat supply, from the perspective of the TES operator.

2.3 Results

2.3.1 Base Case coal power plant analysis

For the base case 500 MW unit CFPP, Figure 2.4 and Table 2.2 highlight the key operational and investment outcomes the from IDS model, respectively. The TES retrofit economic potential is evaluated under the electricity price scenario estimated for Maharashtra in 2030 [9], the state where this plant is located. As summarized in Table 2.2, we estimate that TES

²as discussed later, the LCOS is also an incomplete metric for assessing storage technologies since it does not account for the temporally variable value of electricity on the grid

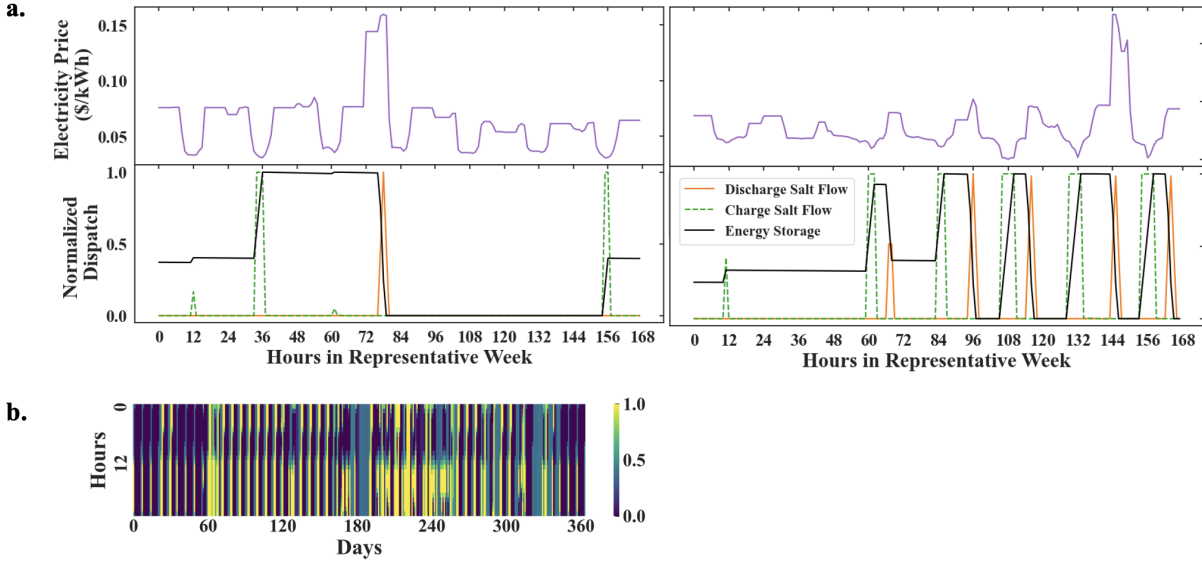


Figure 2.4: **a.** Optimal dispatch over two representative weeks for the retrofitted TES system for base case 500 MW unit CFPP underscores the baseline interweek variability. The plots above show the hourly electricity price over two selected weeks and the plots below display the resulting charging and discharging salt flows with the subsequent energy storage state of charge in a select week. **b.** The estimated TES state of charge over every hour in the year, which showcases daily and multi-day cycling patterns and a small degree of seasonality.

retrofit of this facility would yield \$228,000/year in profits but under a FOM of \$6.9 million per year, it leads to annual loss of \$6.7 million per year. In this case, the optimal charging and discharging capacity utilizes the entirety of the available grid connection capacity (500 MW). The estimated LCOS of the TES system (\$238/MWh) is higher than LCOE calculations of the existing case study coal plant (\$160/MWh), and it is an order of magnitude higher than the operating cost of a coal power plant in the Indian context, which according to one estimate is between \$28-36/MWh [30].

In terms of plant operation, Figure 2.4 highlights how the the TES system largely follows the trends in electricity prices, charging during periods of low prices (period 36, 156) and discharging during periods of high prices (period 75). Interestingly, for one of the highlighted weeks of operation, the TES system operates in charging and discharging modes for only a handful of hours to exploit the maximum price differential observed over the week and forgo exploiting smaller energy arbitrage opportunities. This is presumably due to the relatively low electrical energy storage efficiency of the proposed concept (41%) as compared to Li-ion battery storage systems, which typically operate at higher cycling rates when dispatched against the same electricity price scenario (See Figure A.5).

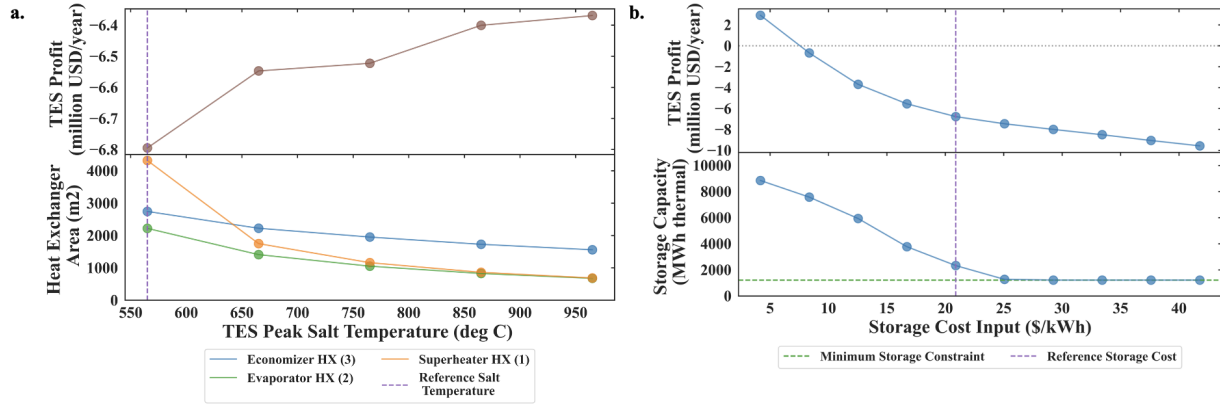


Figure 2.5: **a.** Impact of increasing the storage medium peak temperatures on the heat exchanger network sizing decision and the overall TES annual loss. **b.** The impact of reducing or increasing the storage per-unit cost on the annual profit or loss from the TES is shown in the top graph, and the bottom graph shows the resulting storage capacity, which is a decision variable in the optimization model. Below storage unit costs of \$10 per kWh, the TES system becomes profitable, and above \$25 per kWh the model builds the minimum enforced storage requirement indicating it is uneconomical to deploy storage.

2.3.2 Impact of TES technology parameters

Sensitivity to high temperature storage medium

The heat exchanger represents a major capital cost associated with retrofit and avenues to reduce the overall heat exchange area needed could lower the upfront capital investment and encourage adoption of the TES retrofit strategies. One way to reduce the heat exchange area is to increase the operating temperature range of the salt, via increasing (decreasing) the maximum (minimum) salt temperature. We test the impact of varying maximum salt temperature on the cost-optimal system outcomes, as highlighted in Figure 2.5a. Using higher peak salt temperatures results in two major effects: a) increases the average temperature difference of heat transfer (as reflected in the LMTD), which allows for the same amount of heat to transfer using a smaller exchanger area and thus lower heat exchanger cost (See Eq. A.28 in Appendix), b) using higher temperature range of salt operation allows for storing the same amount of heat using less mass of salt, which reduces the size of storage as well as the size of other equipment for transporting salts (e.g. pumps). For these reasons, we see that it is generally cost-effective to utilize salts with higher operating temperatures, as shown in Figure 2.5a.

The analysis and calculations shown in Figure 2.5 have to be caveated with a few points. First, they are based on varying peak salt temperature while keeping other properties of the salt and the rest of the TES system the same, including salt heat capacity, and tank self-discharge rates. Salts with higher operating temperatures might have different heat capacities than assumed here and thus could reduce the impact of increasing peak salt temperatures. At the same time, higher temperature salt storage might require additional insulation and operational costs to maintain a similar level of heat loss to the environment

as lower temperature salts, which is not considered in this analysis. Finally, we assume the same peak steam temperatures (540°C) as our base case plant design for the case with higher peak salt temperatures. Therefore, we do not account for any operational efficiency gains in the power generation cycle resulting from higher peak salt temperatures. Cycles capable of using higher temperature working fluids would further increase the economic benefit of using salts with higher peak salt temperatures that counteract increased cost of handling higher temperature TES media.

Sensitivity to storage medium cost per unit

The capital cost of energy storage capacity for TES systems includes the cost of the hot temperature and cold temperature molten salt tanks, the foundation, and the salt storage medium. As shown in Figure 2.5, reducing the capital costs of energy storage increases the cost-effectiveness of TES retrofits through installation of larger energy storage systems. Practically, this can be achieved by one or more of the following ways: increasing the operating temperature range of the salt, increasing heat capacity, reducing tank material costs. The energy storage per unit cost also affects the operational dispatch profile, as seen in Figure A.4 in the Appendix, where the lower storage cost increases dispatch activity. These results aligns with prior studies evaluating the techno-economics of standalone TES systems [4],[58],[59].

Impact of plant lifetime

Current coal retirement strategies rely on age-based metrics to establish retirement timelines. We assume that the maximum age for a coal plant is 50 years (though some estimates sit around 60 years), and the TES operates for the duration of the remaining lifetime. For the base case without FOM, varying the remaining lifetime of the power plant affects the overall economic viability, with a minimum remaining lifetime of 22 years warranted for determining break-even conditions (e.g. annual profit = 0, see Appendix Figure A.2).

In general, the benefits of repurposing decreases as the time window to recover investment costs of the conversion shortens. LCOS becomes more expensive from an increase in annualized capital costs. Therefore, younger plants are considered more economically attractive to retrofit from this perspective. Age-based retirement strategies generally pick the oldest plants for retirement despite many other environmental, social, and system costs associated with certain plants. Age also correlates with efficiency, where older plants are typically less efficient, this trend is consistent across India’s coal fleet where age and efficiency are negatively correlated [60].

2.3.3 Impact of Electricity Price Volatility

To understand the impact of electricity price scenarios on the cost-effectiveness of TES retrofits for coal power plants, we evaluate the plant-level IDS model under a range of electricity price scenarios corresponding to a future Indian grid in 2030. As a reminder, the electricity price scenarios are derived from a recent capacity expansion model (CEM) based analysis of the Indian grid, and correspond to prices at 33 nodes of the modeled grid,

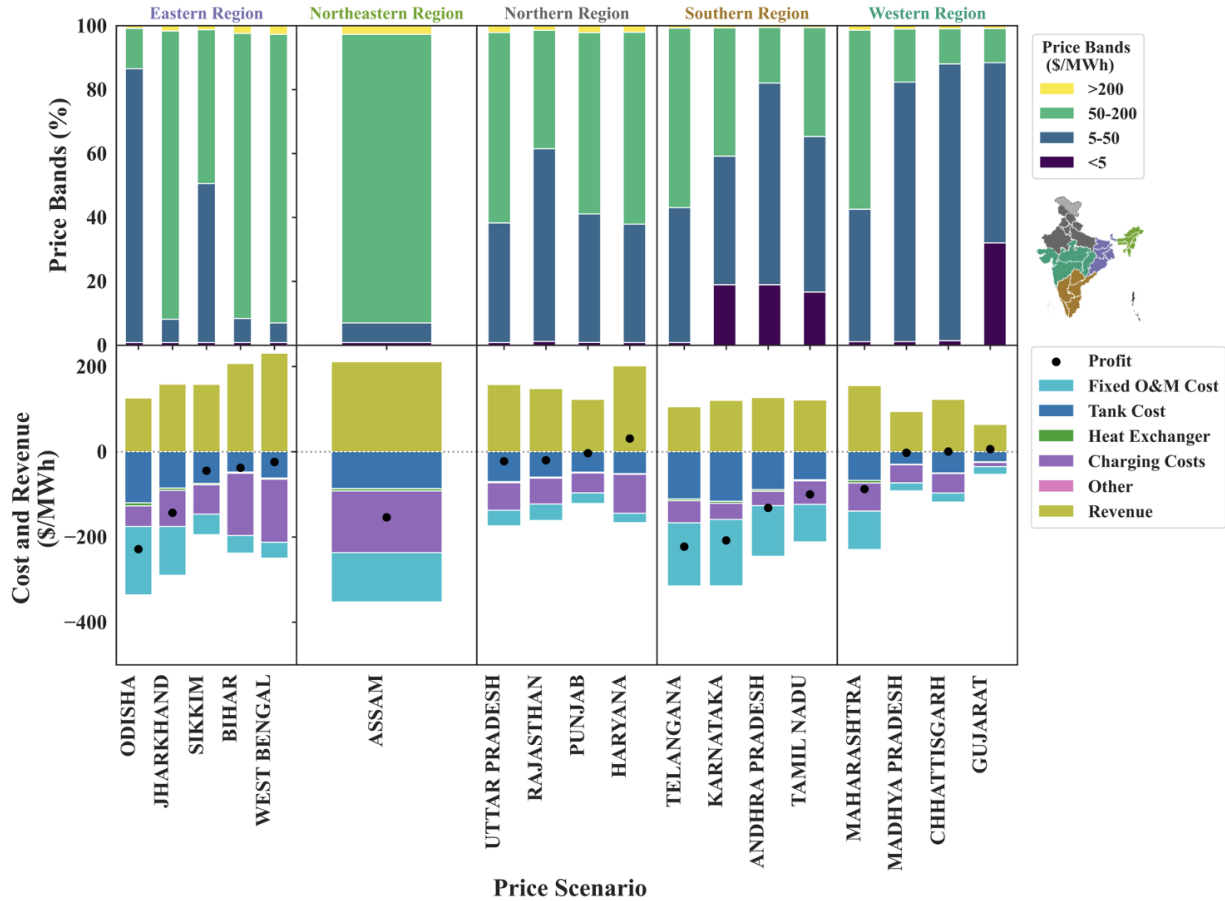


Figure 2.6: The top plot shows a summary of the electricity price distribution by price scenario. These are the inputs to the TES optimization model and the 23 representative weeks drawn from the year-long profiles from [9]. The bottom plot shows annualized revenues and components of annualized cost categories per MWh of discharged electricity for a 500 MW coal-fired unit under the different representative electricity price scenarios considered. The black circle indicate the annual profit for the retrofitted TES system.

denoted by states/regions³, for the year 2030. We evaluate the IDS model against electricity price scenarios corresponding to 18 nodes that have existing coal capacity. Figure 2.6 shows the breakdown in cost-optimal annual revenue and annual cost across the 18 electricity price scenarios for the retrofit of the base case 500 MW coal fired power plant. The annualized cost is consistently dominated by the fixed operating and maintenance (FOM) cost associated with the original coal power plant⁴ and the operational cost of charging the TES, while capital

³Each node in this model is a state, an aggregation of low-load states, or a grid-connected neighboring country of India

⁴The annual fixed operating and maintenance cost (fixed O&M) corresponds to the remaining components of the CFPP that are part of the TES system. It is assumed to be approximately \$6.9 million per year for a 500 MW system. This value is derived from the typical FOM of subcritical coal plants from [55] and is a large source of uncertainty in this model because it could include labor costs and loan repayments, and may vary widely by plant and technology.

costs account for between 32-46% of the annualized cost. Capital costs primarily consist of the molten salt tank infrastructure and storage medium (sized by the energy capacity design variable) and the heat exchanger network (sized by the peak power supply).

Figure 2.6 also highlights how electricity price distributions impact the overall profitability of the TES retrofit concept. In general, the complex nature of electricity price patterns over the year, particularly with increasing VRE penetration in bulk power systems, and their interaction with energy storage operations makes it hard to develop simplistic price measures that can indicate whether an energy storage asset will be profitable or not [61]. In Figure 2.6, we see that the annualized cost (or LCOS) is not synonymous with profitability. There are inconsistencies where the lowest LCOS does not indicate the highest economic viability based on profit. By comparing the profit from the optimal sizing and dispatch of the case study TES facility under each of these marginal cost profiles, we observe that TES retrofits may be more economical with electricity price scenarios corresponding to northern and western regions, while many areas do not show profitable operation. The economically viable TES regions overlap with the northern and western states that have higher predicted solar PV deployment as per the outputs of the CEM study from where the electricity price scenarios were sourced [9]. We also see that even though some scenarios corresponding to states in the southern region have electricity price distributions with many low-price periods, they also have much less high price periods and subsequently these do not perform well in terms of profitability of TES retrofits (See Appendix Figure A.9 and Table A.9).

2.3.4 Impact of Co-production Industrial Process Heat

We quantify the benefit of a TES system operator co-producing industrial process heat using the concept of a break-even price, which refers to the minimum price that the industrial customer pays for heat supply from the TES system, such that the TES operator earns the same net profit as the case without industrial heat supply. We compute this break-even price of heat supply under varying percentages of industrial process heat supply and three electricity price scenarios corresponding to states with relatively high amounts of dairy industrial processing needs that utilize low temperature process heat - Maharashtra, Uttar Pradesh, and Gujarat [62]. The results in Figure 2.7 highlight that the break-even price⁵ is always lower than the cost of heat supply for the industrial customer sourced heat from a resistive heater operated with grid electricity exclusively. This implies that the cost of electrification of heat is lowered with proposed TES retrofit, due to the increased flexibility in grid electricity procurement. The lower break-even price is also a function of the higher efficiency of heat supply vs. electricity supply from the TES system. Moreover, the break-even price is generally not impacted majorly by the magnitude of heat supplied to the industrial customer with a baseload heat demand.

As shown in Figure 2.7, the need to meet constant industrial heat demand alters the cost-optimal dispatch of the TES system to cycle more often than the case without any heat demand and the storage dispatch is more sensitive to the electricity price scenario as seen in Figure A.3 in the Appendix. Figure 2.7 shows broadly the benefit of TES co-production

⁵The break-even price is calculated by taking the difference between the annual profit of the standalone TES system and the TES system with co-located industrial process heat, divided by the total annual MWh provided to the industrial process heat by the TES (Appendix Equation A.52)

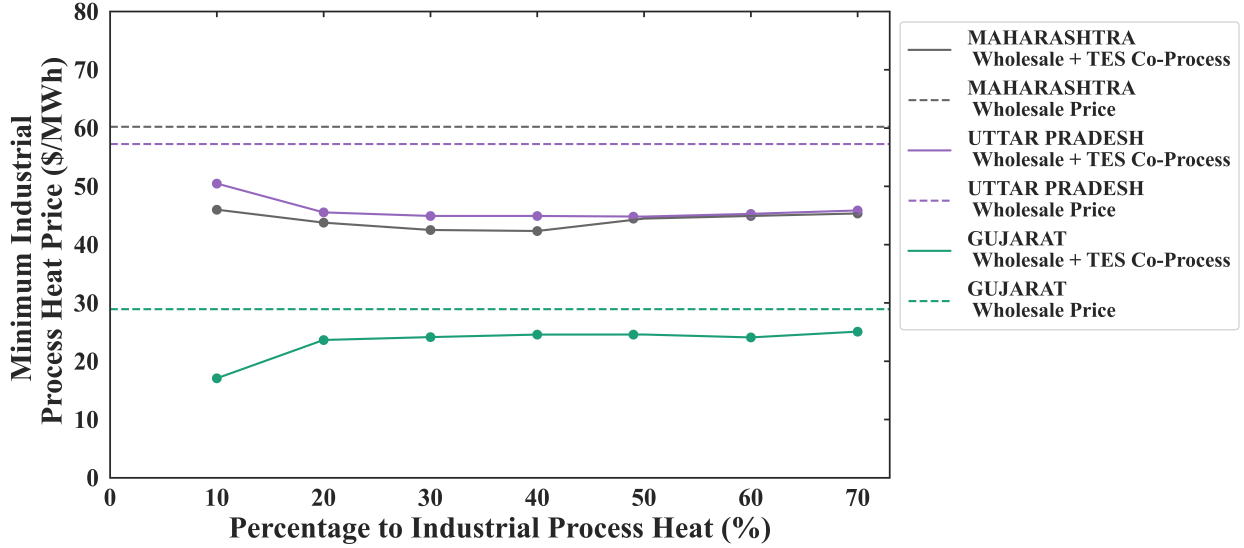


Figure 2.7: The base TES system supplying different amounts of industrial process heat, defined as a percentage of the facility interconnection capacity under three price scenarios shows favorability toward co-located industrial process heat. The minimum industrial process heat price is calculated from the perspective of an industrial customer and reflects the minimum price (\$/MWh) that industrial customers would pay their local TES facility for the industrial process heat so that the TES facility earns the same annual profit as the case where they are only selling electricity. These are compared to the reference price that the industrial customer would pay to supply their constant heat needs under the equivalent wholesale electricity price scenario (dotted lines). We consider three states with higher amounts of industrial process heat needs at the temperature being modeled.

varies by price scenario. When it is economic to sell power and heat, the inclusion of industrial process heat results in 11-75% larger energy storage capacity vs. the base case and longer duration, up to 4 or 5 hours, compared to the 2 hour minimum.

2.3.5 Fleet-level analysis - case study of Uttar Pradesh

We evaluated the cost-effectiveness of TES retrofits across the Uttar Pradesh coal fleet, based on the method described earlier and in Figure 2.1 and under the single state's electricity price scenario corresponding to 2030 grid. In all previous analysis, we include a considerable annual fixed operating and maintenance cost (FOM) of the remaining components of the CFPP that are part of the TES system (assumed to be approximately \$6.9 million per year for a 500 MW system). Since FOM costs for each plant are unavailable and may vary widely by plant and technology, we exclude the FOM cost in the annual profit calculation for the fleet analysis (however the UP results with this FOM included is shown in Figure A.8 in the Appendix). Therefore, the units to the right of the zero-marker indicating profitability are essentially determining the annual FOM thresholds for breaking even, whereas the units to the left of the zero-marker should not be repurposed (18%). If the facility can keep their annual fixed costs below those thresholds, then it can recover its capital cost and other operating costs

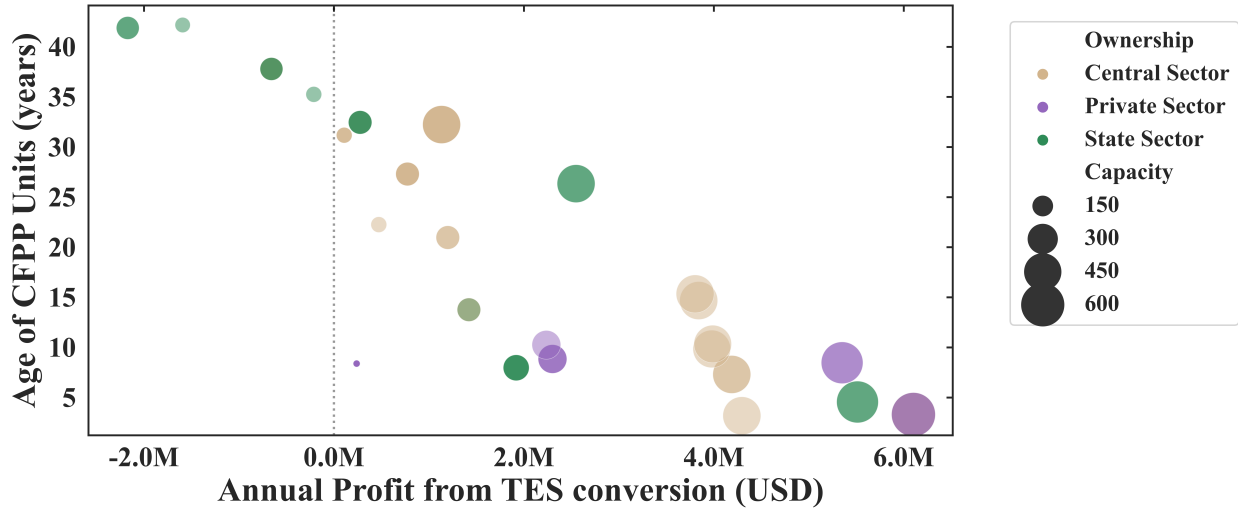


Figure 2.8: Annual profit from IDS for each CFPP in Uttar Pradesh, based on the 26 representative units classified by age and capacity. In this case, the annual fixed operating and maintenance (FOM) costs of the original coal plant are excluded in the profits calculation. The unprofitable units that should be retired are to the left of the zero marker, and are typically in the older age-bands groups.

over the lifetime of the storage system, under this price scenario.

We find that 82% (89% by capacity, 20.2 GW) of the UP units could be profitable as TES under the projected 2030 Uttar Pradesh electricity price scenario, with optimal storage durations varying from 4 to 6 hours. For the more economically viable cases, annual fixed cost thresholds range from 0.11 million to 6.1 million USD per year with capital investment ranging from \$13 to 220 million, driven by the energy storage components (storage medium and tank materials). This corresponds to an average capital cost of \$20.9/kWh for energy components, \$20/kW for discharge components, and \$5.1/kW for charging components. As a point of comparison, these storage capital costs are an order of magnitude less than the projections from the Government of India on Li-ion storage costs in 2030, which stands at approximately \$166/kWh and \$470/kW for installation costs [63]. Of the 82% that operate profitably as TES, 43% are owned by the Central government (9.1 GW), 36% are owned by private entities (6.8 GW), and 21% are owned by the State government (4.3 GW), as seen in Figure 2.8. Central and state owned units are responsible for the majority of the plants within the older, unprofitable group. These results fit well within the current age-based strategy that dominates coal retirement decisions, but offers a way forward for younger, more efficient plants facing stranded asset risks. While there is a visible trend where plants with 25 years or longer of remaining life will have even more favorable economics because the existing system can be retooled for the entirety of the new molten salt system lifetime (assumed to be 25 years), Figure 2.8 also shows viable operation for a wide range of coal plant archetypes. However, the age of a coal plant unit does not fully reflect the actual remaining life of the facility because components age differently and undergo various operational maintenance timelines. Additionally, there are significant effects from environmental, social, and political factors that ultimately determine coal plant decommissioning decisions and costs. These

effects have not been considered in this initial screening analysis.

2.4 Discussion

From the design standpoint, stakeholders should target CFPP unit designs with peak steam temperatures close to the peak temperature of the energy storage medium. Otherwise, system efficiency is likely to drop without extra upgrades or entire overhaul of the steam turbine system, and the profitability of the system is sensitive to efficiency. Newer TES materials reaching higher temperatures have the benefit of minimizing the discharge power component cost by decreasing the size of the heat exchangers and lowering storage costs. Using the TES system to co-produce heat for co-located industrial processes could also be economically attractive than standalone TES systems for grid electricity storage. In particular, such systems can reduce the cost of heat electrification and thus could provide incentives to shift away from coal-based captive power and heat co-generation.

The sensitivity on the storage material cost inputs reflects the uncertainty in reality regarding regulatory and technical uncertainties in the thermal storage technology choice. For example, there could be charges on imported storage materials, or reduction in storage material costs due to increasingly domestic supply chains and incentives. The storage cost sensitivity underscores the economic gains from choosing storage materials that are less expensive (and typically more abundant).

The volatility and temporal pattern of electricity prices significantly impact the profitability of TES, highlighting the need for extensive sensitivity analysis to future price scenarios when evaluating the economic viability of TES repurposed coal facilities. For example, even though there are many low-price periods in parts of the southern region representing opportunities for the system to charge at low cost, the TES dispatch cannot make enough revenue to recover costs.

On the fleet-level analysis in the state of Uttar Pradesh, we find that up to 82% of the coal units can be retrofit based on profit-maximizing, stand-alone grid storage model, but that this is highly dependent on the contextual annual FOM for the facility which should be further investigated. This screening analysis provides a starting point for further assessment of the retrofit potential of the coal fleet, that should account for many other benefits and drivers of retrofits such as local decreased air pollution, workforce reutilization, and system level grid impacts.

There are significant limitations to this work that is addressed in the next chapter. For instance, this analysis uses a price-taker model, implying that energy storage dispatch does not impact grid electricity price patterns. Thus, this analysis does not account for grid impacts of widespread adoption of TES technologies and the declining marginal value seen with addition of energy storage and renewable assets.

Through the case study of a single Indian state, we highlight how the potential for TES retrofits lie with the younger plants owned primarily by Central government and private sector entities and are dependent on annual FOM costs. This screening analysis serves as the starting point for further investigation of the plant-level impacts of retrofits, leveraging detailed plant-level data and lays the groundwork for evaluating grid-level impacts that such retrofits will have on grid dispatch.

Chapter 3

System-level evaluation of repurposing coal plants to TES in India

3.1 Introduction

The previous chapter used a plant-level, price-taker model to explore the potential for TES retrofits as a cost-effective strategy for early coal retirement and identified key techno-economic factors that drive its viability. However, the price-taker assumption has limitations in the context of competition between different types of energy storage technologies and the role of longer duration energy storage in decarbonization strategies. It assumes that the deployment of TES does not impact prices or dispatch of the power system, which may not be realistic if done at scale and secondly, it lacks a quantitative view of the competition between TES and other grid resources, and the relative economic value of these resources.

The framework afforded by capacity expansion models (CEM) offer a system-level perspective to quantify this relative value of repurposing coal plants into TES. This techno-economic framework often focuses on resources, demand, and infrastructure rather than socio-technical or political goals. However they do incorporate and inform these other perspectives particularly in innovation systems and political goals [64]. Specifically, CEMs offer a framework that optimizes investment in generation, transmission, and storage capacity while adhering to detailed system operational objectives to balance supply and demand as well as the various constraints involved in thermal unit commitment (ramp rates, minimum loads, start-up times). Many studies use CEMs to study energy storage technologies, uncovering the ways in which the system can leverage the strengths of different types of energy storage to fulfill system needs at least cost. CEMs exploring the optimal energy technology mix will examine grid scenarios with increasingly high levels of VRE penetration and observe results such as peak load management strategies, methods to avoid costly network infrastructure expansion, and identifying capacity and costs targets for future decades. The chosen spatial-temporal granularity of the system model impacts the portfolio of energy storage technologies and their relative value in some contexts, and must be balanced with broader research objectives and computational costs [4],[65], [7],[8],[66], [5],[9],[67]. This chapter aims to use a simplified CEM framework to introduce the impact of expanding the energy storage technology options (increasing technical granularity), and quantify the system-level value of

TES in the context of energy storage contracts and regulation in India to provide high-level conclusions, while setting the foundation for more detailed CEM-based studies.

The CEM optimization problem has the same fidelity of modeling TES as in the IDS model discussed in Ch. 2, but it employs a slightly different objective function that minimizes the investment costs and operational costs of solar, wind, coal, Li-ion batteries, and TES retrofits to meet a representative demand center. We use the CEM to test the impacts of the key drivers previously studied using the IDS model around the age and efficiency of the existing coal plant, and energy capacity cost of TES. Furthermore, we analyze system dispatch and variables under a flat demand profile in order to understand the difference in CEM results under the structure of typical energy contracts. We aim to understand the system value of TES retrofits by comparing these results to the price-taker model from the previous chapter, primarily in terms of dispatch, sizing, trends in the sensitivities, emissions reductions and system cost trade-off, and curtailment reduction.

This chapter draws on TES in CEM as well as an introduction to the regulatory landscape of utility-scale energy storage from Chapter 1. The next section describes the CEM methods and data, which is followed by the results and discussion.

3.2 Case Study

This case study offers the perspective of a stylized power system consisting of a single coal power plant with options to invest in additional technologies to meet a system peak demand that exceeds the maximum capacity of the coal plant.

We based this case study off of the state of Maharashtra, the same state of the coal plant in the case study from Ch. 2. Then, we arranged the study to represent a load center within the state, such as a metropolitan area, over which a distribution company operates and supplies power to customers. From this perspective, the system includes the load profile and investment for existing and new generation and storage to supply this load within this area, without considering local network constraints or the larger transmission network.

The primary decision variables of this CEM still includes the detailed sizing of key TES components (as explained in Ch. 2, Table 2.1 and Table 2.2), as well as the capacity of VRE and Li-ion batteries, and the generation and storage dispatch for the entire system to meet a given hourly demand. Figure 3.2 shows a sample of this dispatch in a representative week, and the additional constraints of the CEM are described in Appendix A.3.

3.2.1 Data

In addition to the capital and operating costs of the TES retrofits in Ch. 2, the CEM also uses capital and operating costs from the Central Energy Authority of the Government of India for solar, wind, Li-ion, and coal based generation (See Appendix Table A.6)[55]. Economic parameters of the coal plant reflect the base coal plant described in Ch.2. This plant has uncharacteristically high variable operating costs at \$145/MWh, which is around 3 to 4 times higher than most estimates, which lie at \$30 to \$50/MWh.

We use hourly annual capacity factors for solar and wind from the NREL ReEDS model of South Asia for a particular resource bin of the state of Maharashtra (node 29, A103), the

state with the base case coal plant that we evaluate in this chapter as well as Ch. 2 [9]

To reflect a smaller, geographic demand cluster (such as a small city), we use a scaled down profile of hourly demand for the state of Maharashtra in the year 2030 from the stable demand growth scenario of [5]

3.2.2 Capacity Expansion Model Formulation

The objective function of the capacity expansion model (CEM) is formulated to minimize the total system cost - upfront investment cost and operating costs of variable renewable energy capacity (solar, wind) installation and energy storage (TES retrofits, Li-ion batteries) capacity installation in order to meet a representative demand in every hour (See Appendix Equation A.53-A.55). This least-cost objective function is optimized for while abiding by the operational constraints of TES (as described in the IDS), as well as the coal plants and VRE (see Section A.3.2 in Appendix). These include: a) ramp rates and minimum stable power output of steam turbines, b) capacity constraints that ensure operating variables stay within design values (including capacity factors for VRE), c) constraints to define energy balance around the heat exchanger and heat-to-power electrical conversion efficiency, and d) TES and Li-ion energy storage inventory over time. For the coal capacity, we do not allow for investment in new coal generation. For the existing coal generation, allow the model to either continue operation, retire, or retrofit to TES. In Ch. 2, we understood the operation and economic viability of TES under dynamic hourly electricity price profiles. However, the hourly electricity price is endogenous to the CEM and we still must select representative weeks of the year to decrease computational costs and maintain characteristics of the patterns and profiles of VRE and demand that affect long-duration energy storage dispatch throughout the year. To address this challenge, we segment the annual hourly normalized demand, solar, and wind capacity factor data into week-long time series arrays and apply k-means clustering to assign the weeks to one of 23 groups. For each of the arrays of three time series, the week that is closest to the centroid of the group and the weight (the number of weeks in a year in that group) is selected to represent the group.

The CEM with parameters and sources are described in detail in Section A.3 and Table A.6. The overall optimization problem is a mixed-integer linear program (MILP) and is formulated in Julia (1.7.3) and solved using Gurobi (9.5.1). Each optimization is run on the MIT supercloud using 48 Intel Xeon Platinum 8260 cores. The model has 15,456 quadratic constraints and 3 SOS II constraints. There are 78,160 continuous variables and 15,460 integer variables, 15,460 of which are binary variables. The presolved model consists of 77,298 rows, 36,701 columns, and 234,649 nonzeros.

3.2.3 Scenarios

The CEM relies on a set of assumptions per scenario to set up the experimental framework that investigates the value of TES retrofits in the system. The base case CEM assumes there are no TES retrofits available to the existing base coal plant, and serves as a scenario to compare with other cases. The second case assumes TES retrofits are available. We model each case under a progressive amount of total system emissions constraints, as well as a zero emissions case, in order to understand the trade-offs between system cost, curtailment, and

Scenario	Description
Scenario 1: Base Case	continued operation of Base Coal Plant, no TES retrofit allowed
Scenario 2: Base + TES allowed	TES retrofit allowed (along with coal plant retirement or continuation)
Scenario 3: Base + Emissions Constrained	0% to 90% of the baseline emissions are allowed, no TES allowed
Scenario 4: Base + TES allowed + Emissions Constrained	TES retrofit allowed (along with coal plant retirement or continuation) and 0% to 90% of the baseline emissions are allowed

Table 3.1: CEM Scenario Table

energy storage deployment and operation in different emissions-constrained environments. In the sensitivity analysis, we vary the age and efficiency of the existing coal plant, as well as the storage capital cost of the TES. Finally, we explore the case that is more reflective of energy procurement contracts, where the demand profile is static, reflecting the way practitioners often formulate energy procurement contracts. We compare these decision variables and operating trends with the previous cases that serve a dynamic demand profile. These scenarios are summarized in Table 3.1.

3.2.4 Metrics

We define additional metrics to quantify and compare the system-level economic viability and value of TES retrofits. The energy storage duration metric from Ch. 2 remains the same (see Ch. 2.2.7 and Section A.2.3). Curtailment is defined as the fraction of VRE not delivered to a load or stored throughout the year (See Equation A.80). Instead of the annual profit of TES, we use the annual system cost, defined as the value of the objective function of the CEM (See Equation A.81).

3.3 Results

3.3.1 Effect of Emission Constraints

Applying an emissions constraint to the base case reduces the coal plant dispatch and results in larger amounts of installed wind, solar, and battery capacity to supply the load. Figure 3.1 shows this trend in the annual generation and installed capacity breakdown under increasingly limiting emissions constraints. For instance, the generation from solar increases from 9.1 to 12 TWh/year under a 10% of baseline emissions constraint. Wind generation

decreases from 4.6 to 1.8 TWh/year. Li-ion battery capacity increases from 2.0 to 3.0 GW, and 20 to 23 GWh. These results imply that the coal generation is primarily replaced by a solar and Li-ion storage dominant system.

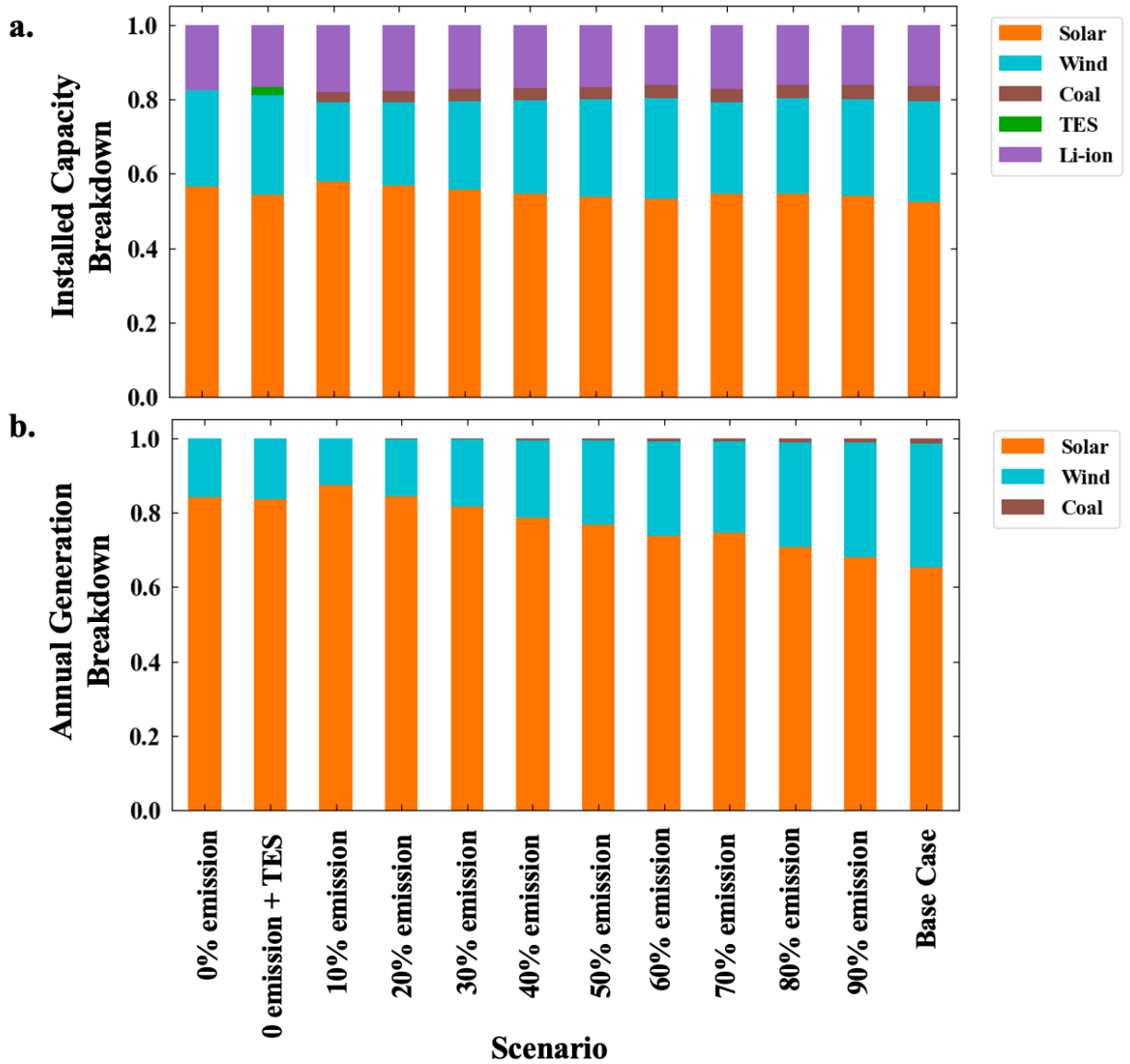


Figure 3.1: a. Installed Capacity Breakdown and b. Annual Generation Breakdown for scenarios with emissions constraints. Installed Capacity Breakdown is the installed capacity (MW) by technology, normalized by the total installed capacity. Annual Generation Breakdown is the annual generation from each resource (MWh) normalized by the total annual generation. With more stringent emissions constraints, the coal plant capacity factor decreases (as seen in the annual generation plot) and the amount of VRE + storage capacity installed increases. TES retrofits are optimal to deploy in the zero emissions case. Both zero emissions cases do not have any installed coal capacity.

In general, we find that the capacity factor of the coal plant decreases as the emissions constraint is tightened to 10% of the baseline emissions, as observed in Figure 3.1b. This is expected since the coal plant is the only generator contributing to emissions, and therefore its number of annual operating hours decreases as the emissions constraint of the system tightens (See Appendix Figure A.10). However, it is important to note that the capacity factor of the coal plant in the base case is 4%, whereas many coal power purchase agreements generally assume the capacity factor to be 80% and serving baseload. When we force a capacity factor of 80% for this coal plant, the system costs of the base case increase to \$1.6 billion/year, up from \$1.2 billion/year primarily because the variable operating cost of this coal plant is much higher than average. Annual system emissions are almost 16 times higher.

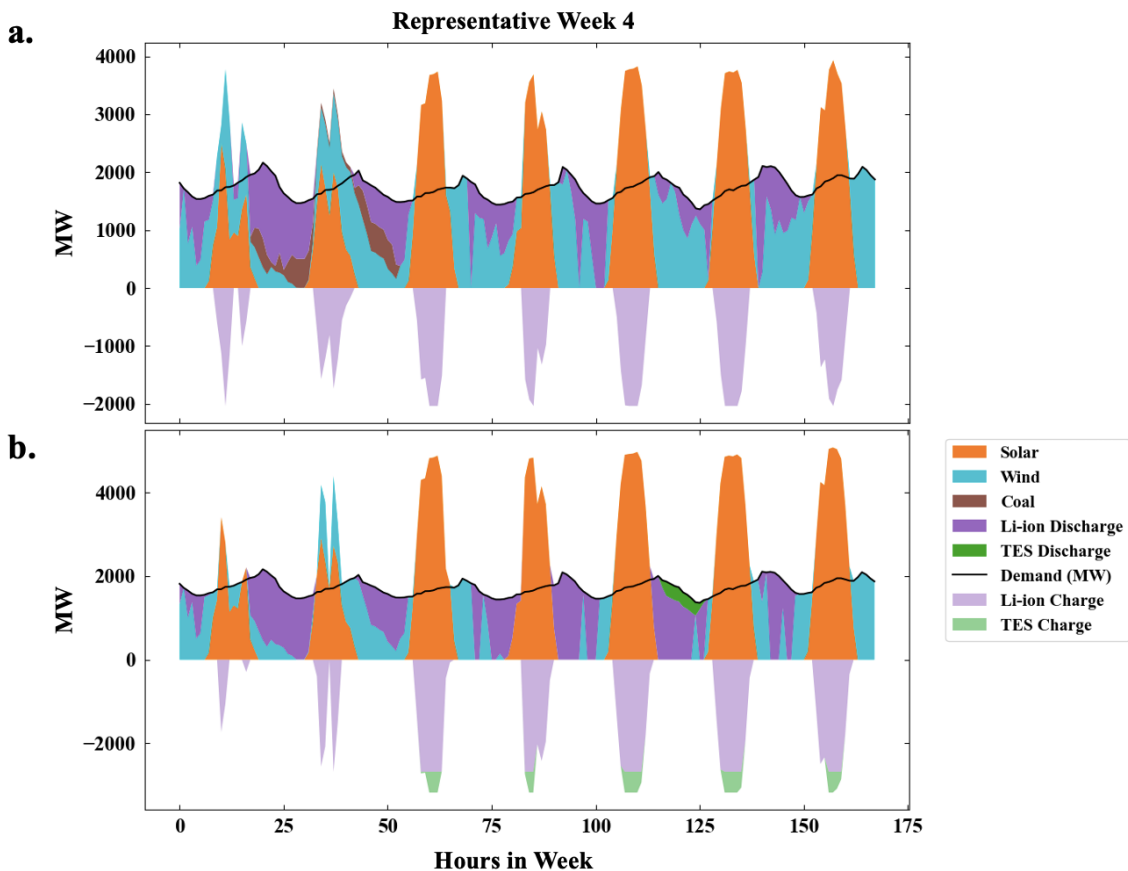


Figure 3.2: Dispatch profile for Representative Week 4 under **a.** the base case, with no emissions constraint and **b.** the zero emissions case with TES dispatch shown in green. In the base case, the coal dispatch does not serve base load.

Figure 3.2 also highlights how system dispatch changes between the case with and without TES in a representative week.

The decision to repurpose the existing coal plant into TES occurs only under the 0% system emissions constraint in Scenario 4. Otherwise, retrofit to TES results in 28% higher system costs compared to the base case (Scenario 1). As the emissions constraint tightens,

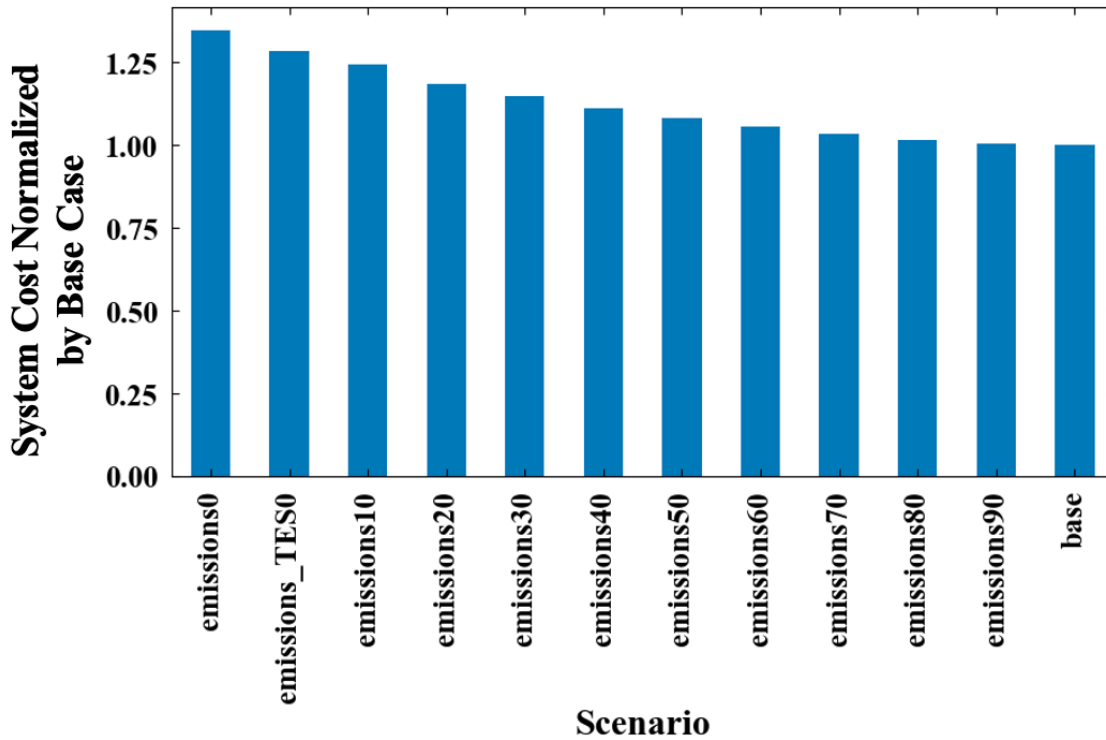


Figure 3.3: System cost normalized by the base case, for scenarios with various emissions constraints. With more stringent emissions constraints, the system cost generally increases from the base case. TES retrofits is optimal to deploy in the zero emissions case, and results in lower system costs than the zero emissions case without TES that simply retires coal.

we also observe higher amounts of installed solar and Li-ion based capacity (Figure 3.1a). Interestingly, the zero emissions case with TES repurposing allowed (Scenario 4), results in slightly more installed wind capacity and wind generation than the zero emissions case with no TES repurposing allowed. Given the trend discussed previously where wind generation decreased under increasingly stringent emissions constraints, the observation of increased use of wind resources suggests that TES complements the intermittency of wind resources over solar in this system valuation. Finally, Figure 3.3 shows increasing system cost with tighter emissions constraints but almost 5% lower system cost when the coal plant is repurposed (Scenario 4) compared to when the coal plant is retired (Scenario 3) in the zero emissions case.

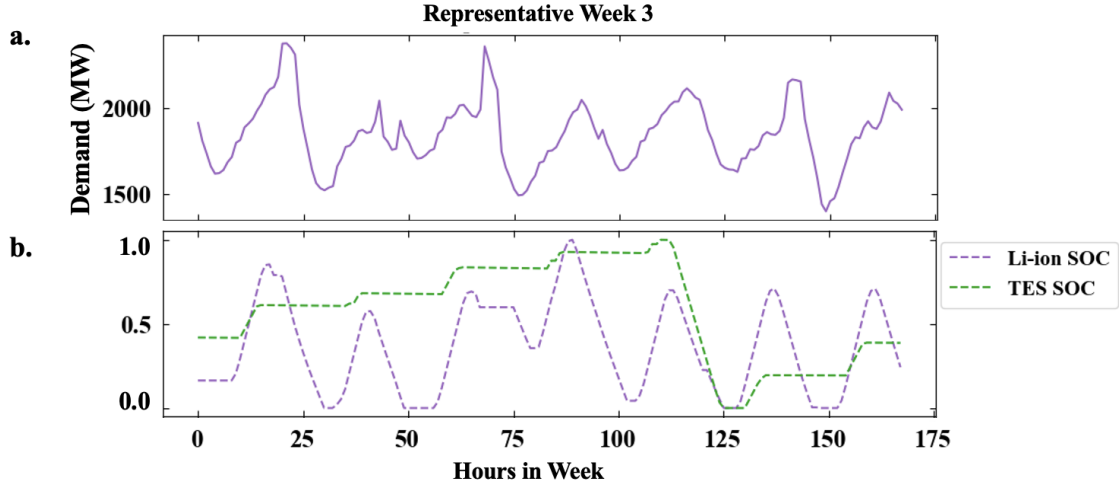


Figure 3.4: a. Shows the demand profile of the representative week, an input to the model. b. Compares the State of Charge (SOC) of the Li-ion batteries and TES. TES generally operates on a longer, weekly cycle whereas Li-ion batteries operate on a daily cycle.

In the zero emission Scenario 4 case with TES, we observe how the the role of TES differs from Li-ion dispatch, particularly in Figure 3.4. TES operates on longer, weekly cycles whereas Li-ion batteries operate on a daily cycle. Under the zero emissions case without TES, Li-ion storage has a duration of 10 hours and installed capacity of 2.8 GW and 31 GWh. With TES, the Li-ion duration decreases to 9 hours and installed capacity decreases to 2.7 GW and 26 GWh. Furthermore, the design of TES differs from the TES in the plant-level model - duration increases to 12-20 hours (from 4-6 hours), the peak capacity is often 350 MW instead of 500 MW, and the energy storage capacity reaches the limits (12 GWh). These comparisons highlight how the value of TES in the system is primarily for low cost, long-duration energy storage and complements Li-ion batteries.

3.3.2 Effect of Age, Energy storage cost, and Efficiency

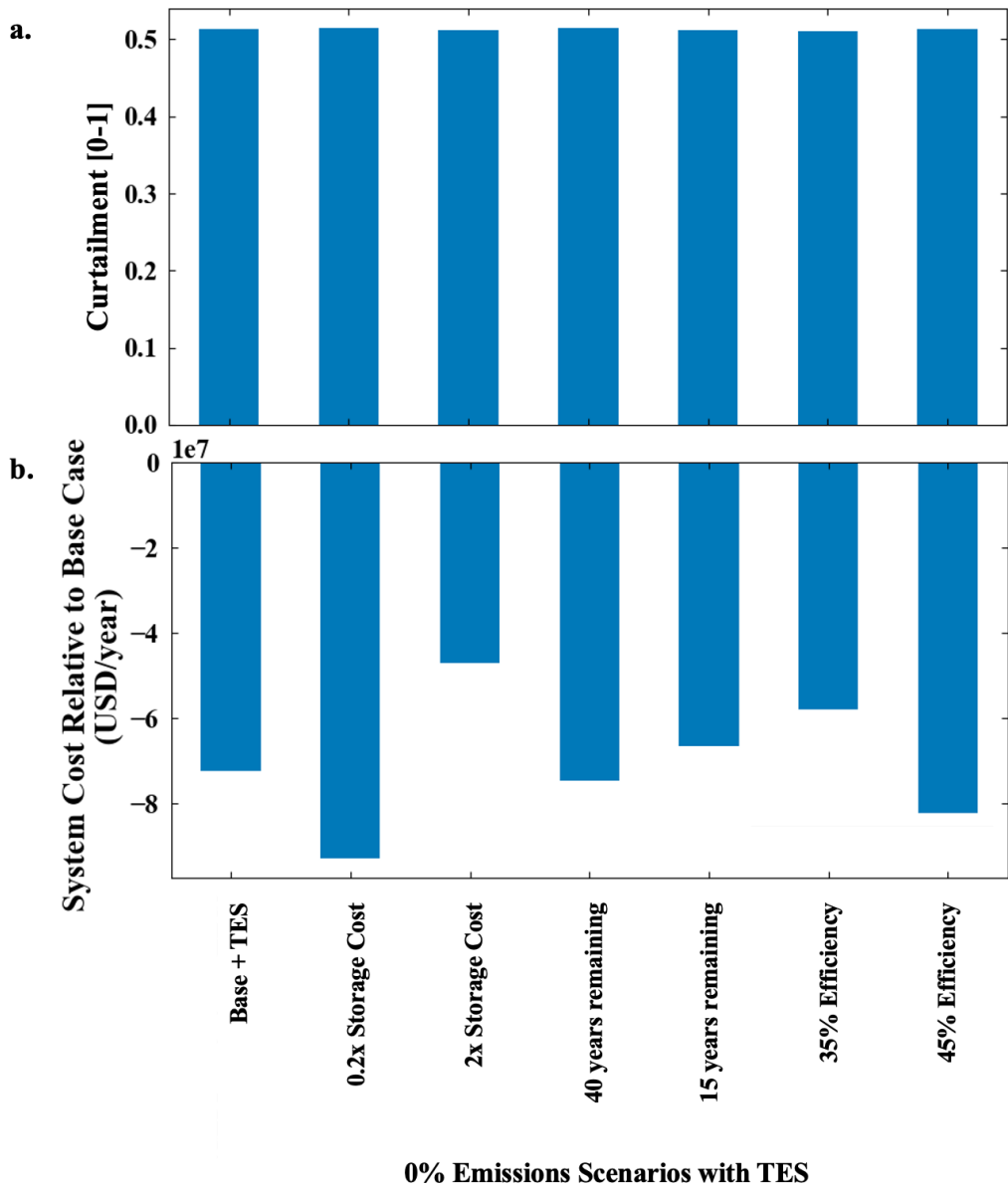


Figure 3.5: For the zero-emissions cases, this figure compares the **a.** total system curtailment and **b.** system cost relative to the zero-emissions case with no option to deploy TES retrofits (full coal retirement is the only option). The sensitivities compared exhibit similar trends to the plant-level modeling sensitivities and include: TES storage capacity cost, years remaining, and steam-turbine efficiency, with the storage and efficiency causing the largest range of impacts on system cost.

We find that the trends observed in the plant-level evaluation of TES economic viability regarding remaining lifetime of the coal plant, energy storage cost, and steam turbine efficiency, largely hold true within the system-level framework. We focus on the analysis of zero-emissions cases because the model only chooses to deploy TES retrofits under the zero emissions case. Figure 3.5 displays the curtailment values and system cost relative to the base case (Scenario 3) with zero emissions, under a sample of sensitivities under the zero emissions-Scenario 4 case (which includes TES). Base TES refers to the zero emissions case described previously that is almost 5% lower system cost compared to the zero emissions case without TES available. This results in almost 1.6% lower VRE curtailment. When energy storage costs are 20% of the base value, we see system costs decrease even further but curtailment increase. The trend in curtailment relates to the dispatch throughout the year, shown in Figure 3.6 and relates to how lower storage costs supports more VRE capacity, which increases curtailment values. Doubling the energy storage cost results in almost half of the original system cost savings from TES. We see similar but less pronounced trends when increasing (decreasing) the remaining lifetime to 40 (15) years or steam turbine efficiency to 45% (35%), which decrease (increase) the system costs even further compared to the Base TES case.

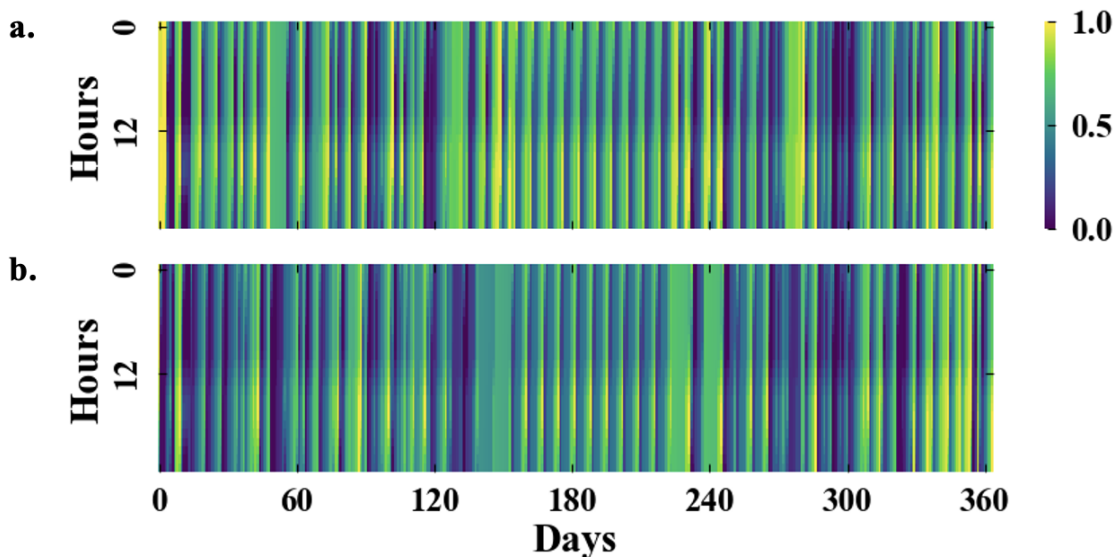


Figure 3.6: These show the State of Charge (SOC) of the TES throughout the year for **a.** the base case and **b.** the case with 0.2x storage capacity cost (lower cost storage). Both exhibit a small degree of seasonality, with the lower storage cost resulting in decreased throughput.

3.3.3 In the Context of Electricity Contracts

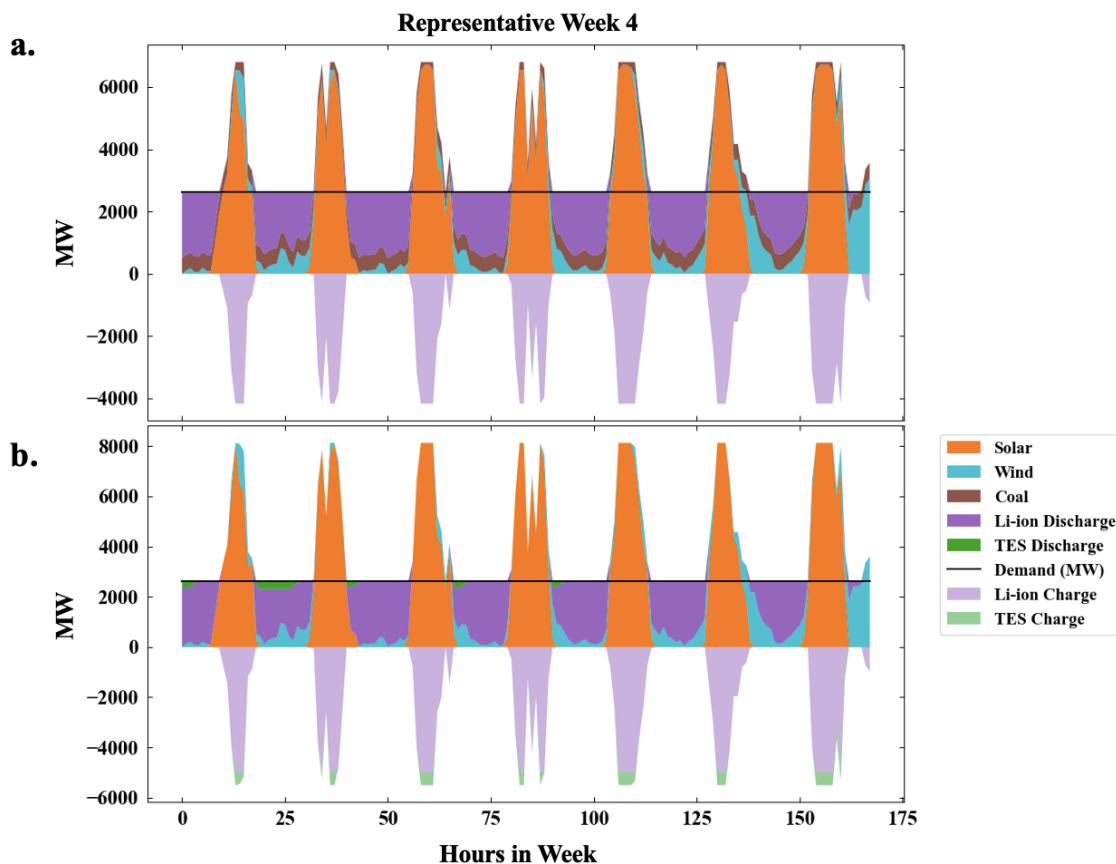


Figure 3.7: Dispatch profile for a flat demand profile, Representative Week 4 under **a.** the base case, with no emissions constraint and **b.** the zero emissions case with TES dispatch shown in green.

Most electricity contracts between generators and off-takers are not structured to supply the hourly dynamic demand profile, especially in highly regulated energy sectors without market-based dispatch. Instead, most contracts occur through power purchase agreements. To reflect this difference, we model the least cost capacity expansion under a static demand that broadly represents the peak demand for a load center such as a city. A particular discom for this load center would likely be under a contract to buy a specified amount of capacity from various generators at any time of the year to ensure quality supply to their customers. In the zero emissions case, the system achieves 3% lower cost (saving \$72 million annually) with TES retrofits than with retirement of the coal plant (but only half as much as before), and 17% higher system cost than the original base case. The dispatch of the coal plant and TES under this flat demand profile is shown in Figure 3.7.

Even within the flat demand profile, the capacity factor of the coal plant sits at approximately 4%, but PPAs often enforce coal plants to operate under a higher capacity factor. An enforced 80% capacity factor for the coal plant in this scenario results in the base case sys-

tem costs increasing from \$2.0 billion/year to \$2.5 billion/year, and annual system emissions are over 15 times higher. With this comparison, the TES conversion results in significant savings - a 6.5% reduction in system costs relative to the base case with the coal plant at 80% capacity factor.

3.4 Discussion

TES retrofits serve as valuable system-level assets in the energy mix for decarbonization strategies. There is demonstrable economic opportunity to include TES retrofits in broader early coal retirement strategies, which should be explored in future work. As explained in this chapter, the dispatch and duration of TES complement shorter-duration energy storage like Li-ion batteries. Therefore, policies should take into consideration the differences between incentives and targets for longer vs. shorter duration energy storage. Furthermore these systems-level results support the call for higher-level coordination between entities in the Indian government and utilities that govern coal retirement and those that oversee energy storage regulations as well as environmental remediation liabilities potentially embedded in coal power plant revitalization or repurposing costs.

This chapter also explored a scenario that reflects how energy generators and consumers in India generally operate under Power Purchase Agreements, bilateral agreements, and an nationwide Power Exchange (without zonal pricing or locational marginal pricing), resulting in almost half as much system costs savings from TES. India is moving toward a market-based dispatch, but there are uncertainties on its effect on dispatch for appropriately incentivizing storage dispatch. In addition, this analysis quantifies the energy time-shifting value of TES in a decarbonized energy system, but excludes the value-stacking opportunity for this stand-alone utility-scale storage to provide value in capacity adequacy markets or ancillary service markets where it could be compensated for operating reserve services such as frequency support.

Finally, we uncover a key tension within the modeling framework that reflects broader tensions among stakeholders and requires further analysis. The decision to repurpose, retire, or continue operation of a coal plant depends on entities such as plant owners, system dispatch operators, off-takers that negotiate power purchase agreements, state and national-level regulations and policy targets, development agencies, and resource constraints. On the global stage, India predominantly calls for continued demand growth and development using the least-cost energy generation (generally coal) and references global climate injustice, where developing economies should not be held responsible for the global emissions caused by the industrialization and development of the wealthiest countries. At the same time, technology costs for VRE have become cost-competitive with coal generation, sometimes rendering certain coal plants as mothballed facilities (not being used for most of the year). For these plants, contract structures could change to be capacity-based rather than based on energy generation. Our analysis suggests that retrofitting these facilities could benefit the coal plant owners, especially if they operate under better energy storage contracts. Repurposing these facilities would make the full discontinued operation of the plant more attractive for the operators, which might be useful for emission-reduction strategists if there is large uncertainty in the decision to retire the plant.

However, since these plants are already stranded assets, not being dispatched often (low capacity factor), and on its way toward retirement, then the financing of the international organizations (such as the Energy Transition Mechanism financing early coal retirement or international Just Energy Transition Partnerships), would not be maximizing a reduction of emissions. On the other hand, a retrofit of this plant set for retirement would be even more valuable to the community members, depending on the number of livelihoods generated by the plant.

If a coal plant with lower variable cost and a high capacity factor were to be on the "early retirement" list from the international entities, retirement would be maximizing reduction of global emissions. Instead of retirement, repurposing this plant could be a better option for those facing livelihood loss by the early retirement, and the community might experience benefits from decreased exposure to local pollutants. Repurposing would allow the financiers to be more cost-effective with their financial resources by negotiating a lower payment to transition the facility to TES. However, the cost of electricity would increase for consumers if the closure of this plant forces off-takers to form power purchase agreements with more expensive energy generation, and subsidies might be needed to mitigate this effect.

In comparison, high capacity factor coal plants with high variable costs would be ideal candidates for repurposing. Retiring these plants would maximize reduction of emissions (a key objective for international planners) as well as decrease system costs if there is generation with lower operating costs in the system. Similarly, repurposing these facilities affords cost-effective resource management and partial mitigation of the locally harmful effects of retirement.

While the last two chapters investigated TES retrofits from a techno-economic lens and identified key technical and economic drivers of economic viability, this discussion relates broader conclusions to strategic decision-makers and exposes the tensions between the values, priorities, and definitions of justice embedded in coal retirement decisions, along with the unequal distribution of benefits and costs of transition plans. To better understand these implications for a decarbonization strategy involving repurposing coal plants, the next chapter explores the political economy and energy justice implications embedded in prevailing coal retirement strategies.

Chapter 4

Relation to the Just Energy Transition

4.1 Introduction

A just transition requires elements of energy justice frameworks such as recognition, distributional, reparative, and procedural justice. However, international entities hold different interests that influence their position and prioritization of these evolving elements of justice. This lack of clarity around this definition allows for different and sometimes conflicting interpretation and implementation of energy policies within countries. Private and public organizations often seek unbiased legitimacy in their decision-making process, frequently relying on models and quantitative analysis to achieve this goal [68]. This allows decision-makers to avoid blame for certain decisions; simultaneously, the practitioners creating quantitative models know that their models are not always impartial, containing inherent judgements, values, and different flaws. The ambiguous visioning of a just energy transition percolates into the underlying motivations from which energy system modelers frame their modeling objectives and assumptions, which can lead to conclusions that are more relevant for one interest over another.

This chapter begins by defining elements of energy justice followed by a critical review of how one element, distributive justice, is embedded in modern day coal retirement planning. We then identify key barriers of India’s energy transition from a political economy perspective, drawing on theories of distributive conflict. Subsequently, we discuss our theory around the importance of investigating political economy barriers in the context of distributive conflict and distributive justice. We conclude with suggestions for equitable energy transition strategies.

4.2 Energy Justice

This chapter uses the definition of energy justice as “the goal of achieving equity in both the social and economic participation in the energy system, while also remediating social, economic, and health burdens on those by the energy system” [69]. When evaluating policies through this lens, actors should ask themselves about the procedural elements – “have marginalized communities participated meaningfully in the policymaking process with sufficient support?”; restorative elements – “does the policy aim to remedy prior and present

harms faced by communities negatively impacted by the energy system?"; decision-making concerns – “does the policy center the decision-making of marginalized communities?"; benefits – “does the policy center economic, social, or health benefits for marginalized communities"; and finally access—“does the policy make energy more accessible and affordable to marginalized communities?" [69]. In general, procedural justice concerns who is making decisions and if their voices are heard. This chapter focuses on distributive justice, which is more outcomes-focused than procedural justice and has further dimensions when applied to technology policy. Cozzens outlines four views of distributional justice, the first being the libertarian view, where value comes from the equal protection of property rights and justice is achieved when individuals can exercise their rights to property in a free market. The dominant utilitarian view argues that some set of social arrangements is fair so long as it increases the total welfare (i.e. grow the pie, someone else will cut it). The contractarian viewpoint posits that a fair system of distribution includes rational individuals freely coming to agreement after discussion. This viewpoint relies on elements of procedural justice (defined above). And finally, the communitarian perspective defines an action as moral when it strengthens community life. Social responsibility, individual freedom, and society wide values are important in this perspective. Actions that shift power away from the community would be challenged. In this way, the communitarian perspective demands a mutual respect for knowledge. This chapter asserts that both the top-down and bottom-up coal transition strategies in India embed utilitarian perspectives on distributional justice, but that the bottom-up approach can be modified to prioritize contractarian and communitarian viewpoints; these can further be incorporated by evaluating the political economy barriers to coal plant closures by different states in India [70].

4.2.1 Existing Methods and their distributive justice implications

Transitioning coal assets give rise to many knowledge appraisals questions. Where and when should these assets be retired? How should they be replaced? How will jobs, local government revenue, welfare spending, industrial fuel and social aspects change as a result of retiring assets? We focus specifically on the knowledge assessment regarding the timeline that coal plants are retired, which is an open research question that embeds different values of procedural justice, since often only a subset of constituents are involved in the decision-making process. This makes the proposed solutions prone to disproportionate allocation of positive and negative impacts and exacerbation of existing inequities.

National, long-term energy models implement a top-down, utilitarian perspective on distributional justice and have long been used to evaluate energy infrastructure investment pathways. These models are formulated at different granularities depending on if the audience consists of policymakers, power system planners, or energy economists. Some power system models are open source, such as MIT’s GenX tool, but many of the energy planning studies are conducted via government bodies outsourcing to consultants, which introduces an information asymmetry problem, especially for the detailed technical assumptions of energy infrastructure costs [71]. Similar to the model in Ch. 3, these long-term energy models have been adopted to analyze electricity sector decarbonization strategies. They optimize the investment in generation capacity across time and space, as well as operation of the system at a nodal level in such a way that minimizes system costs, while being subject to

various physical constraints and policy constraints such as a carbon tax or cap and trade system. This high-level planning approach fundamentally embeds a utilitarian viewpoint on coal plant closures because retirement is justified so long as the entire system's costs are minimized. Depending on the granularity, one could broadly gain insights on where and when energy transitions occurs. The technical formulation has its merits for determining where flexible operation of energy resources can provide system benefits and allow more VRE overall. However, the results treat the unequal distribution as an afterthought to be managed by others. There have been some studies that seek to shift the energy policy paradigm by developing methodologies that find the optimal expansion of a power system by maximizing social benefit, specifically in relation to distributional equality for electricity access in the nodes and subject to budget constraints [72]. Though the modelers seek to gain broad insights from interpreting these models as opposed to specific financial commitments to investment, they still generally imply to policymakers that where outcomes might differ from this model, reality should move to fit the model outputs.

Coal plants can also be justified for retirement based on plant-level indicators in a bottom-up approach that currently still embodies a utilitarian perspective on distributional justice but could be modified to prioritize community values (communitarian) or meaningful deliberation with local stakeholders (contractarian). This method is also subject to knowledge assessment concerns. The Central Electricity Agency (CEA) has identified coal plants to be retired in 2022 based on age and 2027 based on compliance with environmental regulation. However, the retirement list is non-binding, and these units might just be replaced by more efficient units. Globally, the criteria for decommissioning are age, pollution, and costs. As coal plants age, their machinery deteriorates and becomes even more inefficient. Various studies have used more indicators than the Government of India to determine more cost-effective strategies to retire coal plants. Coal plants are dispatched in a merit order stack by variable cost. Therefore, older plants with low fixed costs and low variable costs would out compete younger (more efficient) plants with higher fixed costs and variable costs. The Center for Energy Environment and Water (CEEW) in a recent report found that this operational strategy results in lower thermal efficiency of the entire fleet (29.7%) and a tendency of regulators to be lax on this poor technical performance. They find that by dispatching coal plants based on efficiency instead of variable cost, almost 50 GW of capacity would be surplus to the system, they would save nearly 42 MT of coal annually, reduce greenhouse gas and emissions, and achieve higher fleet utilization (78%). The CEEW strategy emphasizes a utilitarian distributional justice perspective by focusing on the system-wide benefits [30].

Maamoun et. al. develops another bottom-up strategy that include environmental variables as well as the technical and economic characteristics of the plant. The use of environmental variables like water stress, exposure to air pollution, and carbon emissions incorporates a more localized, value-driven reason to retire coal plants [73]. Though the metric for comparison among these methods are system-wide costs and utilization factors, they offer an ability for community values like pollution exposure and management of local water resources to be incorporated in the process. An emphasis on more polluting plants being retired earlier could be more beneficial for the local community. Therefore, this approach embeds a utilitarian perspective on distributional justice, with opportunity to engage with communities and enact communitarian or contractarian perspectives. For example, community-oriented indicators such as labor, retrofit potential, or local government revenues from coal opera-

tions could be included in this framework. These two plant-level studies offer a glimpse of how reliable access to these indicators can be contested. The lack of transparency and accountability of self-reported pollution, operational economic and technical data from plant owners can skew results. This uncertainty in indicators as well as access to the data renders it difficult for policymakers to implement a more equitable retirement strategy that accounts for externalities.

Political Economy of the Energy Transition in India

State-level political economies wield the most power to block coal plant retirements. Therefore, ranking state political economy perspectives on coal transitions could better identify where regulators should focus to accelerate a just energy transition. Coal plant retirement strategies fit within the sphere of climate policies because of national and company-wide goals for decarbonization. By understanding the distributive conflict among concentrated interests through related climate policies, we can gauge how effectively coal plant retirement plans can be implemented. Aklin and Mildenerger (2020) argue that distributive conflict among proponents and opposition shapes climate policy. They show that framing climate policy as a response to the collective action free-riding problem is not supported by empirical evidence, and thus climate policy should not be written as a response to this faulty underlying assumption [74]. This viewpoint embeds a contractarian perspective on distributional justice, since it pushes forth a narrative where informed parties with conflicting interests shape these policies. States have their own generating coal plants, mining operations and electricity infrastructure. Though energy policies have sought to liberalize the electricity system, states still represent a very concentrated interest in India. National climate policies might be most effective by encouraging distributive conflict between states or regions within states instead of assuming states would not act because of the collective action freeriding problem. In the collective action freeriding problem, states do not have an incentive to invest in decreasing emissions through rigorous environmental standards and retiring coal assets because they would expect other states to continue with the status quo, and altogether the entire country would not achieve their national goals of sustainable economic development. Instead, there have been efforts by states to promote renewables, enforce environmental regulations on coal plants, and encourage healthier financial operation of their discoms.

The full contractarian view on distributional justice would go a step further to include informed communities in the deliberation process. This is important for allowing communities to facilitate a broader transition away from coal dependent economies, instead of facilitating a transition wherever is most politically favorable. Including communities in this process can also assist with mitigating any resistance to energy transitions.

The communitarian perspective on distributional justice would only allow power plant retirement if the community were strengthened. This implies that there must be more power shifted toward communities in the restructuring of the energy system, and that the community's interests are well represented and communicated. This could be in the form of renewable energy jobs, capacity building, community-based energy systems, replacement industries, and stimulation of local economic diversity. However, it is important to note that simply retraining and replacing coal jobs with renewable energy jobs is not a one-to-one replacement [75]. It has the potential to dissolve community identity if these communities

are not meaningfully involved in reshaping their identity.

Research about the political economy of the coal transition in the UK, US, Germany, and Eastern Europe have relevant advice for India despite their plants being older and reaching their end of life. This body of literature aims to identify who wins and who loses from coal plant retirements, who can shape policy, the actors involved, policy instruments used, management policies, drivers, and barriers to the energy transition. In India, the main actors are the state and central governing bodies. The generators (privately owned, state-owned, and centrally-owned) operate with the discoms under financial contracts. The states also have electricity regulatory commissions. National bodies like the CEA oversee the retirement list, and Power System Operation Corporation Limited (POSOCO) manages the operations nationally through five regional load dispatch centers and facilitates interstate transmission, ensuring power balance, reliability, security and efficiency of the entire system.

The just transition literature largely advocates for assessing jobs and pensions in coal communities through gathering data on direct jobs, indirect jobs, induced jobs, and pensioners. Recently, indicators have expanded from this definition to also include county revenues like local level taxes, welfare spending through corporate social responsibility, industrial fuel, infrastructure and induced spillover, and social and justice aspects like generational identity, environmental justice, and labor demographics. This wider indicator base reframes the transition as an opportunity to optimize government support and opens the door to more creative, localized solutions. Particularly in India, these cross-subsidies with the coal industry and transportation, social service funds, and other public benefits creates a market failure in terms of imperfect competition, creating a barrier to entry for more efficient firms [76].

Proxy barriers to coal plant retirement can be identified by state-level political economies and by tracking their implementation status overtime. To understand barriers to the coal transition, the following section examines common barriers to renewable energy development in India, recent energy policies by state, and the diversity in subsidies to energy supplies. The major power producing states are Maharashtra, Gujarat, Tamil Nadu, Uttar Pradesh, Karnataka, Madhya Pradesh, Andhra Pradesh [77].

Land requirements

First, land requirements for scaling up renewables relies on the availability of cheaper land. States with less regulation and cheaper land will generally have better sites for renewables, which is significant for a renewable energy such as utility scale PV. These tend to be rural areas. In rural coal sites, a coal plant would form a primary revenue source for local communities, which may make it even more difficult to consider a decommissioning and repurposing of coal plants in these areas [78]. There is lack of clarity over land titles, with outdated records and fragmented landholdings, particularly in Jharkhand, Uttar Pradesh, Bihar and Odisha [79].

Favorable to VRE

States with favorable renewable policies and abundant solar potential are Maharashtra, Gujarat, Andhra Pradesh, Karnataka, Tamil Nadu, Uttar Pradesh, and Telangana according to

recent studies [78]. Net-metering policies are being implemented in 28 states and could enable faster expansion of distributed solar PV, but tariff reform and the presence of aggregators could improve the approvals process and system design, especially for residential applications where retail tariffs are subsidized significantly [80]. Indrajayanathan and Mohanty assess the clean energy transition potential in the major power producing states (Maharashtra, Gujarat, Tamil Nadu, Uttar Pradesh, Karnataka, Madhya Pradesh, and Andhra Pradesh) using multi-criteria decision analysis processes and find that Gujarat has the highest clean energy transition potential and Uttar Pradesh exhibited the least performance [77]. Pathak et.al. use an integrated Modified Delphi and AHP method to identify the prioritization of barriers to development of renewable energy and find policy and political barriers to be the highest priority [81].

Discom health

Distribution company health also serves as a key barrier to energy development, with many state discoms being in poor financial health and filing for bankruptcy often. IEA 2018 identifies Uttar Pradesh and Rajasthan as the worst performing discoms, with Bihar and Kerala receiving the second worst rating. Maharashtra and Andhra Pradesh outperform Punjab and Karnataka slightly, and Gujarat has the top score [31].

Coal Capacities

The most expensive coal capacities are in Uttar Pradesh (12.078 GW), Maharashtra (11.29 GW), Andhra Pradesh (9.05 GW), West Bengal (8.89 GW), and Tamil Nadu (7.645 GW). These are not correlated with states with largest coal reserves like Jharkhand (83.15 billion metric tons), Odisha (79.30 billion metric tons), Chhattisgarh (57.21 billion metric tons), West Bengal (31.67 billion metric tons), and Madhya Pradesh (27.99 billion metric tons)[31].

Policies and Funding

The Energy Policy Tracker has identified at least \$37.89 billion for unconditional fossil fuels and \$6.42 billion for conditional fossil fuels; on the other hand there has been at least \$4.69 billion for unconditional clean energy and \$32.34 billion for conditional clean energy. A significant \$68.77 billion was put forth for “other” energy. There exists a disparity between how policies differ between fossil fuel and clean energy, where conditionality exists for the larger percentage of clean energy than for fossil fuels. From this policy tracker, the states involved with any policies have been: Punjab, Tamil Nadu, Gujarat, Bihar, Bhutan, Maharashtra, Kerala, Uttar Pradesh, Chandigarh, Delhi, Uttarakhand, and Andhra Pradesh. Implementation status for these have yet to be realized, but still they offer insight on the general coordination of energy transition policy [82].

4.3 Discussion

Some states like Gujarat and Maharashtra are well poised for coal plant retirement and an energy transition. This examination of coal plant retirement strategies in India can in-

form the differentiation between short-term and long-term planning and direct where unique governmental or international support would be needed to ensure more equitable access to the benefits of an energy economy dominated by renewables. Including these factors can shift the paradigm of distributional justice from utilitarian to contractarian or communitarian since the focus shifts to community-level interests and making these voices heard in the political process. Furthermore, treating these states as unique parties with conflicting interests can help enact meaningful climate policies through distributive conflict. It is apparent that these climate policies promoting renewables or closing coal plants creates new economic winners and losers. There must be a balance of power between economic actors for all states to implement the energy transition over time, otherwise strong opponents can retrench promising energy transition policies. Therefore, identifying state-wide barriers at this stage of energy transition planning in India can determine where interests groups need more support. For instance, this support could be through reducing information asymmetries between the carbon-intensive industry and pro-climate policy groups; or it could aid in identifying opportune areas for pilot projects to determine technical and social feasibility.

An equitable energy transition away from fossil fuels relies on effective technology deployment as well as strategic retirement of existing coal assets. Under zero-emission energy systems, coal fired power plants are on track to be stranded assets and financial burdens to India's energy system, as well as toxic facilities that poison communities disproportionately and create an inefficient economic dependence with communities and even industries. India's energy landscape is heavily dependent on coal, but there are ambitious national renewable energy targets and state level policies and deployment of renewable capacity that point to a decarbonized future. We used an energy justice framework, focusing on the dimensions of distributional justice to analyze coal plant retirement strategies. From this framework, we suggest that coal plant retirement strategies should examine state level political economies to understand which states have higher barriers to energy transitions. We drew on related theories of distributive conflict and just transition literature to support this theory. After identifying political economy barriers by state, we identified suggested areas of where to direct support, and compared the justice frameworks incorporated in this approach with existing theories. This analysis serves as a basis for integrating innovative coal plant repurposing strategies.

Chapter 5

Discussion and Conclusion

In coordination with early retirement payouts, the repurposing strategy could be included in energy planning models as well as government retirement timelines. While coal retirement planning in the context of just energy transitions often reference an ambiguous "repurposing" option, few studies seek to quantify the value of such a proposal from a modeling standpoint. Our edge case analysis of repurposing a CFPP unit with commercially available thermal energy storage technology in a coal heavy electricity system indicates technical and economic feasibility. Key levers for plant-level viability include location in more renewable-heavy regions and operating under certain design conditions.

Specifically, we find that TES retrofits of coal power plants have economic potential under certain plant-level and grid contexts by the end of this decade. Storage durations lie between 4-6 hours when economically viable and up to 12-24 hours in the system-level model. We find factors that improve the potential for TES retrofits include the availability of lower energy capacity cost TES media, higher peak salt temperatures, longer remaining lifetime of coal power plant, higher steam cycle heat to power conversion efficiency, and especially local process heat co-production. We also find 3-6% decrease in total system costs by retrofitting coal plants to TES rather than retiring them in the context of a zero-emissions sub-regional demand cluster.

Global calls for a just energy transition motivated this study, since there are certain unquantifiable aspects of a just transition that appeal to repurposing existing facilities, such as livelihood retention. However, the interests and positions underlying emission reduction strategies in India provoked a deeper discussion around the definitions of a "just transition" and how the unequal state-level energy policy landscape lays a foundation for identifying where TES retrofits would have positive impact for asset owners, and/or perpetuate distributive injustices without additional systemic support. These results warrant further investigation into articulating the value of repurposing coal plants from the perspective of different just energy transition stakeholders.

5.1 Limitations and Future Work

The techno-economic analysis of the first two chapters contain certain limitations. Firstly, improvements to the optimal sizing and dispatch model could consider dynamic operating

constraints for the heat exchanger as well as alternative thermal storage schemes [23],[83]. In addition, ramp rates are assumed to be the same as the CFPP even though TES could have more flexibility because it will be mostly limited by thermal creep instead of coal combustion and boiler related processes.

Based on the favorable economic viability of TES for captive coal customers (from Chapter 2), future work should aim to quantify the electricity system opportunities afforded by coupling industrial processes and industrial demand centers with TES technologies that serve a wider range of temperatures while addressing industrial decarbonization.

There are also under-explored opportunities for data-driven approaches considering local socio-economic and environmental costs and benefits from decreased air pollution and social effects in the face of potential economic tensions in communities and for workers dependent on the fossil fuel industry. Many local governments are economically tethered to these industries through their tax bases, and abrupt removal can result in undue economic stress and significant social backlash. This TES strategy has potential to utilize the existing workforce and expertise from local companies that have experience with power plant development, turbine manufacturing control systems, steel, and civil construction. This can make TES attractive for piloting in this decade, which can be part of the longer-term strategy as the country grows its low-carbon power system workforce.

Future work will apply the bottom-up framework to other states in India for a full country-level fleet analysis of TES repurposing potential and relative costs. An expanded scope could explore different types of TES and other retooling possibilities at the site, as well as estimating the value of TES in the power system network of a specific state or region. Finally, some TES grid-scale storage may have other value-stacking revenue streams such as providing low-cost inertia compared to other storage options, which could decrease overall system costs in a grid with higher penetration of renewables.

5.2 Conclusions

Based on the beneficial techno-economic value of TES repurposing at the plant-level and system-level under the specified conditions, policy approaches seeking to decarbonize coal-dominant energy systems should incentivize TES repurposing as part of cost-effective early retirement plans. TES retrofits can also appeal to stakeholders focused on global emission reductions, investors who require a low-cost method to alleviate their stranded asset risk, and facility owners. While the CFPP conversion is motivated by the just transition, it does not address any injustices experienced by coal miners and other cross-subsidized, coal-dependent sectors that further entrench coal-based power generation. However, by introducing critical perspectives and understanding implicit values in solutions such as coal plant repurposing and coal retirement strategies, practitioners can better focus their research on shared visions of the evolution of the energy system and have a more open dialogue on steps to get there.

Appendix A

Model Description

A.1 Nomenclature and Data Inputs

The section below describes the nomenclature used in both model formulations as well as the data inputs. All economic parameters are converted from their respective sources to 2020 USD using either the Consumer Price Index (CPI) or the Chemical Engineering Plant Cost Index (CEPCI) when appropriate.

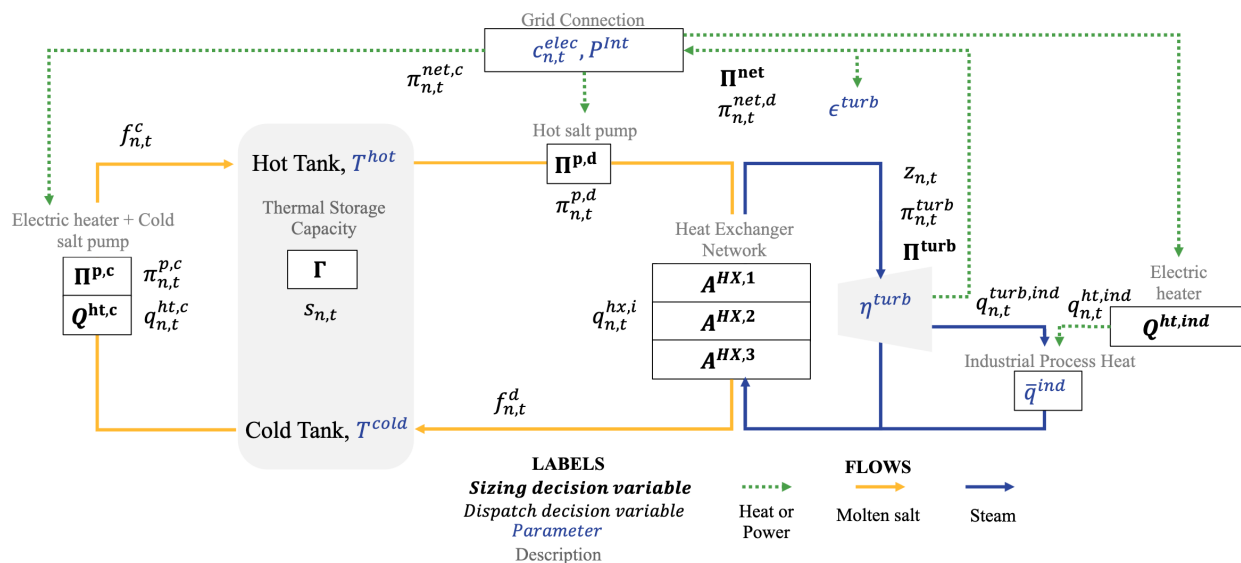


Figure A.1: Diagram describing the decision variables and some parameters in the integrated sizing and dispatch optimization model.

Set	Description
$t \in T$	Set of time periods in each week ranging from 1 to t_{end} (i.e. 168)
$n \in N$	Set of representative weeks modeled ranging from 1 to n_{end} (i.e. 23)
$w \in W$	Set of weeks over the years ranging from 1 to w_{end} (i.e. 52)
$i \in I = ec, ev, su$	Set of heat exchangers modeled
$g \in G = solar, wind, coal$	Set of generators
$g \in G^{VRE} = solar, wind$	Set of variable renewable generators

Table A.1: Sets and Indices

Variable	Description
Γ	Installed energy storage capacity ($MWh_{thermal}$)
Γ^b	Installed energy storage capacity of Li-ion battery b (MWh)
$\Pi^{p,d}, \Pi^{p,c}$	Size of salt pumps for discharging and charging, respectively (MW)
Π^{turb}	Peak capacity of steam cycle (MW)
Π^g	Peak capacity of generator g (MW)
Π^b	Peak capacity of Li-ion battery b (MW)
$Q^{ht, TES}, Q^{ht, IND}$	peak charging thermal power capacity for heating molten salt and heater used to provide industrial process heat ($MW_{thermal}$)
$A^{HX, i}$	areas of three heat exchanger $i \in I$ (economizer, evaporator, and superheater) part of the heat exchanger network
$\lambda_k^{ec}, \lambda_k^{ev}, \lambda_k^{su}$	SOS variables of type 2 to model piece-wise linear approximation of capital costs for heat exchanger $i \in I$
$C^{HX, i}$	Capital cost of heat exchanger $i \in I$

Table A.2: Time-independent Variables

Variable	Description
$q_{n,t}^{hx,i}$	Rate of heat exchanged via heat exchanger $i \in I$ during subperiod t of representative week n ($MW_{thermal}$)
$q_{n,t}^{ht,c}, q_{n,t}^{ht,ind}$	Heat supplied by resistive heater during for heating up salt and providing industrial process heat, respectively, during sub-period t of representative week n ($MW_{thermal}$)
$q_{n,t}^{turb,ind}$	Heat supplied by steam to meet industrial process heat, respectively, during sub-period t of representative week n ($MW_{thermal}$)
$f_{n,t}^c, f_{n,t}^d$	Flow rate of salt for charging and discharging during sub-period t of representative week n (tonne per s)
$\gamma_{n,t}$	TES storage inventory for during sub-period t of representative week n ($MW_{thermal}$)
$\gamma_{n,t}^b$	Li-ion battery storage inventory for during sub-period t of representative week n (MW)
$\pi_{n,t}^g$	generation in sub-period t of representative week n (MW) for generator g
$\pi_{n,t}^{b,c}, \pi_{n,t}^{b,d}$	Li-ion battery, b , charging (c) and discharging (d) in sub-period t of representative week n (MW)
s_w	TES storage inventory at the beginning of week $w \in W$ ($MWh_{thermal}$)
δ_n	Change in energy storage inventory over the course of representative week n ($MWh_{thermal}$)
$y_{n,t}^{TES}, y_{n,t}^{coal}$	Binary variable tracking whether steam turbine system is in discharging (=1) or charging mode (=0) during sub-period t of representative week n for TES and coal
$\tilde{z}_{n,t}^{TES}, \tilde{z}_{n,t}^{coal}$	Binary variable used track start-up of steam cycle during sub-period t of representative week n for TES and coal

Table A.3: Time-dependent Variables

Variable	Parameter	Value
M	Big M parameter	6000
$\lambda^a, \lambda^b, \lambda^c$	Special Ordered Set Type 1 for heat exchanger a,b,c	-
k	Increment for piece-wise linearization of cost function for heat exchangers	0.1
m_n	Weight of each representative week n	-

Table A.4: Modeling Parameters

Symbol	Parameter	Value	Source
c^{TES}	Storage cost ($\$/kWh_t$)	20.89	See S.I. Table A.8
$c^{ht,c}$	Charger cost ($\$/kW_t$)	3.3	[4]
$c^{ht,ind}$	Heater cost ($\$/kW_t$)	3.3	[4]
c^{pipes}	Pipes and valves cost ($\$/kW_e$)	4.66	[84]
c^{start}	Start up-cost ($\$/MW$)	10.15	[52], [53], [54]
$\bar{n}^{HX,ec}$	Exponent describing relationship of economizer size and cost	0.684	Table 11 from [45]
$\bar{n}^{HX,ev}$	Exponent describing relationship of evaporator size and cost	0.788	Table 11 from [45]
$\bar{n}^{HX,su}$	Exponent describing relationship of superheater size and cost	0.741	Table 11 from [45]
$\bar{C}^{HX,ec}$	Economizer base cost associated with $\bar{A}^{HX,ec}$ (\$)	2,225,472	[45]
$\bar{C}^{HX,ev}$	Evaporator base cost associated with $\bar{A}^{HX,ev}$ (\$)	2,752,992	[45]
$\bar{C}^{HX,su}$	Superheater base cost associated with $\bar{A}^{HX,su}$ (\$)	434,693	[45]
U^{ec}	Economizer heat exchange coefficient (kW/m^2K)	1.448	Table 4 from [46]
U^{ev}	Evaporator heat exchange coefficient (kW/m^2K)	1.295	Table 4 from [46]
U^{su}	Superheater heat exchange coefficient (kW/m^2K)	1.241	Table 4 from [46]
$\bar{A}^{HX,ec}$	Economizer base area (m^2)	10,000	Table 11, 12 from [45]
$\bar{A}^{HX,ev}$	Evaporator base area (m^2)	5000	Table 11, 12 from [45]
$\bar{A}^{HX,su}$	Superheater base area (m^2)	505	Table 11, 12 from [45]
R	Annual real discount rate.	0.09	[48]
L^{REM}	Remaining lifetime, used for the retrofitted system (yrs)	25	[47]
$c_{n,t}^{elec}$	Marginal cost of electricity at time t in representative week n	-	[9]
$d_{n,t}$	Electricity demand at time t in representative week n	-	[5]
$FOM^{turbine}$	Fixed Operational & Maintenance Cost of TES turbine ($\$/kW/year$)	13.5	

Table A.5: Economic Parameters

Symbol	Parameter	Value	Source
FOM^{coal}	Fixed Operational & Maintenance Cost of coal plant (\$/kW/year)	31.248	[55]
FOM^{solar}	Fixed Operational & Maintenance Cost of solar installations (\$/kW/year)	2.644	[55]
FOM^{wind}	Fixed Operational & Maintenance Cost of wind installations (\$/kW/year)	7.691	[55]
FOM^b	Fixed Operational & Maintenance Cost of Li-ion battery (\$/kW/year)	6.009	[55]
$c^{solar,inv}$	Investment cost for solar (\$/kW)	46.355	[55]
$c^{wind,inv}$	Investment cost for wind (\$/kW)	72.99	[55]
$c^{p,inv}$	Investment cost for Li-ion battery power capacity (\$/kW)	48.89	[55]
$c^{e,inv}$	Investment cost for Li-ion battery energy capacity (\$/kWh)	17.3089	[55]
$OPEX^{solar}$	Operational cost of solar (\$/kWh)	0	[55]
$OPEX^{wind}$	Operational cost of wind (\$/kWh)	0.0027	[55]
$OPEX^{coal}$	Operational cost of coal (\$/kWh)	0.145	[55]
$OPEX^{dis}$	Operational cost of Li-ion battery dispatch (\$/kWh)	0.0001	[55]
$OPEX^{ch}$	Operational cost of Li-ion battery charge (\$/kWh)	0.001	[55]

Table A.6: Additional Economic Parameters for CEM

Symbol	Parameter	Value	Source
C_p	Specific heat capacity (kJ/kgK)	1.56	[47], [51]
β^{min}	Minimum Power Fraction	0.17	[50]
η^{ht}	Charging efficiency for TES (%)	0.95	[4]
$\eta^{b,c}, \eta^{b,d}$	Charging (c) and discharging (d) efficiency for Li-ion battery (%)	0.95	[4]
η^{pump}	Pump efficiency (%)	0.75	[85]
G	Gravitational constant (m/s^2)	9.81	-
H	Pump head (m)	15	[85]
ϵ^{sd}	Hourly self-discharge rate (%/hr)	0.000416667	[49]
ϵ^b	Hourly self-discharge rate for Li-ion battery (%/hr)	0	-
$\epsilon^{sd,wk}$	Weekly self-discharge rate (%/week)	7	[49]
P^{Int}	Interconnection power limit (MW_e)	500	Base Case
$\beta^{ramp,i}$	Ramp Rate, $i \in \{up, dn\}$ (%/hr)	50	[30]
η^{turb}	Steam turbine cycle efficiency (%)	0.41	Base Case [43], [42], [41]
q^{ind}	Constant industrial process heat demand (MW)	-	-
$\bar{\alpha}^c, \bar{\beta}^c$	Coefficients describing relationship between cold salt pump power consumption cost	200.56, 475	[49]
$\bar{\alpha}^d, \bar{\beta}^d$	Coefficients describing relationship between hot salt pump power consumption cost	154.73, 1433.9	[49]
$\Delta T^{LM,su}$	Log mean temperature difference of the superheater	66.57	Base Case
$\Delta T^{LM,ec}$	Log mean temperature difference of the economizer	145.5	Base Case
$\Delta T^{LM,ev}$	Log mean temperature difference of the evaporator	102.64	Base Case
ΔT^{salt}	Molten salt temperature difference	277	[47], [51]
Π^{turb}	Maximum capacity of steam cycle (MW)	-	-
β^{coal}	Emission Rate of coal power plant (tCO_2/MWh)	0.97	-
$cf_{n,t}^g$	capacity factor of VRE g	-	-
$\bar{\alpha}^e$	percentage of baseline emissions	-	-
\bar{E}	Baseline emissions (tCO_2)	-	-

Table A.7: Technical Parameters

Description	Value	Source
Specific heat capacity (kJ/kgK)	1.56	[51], [47]
Tank Insulation ($\$/m^2$)	252	[47]
Tank Foundation ($\$/m^2$)	1296	[47]
Hot Tank Shell Material ($\$/kg$)	7.02	[47], [84]
Cold Tank Shell Material ($\$/kg$)	0.59	[47], [84]
Salt Cost ($\$/kg$)	1.3	[47],[84], [51]
Salt Density (kg/m^3)	1835.6	[58], [47], [51]
Hot Tank Shell Density (kg/m^3)	7959.5	[47]
Cold Tank Shell Density (kg/m^3)	7850	[47]
Shell Design Thickness (m)	0.00635	[56]
Maximum Tank Height (m)	12	[56]

Table A.8: Thermal Energy Storage Characteristics

A.2 Integrated Dispatch and Sizing (IDS) Model Formulation

A.2.1 Objective Function

The objective function minimizes the sum of annualized capital cost ($CAPEX^e$), operating cost ($OPEX^e$), minus the annual revenue from grid electricity sales (REV^e). In case, we are modeling industrial heat the objective function also includes corresponding capital cost, operating cost and revenue terms for industrial process heat ($CAPEX^{ind}$, $OPEX^{ind}$, REV^{ind})

$$Z^{Obj,e} = \min(CAPEX^e + OPEX^e - REV^e) \quad (A.1)$$

The capital cost of TES system without heat co-production is defined in Eq. A.2 includes: 1) cost of storage, 2) cost of heat exchangers, 3) cost of resistive heaters for charging salt, 4) cost of pumps for salt flow, and 5) cost of pipes and valves that scales with discharge power capacity.

$$CAPEX^e = CRF \times (c^{TES}\Gamma + \sum_{i \in I} C^{HX,i} + c^{ht,c}Q^{ht,c} + \sum_{r=c,d} c^{p,r} + c^{pipes}\Pi^{turb}) \quad (A.2)$$

Here, CRF refers to the capital recovery factor is calculated based on discount rate (R) and project lifetime, which is set to be equal to the remaining lifetime of the steam cycle (L^{REM}) as $CRF = \frac{R(1+R)^{L^{REM}}}{(1+R)^{L^{REM}} - 1}$

When modeling industrial process heat, we add the following additional terms to the $CAPEX$, corresponding to the cost of the resistive heater used to directly provide process heat.

$$CAPEX^{Ind} = CRF \times c^{ht,ind} \times Q^{ht,ind} \quad (A.3)$$

The annual operating cost of the system is given by Eq. A.4, as the sum of fixed operating cost and variable operating cost. The variable operating cost includes the cost of power plant startups and electricity purchases from the grid during charging. Note that ω_n corresponds to the weight of representative week n , such that $\sum_{n \in N} \omega_n = 52$.

$$OPEX^e = FOM^{turbine}\bar{\Pi}^{turb} + \sum_{n \in N} \sum_{t \in T} \omega_n \times (c^{start}z_{n,t} + c_{n,t}^{elec} \times \pi_{n,t}^{net,c}) \quad (A.4)$$

When modeling the industrial heater, the net power consumption will include an additional term corresponding to the electricity consumption by the resistive heater providing process heat ($\sum_{n \in N} \sum_{t \in T} \omega_n \times c_{n,t}^{elec} \times \frac{1}{\eta^{ht}} q_{n,t}^{ht,c}$)

The annual operating revenues are described by Eq. A.5. When modeling heat co-production, we include an additional term equal the revenue earned from providing process heat.

$$REV^e = \sum_{n \in N} \sum_{t \in T} \omega_n \times c_{n,t}^{elec} \times \pi_{n,t}^{net,d} \quad (A.5)$$

A.2.2 Constraints

Net power consumption and production constraints

Net power consumption during charging is defined as power consumption by electrical heater and pumps for salt flow during charging mode.

$$\pi_{n,t}^{net,c} = \frac{1}{\eta^{ht}} q_{n,t}^{ht,c} + \pi_{n,t}^{p,c} \quad \forall t \in T, n \in N \quad (\text{A.6})$$

Net power consumption during discharging is defined turbine power output minus turbine auxiliary load and salt pumping power requirements during discharging.

$$\pi_{n,t}^{net,d} = \pi_{n,t}^{turb}(1 - \epsilon^{turb}) - \pi_{n,t}^{p,d} \quad \forall t \in T, n \in N \quad (\text{A.7})$$

Net power output and consumption from the facility cannot exceed existing interconnection capacity

$$\pi_{n,t}^{net,k} \leq P^{Int} \quad \forall t \in T, n \in N, k = d, c \quad (\text{A.8})$$

Charging mode constraints

Heat supplied during charging process and associated capacity constraint.

$$q_{n,t}^{ht,c} = f_{n,t}^c \bar{C}_p \Delta T^{salt} \quad \forall t \in T, n \in N \quad (\text{A.9})$$

$$q_{n,t}^{ht,c} \leq Q^{ht,c} \quad \forall t \in T, n \in N \quad (\text{A.10})$$

Discharging mode constraints

Turbine power output at any period is less than steam cycle capacity and greater than minimum stable power output when power plant is on or zero when power is off.

$$\pi_{n,t}^{turb} \geq \beta^{min} \Pi^{turb} y_{n,t} \quad \forall n \in N, t \in T \quad (\text{A.11})$$

$$\pi_{n,t}^{turb} \leq \Pi^{turb} y_{n,t} \quad \forall n \in N, t \in T \quad (\text{A.12})$$

Startup constraints for steam cycle:

$$z_{n,t} \geq y_{n,t} - y_{n,t-1} \quad \forall t \in T/\{1\}, n \in N \quad (\text{A.13})$$

$$z_{n,t} \geq y_{n,t} - y_{n,T} \quad \forall t = 1, n \in N \quad (\text{A.14})$$

Ramping constraints for steam cycle:

$$\pi_{n,t}^{turb} - \pi_{n,t-1}^{turb} \leq \beta^{ramp,up} \Pi^{turb} \quad \forall t \in T/\{1\}, n \in N \quad (\text{A.15})$$

$$\pi_{n,t}^{turb} - \pi_{n,t-1}^{turb} \geq \beta^{ramp,dn} \Pi^{turb} \quad \forall t \in T/\{1\}, n \in N \quad (\text{A.16})$$

$$\pi_{n,t}^{turb} - \pi_{n,T}^{turb} \leq \beta^{ramp,up} \Pi^{turb} \quad \forall t = 1, n \in N \quad (\text{A.17})$$

$$\pi_{n,t}^{turb} - \pi_{n,T}^{turb} \geq \beta^{ramp,dn} \Pi^{turb} \quad \forall t = 1, n \in N \quad (\text{A.18})$$

Relating turbine power output to salt flow rate accounting for heat to power conversion efficiency.

$$\pi_{n,t}^{turb} = \eta^{turb} f_{n,t}^d \bar{C}_p \Delta T^{salt} \quad \forall t \in T, n \in N \quad (\text{A.19})$$

Peak turbine capacity has to be less than available turbine capacity. Note that the steam turbine power capacity will be larger than from the nameplate capacity of the original coal power plant owing to auxiliary losses. For example, according to one estimate, auxiliary power demand at a coal power plant amounts to 5% of the steam turbine capacity implying that the power plant capacity be corresponding smaller than the steam turbine capacity.

$$\Pi^{turb} \leq \bar{\Pi}^{turb} \quad (\text{A.20})$$

Mode Switching Constraints

Discharging (charging) salt flow rates can take non-negative values when plant is in discharging (charging) mode:

$$f_{n,t}^d \leq M y_{n,t} \quad \forall t \in T, n \in N \quad (\text{A.21})$$

$$f_{n,t}^c \leq M(1 - y_{n,t}) \quad \forall t \in T, n \in N \quad (\text{A.22})$$

Salt Pump Constraints

Pumping power requirements are proportional to salt flow rates

$$\pi_{n,t}^{p,k} = f_{n,t}^k \frac{GH}{\eta^{pump}} \quad \forall t \in T, n \in N, k = \{d, c\} \quad (\text{A.23})$$

Pumping power output in each timestep cannot exceed installed pump capacity.

$$\pi_{n,t}^{p,k} \leq \Pi^{p,k} \quad \forall t \in T, n \in N, k = \{d, c\} \quad (\text{A.24})$$

The cost of the pump is a linearized function of the pump power rating. m is a binary variable that enforces the cost of the pumps to be 0 when $m = 0$ and nonzero as per the linear equation when $m = 1$.

$$c^{p,k} = \Pi^{p,k} \bar{\alpha}^{p,k} + \bar{\beta}^{p,k} m \quad k = \{d, c\} \quad (\text{A.25})$$

$$\Pi^{p,k} \leq m \bar{M} \quad k = \{d, c\} \quad (\text{A.26})$$

Heat Exchanger Design Constraints

Total heat exchange across three heat exchangers must be equal to the heat delivered to steam cycle.

$$\sum_{i \in I} q_{n,t}^{hx,i} = f_{n,t}^d \bar{C}_p \Delta T^{salt} \quad \forall t \in T, n \in N \quad (\text{A.27})$$

Heat exchanged via each heat exchanger cannot exceed heat exchanger design capacity.

$$q_{n,t}^{hx,i} \leq U^i A^{HX,i} \Delta T^{LM,i} \quad \forall t \in T, n \in N, i \in I \quad (\text{A.28})$$

To ensure feasible heat transfer, we enforce a minimum heat exchange requirement across each heat exchanger that is computed from the Aspen simulations. Here, parameter $\beta^{hx,i}$ is such that $\sum_{i \in I} \beta^{hx,i} = 1$. This constraint ensures that each heat exchanger is utilized for heat transfer across all time periods.

$$q_{n,t}^{hx,i} \geq \beta^{hx,i} \sum_{i \in I} q_{n,t}^{hx,i} \quad \forall t \in T, n \in N \quad (\text{A.29})$$

Capital cost of heat exchanger is calculated as piece-wise linear approximation using the following equations. Here, $k \in K$ represent the index corresponding to various piece-wise segments.

$$\bar{C}_k^{HX,i} = \bar{C}^{HX,i} (A_k^{HX,i} / \bar{A}^{HX,i})^{\bar{n}^{HX,i}} \quad (\text{A.30})$$

$$C^{HX,i} = \sum_{k \in K} \bar{C}_k^{HX,i} \lambda_k^i \quad \forall i \in I \quad (\text{A.31})$$

$$A^{HX,i} = \sum_{k \in K} \bar{A}_k^{HX,i} \lambda_k^i \quad \forall i \in I \quad (\text{A.32})$$

$$\sum_{k \in K} \lambda_k^i = 1 \quad \forall i \in I \quad \text{SOS2} \quad (\text{A.33})$$

Energy Storage Constraints

Storage energy inventory balance within a representative week is given by Eq. A.34-A.35. Note that we allow for state of charge at beginning and end of each representative week to be different by the amount, $\delta_n \in R$, a decision variable. This allows for energy to be shifted across weeks, as described further below, and thus enables long-term energy storage via TES.

$$\gamma_{n,t} = (1 - \epsilon^{sd}) \times \gamma_{n,t-1} + (f_{n,t}^c - f_{n,t}^d) \bar{C}_p \Delta T^{salt} \quad \forall n \in N, t \in T \setminus \{1\} \quad (\text{A.34})$$

$$\gamma_{n,t} = (1 - \epsilon^{sd}) \times (\gamma_{n,t_{end}} - \delta_n) + (f_{n,t}^c - f_{n,t}^d) \bar{C}_p \Delta T^{salt} \quad \forall n \in N, t = 1 \quad (\text{A.35})$$

Storage inventory balance across weeks of the year is modeled via the set of equations described below. Here, the net change in each storage inventory of each week is approximated

by the change in storage inventory for the corresponding representative period (as per the mapping $f(n)$). Note that weeks are in chronological order, while representative weeks are not.

Eq. A.36 relates the storage level of the last modeled period with the storage level at the beginning of the first modeled period. If the modeled week is also a representative week, then Eq. A.38 enforces that initial storage level estimated by the intra-week storage balance constraint should equal the initial storage level estimated from the inter-week storage balance constraint.

$$s_{w+1} = (1 - \epsilon^{sd, wk})s_w + \delta_{f(w)} \quad \forall w \in W \setminus \{w_{end}\} \quad (\text{A.36})$$

$$s_1 = (1 - \epsilon^{sd, wk})s_{w_{end}} + \delta_{f(w_{end})} \quad \forall w = w_{end} \quad (\text{A.37})$$

$$s_w = \gamma_{f(w), t_{end}} - \delta_{f(w)} \quad \forall w \in W^{REP} \subset W \quad (\text{A.38})$$

Eqs. A.39-A.40 enforce that initial storage level for each week and storage level during each sub-period of each representative week must be non-negative and adhere to installed energy capacity limits. The constraint in Eq. A.41 enforces that the storage inventory level in each sub-period of weeks other than representative weeks are also less than or equal to the installed capacity limit.

$$0 \leq s_w \leq \Gamma \quad \forall w \in W \quad (\text{A.39})$$

$$0 \leq \gamma_{n,t} \leq \Gamma \quad \forall n \in N, t \in T \quad (\text{A.40})$$

$$0 \leq s_w + \gamma_{f(w), t} - \gamma_{f(w), 1} \leq \Gamma \quad \forall w \in W, t \in T \quad (\text{A.41})$$

The minimum energy duration constraint is added for when we enforce the model to build a minimum amount of energy storage for \bar{h} hours.

$$\Pi^{net} \bar{h} / \eta^{turb} \leq \Gamma \quad (\text{A.42})$$

Industrial process heat constraints

When industrial process heat supply is also modeled, the following additional constraints are added along with modifying some of the above constraints.

The constraint defining the heat supply to the steam cycle (Eq. A.43) is modified to account for heat siphoned for process heat supply:

$$\pi_{n,t}^{turb} = (f_{n,t}^d \bar{C}_p \Delta T^{salt} - q_{n,t}^{turb, ind}) \eta^{turb} \quad \forall t \in T, n \in N \quad (\text{A.43})$$

Process heat supply is met via a combination of resistive heat or heat from power cycle

$$q_{n,t}^{turb, ind} + q_{n,t}^{ht, ind} = \bar{q}^{Ind} \quad \forall t \in T, n \in N \quad (\text{A.44})$$

Sizing resistive heater

$$q_{n,t}^{ht,ind} \leq Q^{ht,ind} \quad \forall t \in T, n \in N \quad (\text{A.45})$$

Steam from turbine can only be provided when steam cycle is operational

$$q^{turb,ind} \leq \bar{q}^{ind} y_{n,t} \quad \forall t \in T, n \in N \quad (\text{A.46})$$

A.2.3 Metrics

TES Power Dispatch is defined on a yearly basis, scaled with the weighting for the representative weeks:

$$dispatch[MWh/year] = \sum_{n \in N} \sum_{t \in T} \omega_n \times \pi_{n,t}^{net,d} \quad (\text{A.47})$$

Industrial Heat TES Dispatch is defined by the dispatch from the steam-turbine to the industrial demand:

$$dispatch_{ind}[MWh/year] = \sum_{n \in N} \sum_{t \in T} \omega_n \times q_{n,t}^{turb,ind} \quad (\text{A.48})$$

Levelized Cost of Storage (LCOS):

$$LCOS[\$/MWh_e] = \frac{CAPEX^e + OPEX^e}{dispatch} \quad (\text{A.49})$$

Duration (d):

$$d[hrs] = \frac{\eta^{turb} \Gamma}{\Pi^{net,d}} \quad (\text{A.50})$$

Revenue per Dispatch ($\$/MWh$):

$$\frac{REV^e}{dispatch} \quad (\text{A.51})$$

Industrial process heat price (p_{ind}):

$$p^{ind}[\$/MWh_t] = \frac{Z^{Obj,e} - Z^{Obj,ind}}{dispatch_{ind}} \quad (\text{A.52})$$

A.3 Capacity Expansion Model (CEM) Formulation

The capacity expansion model (CEM) is formulated as an extension of the IDS model.

A.3.1 Objective Function

The objective function minimizes the sum of annualized capital cost ($CAPEX^c$) and operating cost ($OPEX^c$).

$$Z^{Obj,c} = \min(CAPEX^c + OPEX^c) \quad (A.53)$$

The capital cost of entire energy system is defined in Eq. A.54 includes $CAPEX^e$, the annualized cost of TES described in Eq. A.2, as well as the investment cost for Li-ion batteries, solar installations, and wind installations.

$$CAPEX^e = CRF \times (c^{TES}\Gamma + \sum_{i \in I} C^{HX,i} + c^{ht,c}Q^{ht,c} + \sum_{r=c,d} c^{p,r} + c^{pipes}\Pi^{turb}) + \sum_{g \in G^{VRE}} c^{g,inv}\Pi^g + c^{e,inv}\Gamma^b + c^{p,inv}\Pi^b \quad (A.54)$$

The annual operating cost of the system is given by Eq. A.55, as the sum of fixed operating cost and variable operating cost of each generator or storage device. The variable operating cost also includes the cost of power plant startups and electricity purchases from the grid during charging applied to the coal power plant and TES system. Note that ω_n corresponds to the weight of representative week n, such that $\sum_{n \in N} \omega_n = 52$.

$$OPEX^e = FOM^{turbine}\bar{\Pi}^{turb} + \sum_{g \in G} FOM^g\Pi^g + FOM^b\Pi^b + \sum_{n \in N} \sum_{t \in T} \omega_n \times (c^{start}z_{n,t}^{TES} + c^{start}z_{n,t}^{coal} + \sum_{g \in G} OPEX^g\pi_{n,t}^g + OPEX^{dis}\pi_{n,t}^{b,d} + OPEX^{ch}\pi_{n,t}^{b,c}) \quad (A.55)$$

A.3.2 Constraints

The CEM model applies constraints described by Eq A.56-A.79 to the TES system in this model.

Power Balance Constraints

Demand

$$d_{n,t} = \pi_{n,t}^{net,d} - \pi_{n,t}^{net,c} + \pi_{n,t}^{b,d} - \pi_{n,t}^{b,c} + \sum_{g \in G} \pi_{n,t}^g \quad \forall n \in N, t \in T \quad (A.56)$$

Emissions Constraints

Emissions

$$\sum_{n \in N} \sum_{t \in T} \omega_n \times \bar{\beta}^{coal}\pi_{n,t}^{coal} \leq \bar{\alpha}^e \bar{E} \quad (A.57)$$

Li-ion storage constraints

energy balance Initialization

$$\gamma_{n,t}^b = \gamma_{n,t-1}^b + \pi_{n,t}^{b,c}\eta^{b,c} - \pi_{n,t}^{b,d}/\eta^{b,d} - \epsilon^b\gamma_{n,t-1}^b \quad \forall t \in T/\{1\}, n \in N \quad (A.58)$$

Initialize

$$\gamma_{n,t}^b = (1 - \epsilon^b)\gamma_{n,T}^b + \pi_{n,t}^{b,c}\eta^{b,c} - \pi_{n,t}^{b,d}/\eta^{b,d} \quad \forall t \in \{1\}, n \in N \quad (\text{A.59})$$

Sizing

$$\pi_{n,t}^{b,c} \leq \Pi^b \quad \forall t \in T, n \in N \quad (\text{A.60})$$

$$\pi_{n,t}^{b,d} \leq \Pi^b \quad \forall t \in T, n \in N \quad (\text{A.61})$$

$$\gamma_{n,t}^b \leq \Gamma^b \quad \forall t \in T, n \in N \quad (\text{A.62})$$

Capacity constraints

$$\Pi^{ret} + \Pi^{coal} + \Pi^{net,d} = P^{int} \quad (\text{A.63})$$

Binary exclusivity

$$x^{ret} + x^{coal} + x^{TES} = 1 \quad (\text{A.64})$$

$$\Pi^{coal} \leq P^{int} x^{coal} \quad (\text{A.65})$$

$$\Pi^{ret} \leq P^{int} x^{ret} \quad (\text{A.66})$$

$$\Pi^{net,d} \leq P^{int} x^{TES} \quad (\text{A.67})$$

$$y_{n,t}^{coal} \leq x^{coal} \quad \forall n \in N, t \in T \quad (\text{A.68})$$

$$y_{n,t}^{TES} \leq x^{TES} \quad \forall n \in N, t \in T \quad (\text{A.69})$$

Capacity Factor

$$\pi_{n,t}^g \leq \Pi^g c f_{n,t}^g \quad \forall n \in N, t \in T, g \in G^{VRE} \quad (\text{A.70})$$

$$\pi_{n,t}^{coal} \leq \Pi^{coal} y_{n,t}^{coal} \quad \forall n \in N, t \in T \quad (\text{A.71})$$

$$\pi_{n,t}^{net,d} \leq \Pi^{net,d} y_{n,t}^{TES} \quad \forall n \in N, t \in T \quad (\text{A.72})$$

Coal Plant Constraints

ramp rates initialization

$$\pi_{n,t}^{coal} - \pi_{n,t-1}^{coal} \leq \beta^{ramp,up} \Pi^{coal} \quad \forall t \in T/\{1\}, n \in N \quad (\text{A.73})$$

$$\pi_{n,t}^{coal} - \pi_{n,t-1}^{coal} \geq \beta^{ramp,dn} \Pi^{coal} \quad \forall t \in T/\{1\}, n \in N \quad (\text{A.74})$$

$$\pi_{n,t}^{coal} - \pi_{n,T}^{coal} \leq \beta^{ramp,up} \Pi^{coal} \quad \forall t = 1, n \in N \quad (\text{A.75})$$

$$\pi_{n,t}^{coal} - \pi_{n,T}^{coal} \geq \beta^{ramp,dn} \Pi^{coal} \quad \forall t = 1, n \in N \quad (\text{A.76})$$

startup

$$z_{n,t}^{coal} \geq y_{n,t}^{coal} - y_{n,t-1}^{coal} \quad \forall t \in T/\{1\}, n \in N \quad (\text{A.77})$$

$$z_{n,t}^{coal} \geq y_{n,t}^{coal} - y_{n,T}^{coal} \quad \forall t = 1, n \in N \quad (\text{A.78})$$

min power

$$\pi_{n,t}^{coal} \geq \beta^{min} \Pi^{coal} y_{n,t}^{coal} \quad \forall n \in N, t \in T \quad (\text{A.79})$$

A.3.3 Metrics

Curtailement is defined as the fraction of VRE that is not delivered to a load or stored throughout the year.

$$curtailment = 1 - \frac{\sum_{g \in G^{VRE}} \sum_{n \in N} \sum_{t \in T} \omega_n \times \pi_{n,t}^g}{\sum_{g \in G^{VRE}} \sum_{n \in N} \sum_{t \in T} \omega_n \times f_{n,t}^g \Pi^g} \quad (\text{A.80})$$

System cost is the value of the objective function.

$$system\ cost = Z^{Obj,c} \quad (\text{A.81})$$

A.4 Aspen Modeling

1) Steam turbine efficiency calculated from the coal plant simulation. $W^{HP,IP,LP}$ refers to the work from the high pressure, intermediate pressure, and low pressure turbines, W^{PUMP} is the power consumed by the water pump, and $Q^{BOILERS}$ is the heat input from the coal boilers:

$$\eta^{coal} = \frac{W^{HP} + W^{IP} + W^{LP} + W^{PUMP}}{Q^{BOILERS}} \quad (\text{A.82})$$

2) Target power output of the coal plant is the rated output of the coal plant unit plus the aux power consumption. Both are reported values.

$$W^{target} = W^{rated} + W^{aux,coal} \quad (\text{A.83})$$

3) We find the steam flow rate, efficiency, and other results where the power output is closest to the target power.

4) We input that steam flow rate into the TES simulation.

5) Steam Turbine Efficiency for the TES is determined from the Aspen simulations, where Q^{SALT} refers to the thermal heat input from the molten salt ($mC_p\Delta T^{Salt}$)

$$\eta^{steam} = \frac{W^{HP} + W^{IP} + W^{LP} + W^{PUMP}}{Q^{SALT}} \quad (\text{A.84})$$

6) The TES calculated peak power output is the following:

$$W^{TES} = W^{HP} + W^{IP} + W^{LP} + W^{PUMP} + W^{aux, TES} \quad (\text{A.85})$$

7) The interconnection capacity constraint W^{CAP} in the optimization model is either set by W^{TES} or the reported power rating of the coal plant, whichever is smaller.

A.5 Note on Land-Use

We conducted a back-of-envelope land use assessment with the case-study 500 MW unit and found that the land requirement for 1 to 8 $GW h_t$ TES molten salt tanks was 1900 to 6500 square meters (which includes a 10 meter buffer). This is much less than the space available at the site, which is approximately 180,060 square meters using topical Google Maps measurements. Therefore, we do not include land availability as a constraint in the model.

A.6 Notes on Price Scenarios

The variability of the price profiles underpinning each price scenario affects the energy arbitrage opportunity and thus the profitability of the TES system. Table A.9 below summarizes and compares the key price scenarios used in this study from 2030 [9] to the Indian Energy Exchange (IEX) average hourly market data from 2019 and 2021.

Price Scenario	Mean (\$/MWh)	std	Portion of hours less than \$5/MWh	Portion of hours greater than \$200/MWh
IEX 2019	39	11	0%	0%
IEX 2021	49	34	0%	1.5%
Maharashtra 2030	53	27	1.1 %	1.4%
Uttar Pradesh 2030	56	30	0.82%	2.15 %
Gujarat 2030	27	30	32%	0.89%
Haryana 2030	56	30	0.82%	2%
Odisha 2030	40	24	0.82%	0.85%

Table A.9: Price Scenario Characteristics

A.7 Supporting Figures

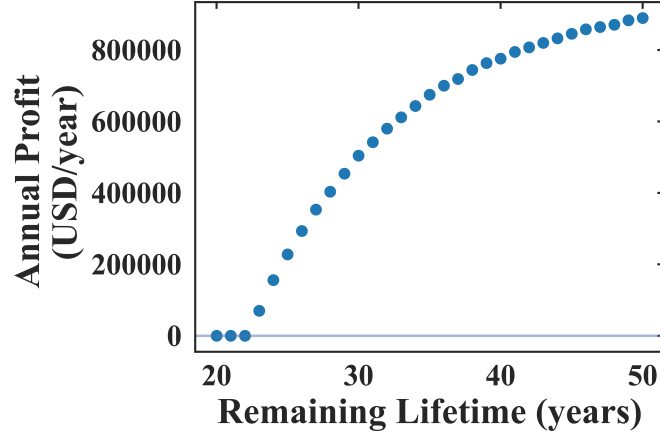


Figure A.2: The remaining lifetime of the coal plant affects the annual profit. In this base case and price scenario, and without FOM, the break-even point occurs (e.g. annual profit = 0) when the remaining lifetime is 22 years.

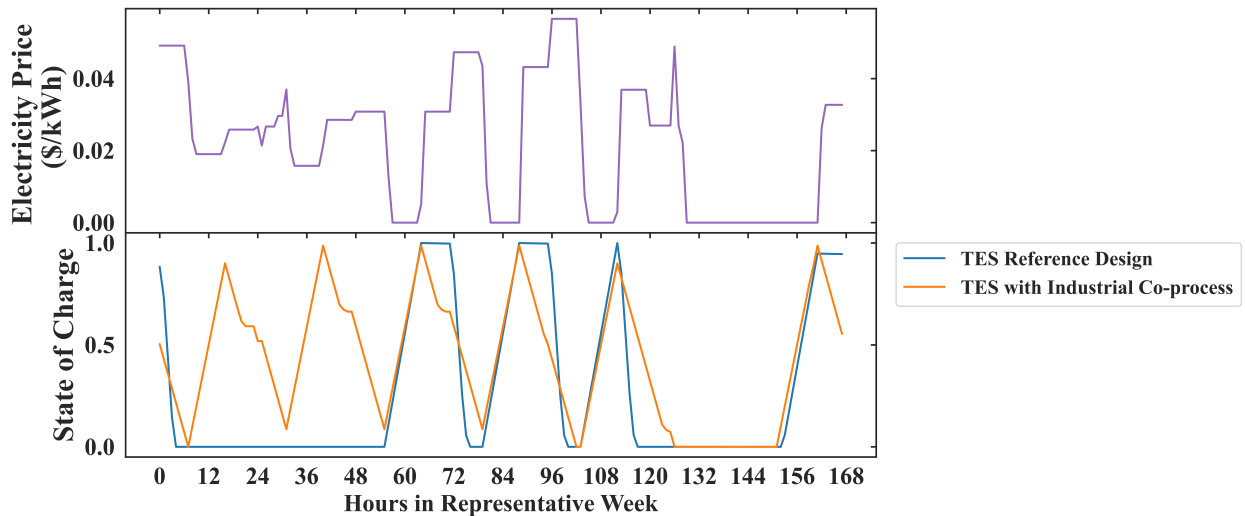


Figure A.3: The TES dispatch is more sensitive to electricity price profile and exhibits more cycling under the TES design with 350 MW_t co-located industrial process heat supplied at a constant 180°C compared to the the base stand-alone TES system design under the 2030 Gujarat price scenario. TES could technically serve lower industrial heat demands and assist in industrial decarbonization efforts particularly in industrial parks with high percentages of captive coal units. It is an economically viable method when compared to using electric resistive heaters to supply the heat load, but the ultimate economic viability of such a system depends on site-specific decisions.

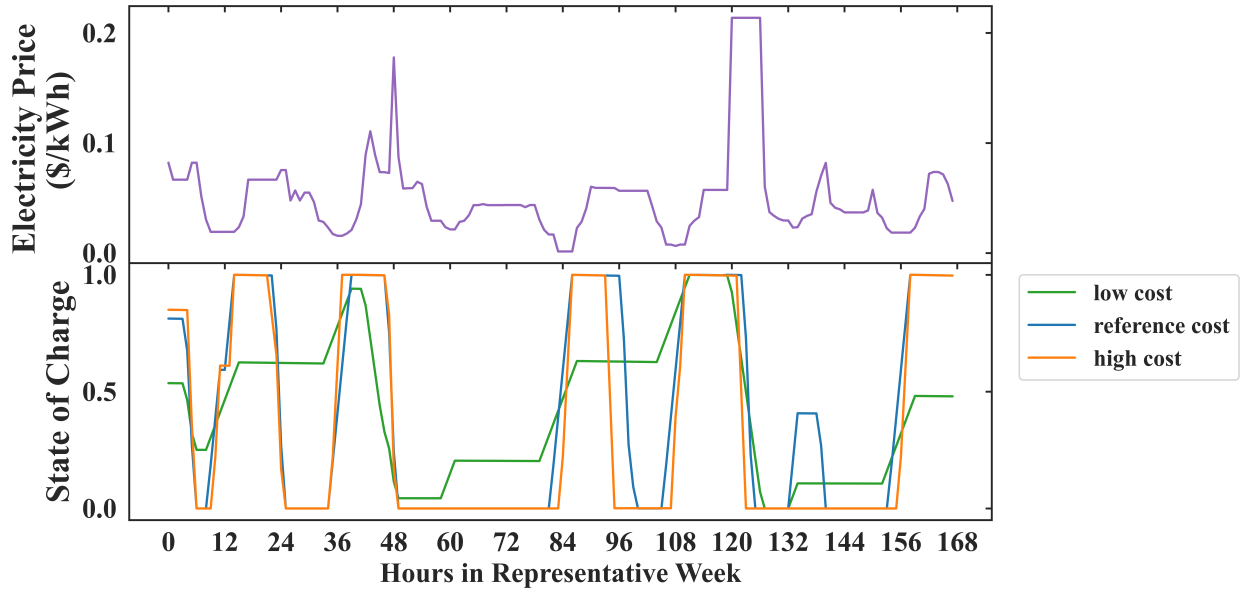


Figure A.4: The TES dispatch is sensitive to storage costs. The lowest cost storage (\$4/kWh) cycles more often than the reference cost (\$21/kWh) and high cost (\$41/kWh).

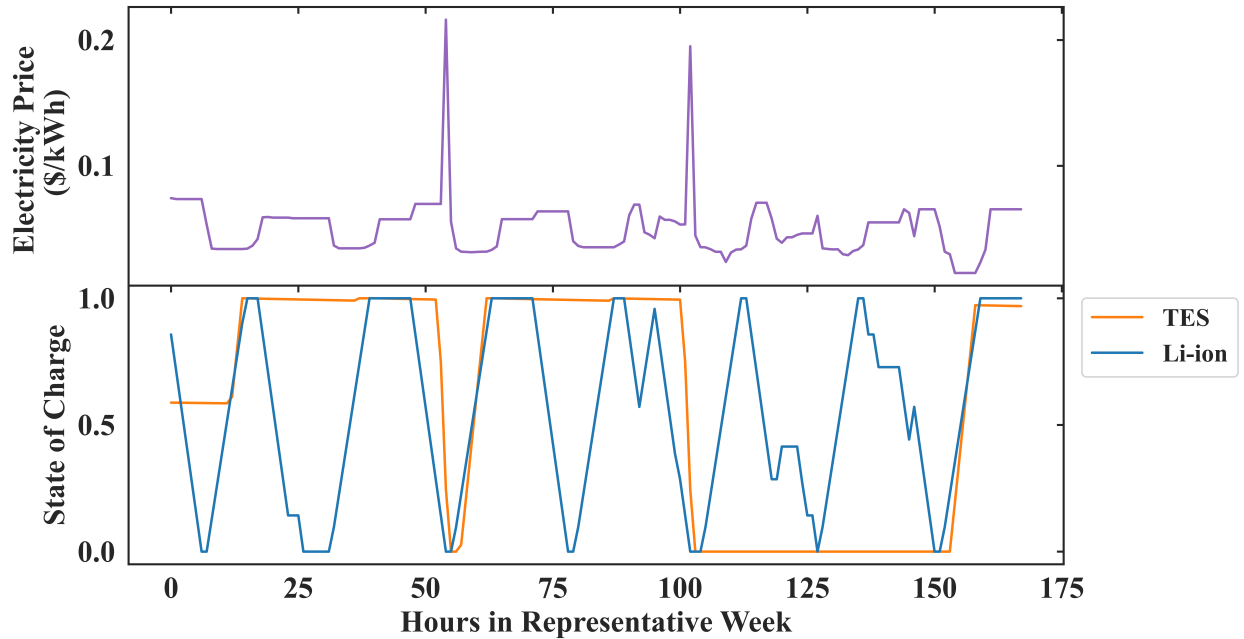


Figure A.5: Li-ion dispatch shows more cycling and sensitivity to the price profile compared to TES dispatch which exhibits a longer, weekly cycle. Li-ion assumptions include: investment costs (\$49/kW per year and \$17/kWh per year), FOM (\$6/MW/year), OPEX (\$0.1/MWh), charging and discharging efficiency (0.95). In this result with a 2 hour minimum build enforced, the Li-ion cost is \$110/MWh and TES is \$242/MWh.

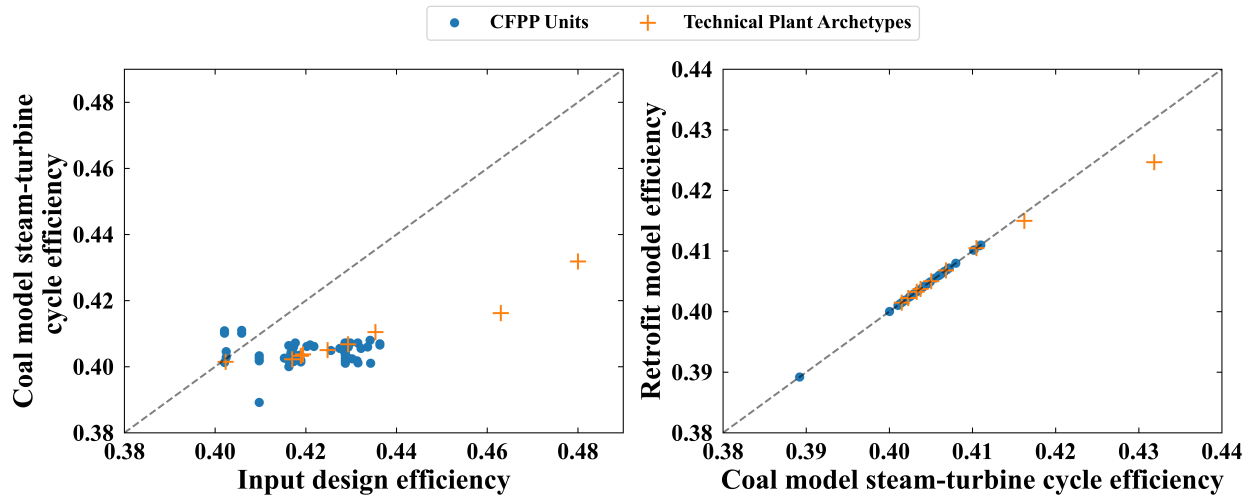


Figure A.6: The left plot shows that the coal plant model in Aspen is calibrated to the input design efficiency of the steam turbine as reported, but the model often does not reach the same design steam turbine efficiency under the practical design limits imposed. This serves as a lower bounded value for efficiency. The right plot shows the coal model steam turbine efficiency calibrating. the thermal energy storage retrofit discharge efficiency for the same units.

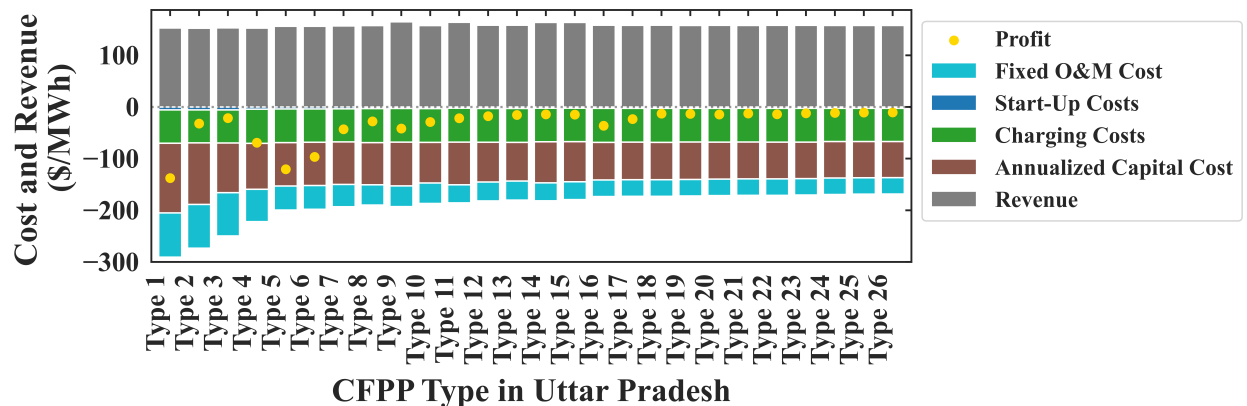


Figure A.7: Levelized Cost of Storage (LCOS) values for each representative group of CFPP unit in Uttar Pradesh. These groups were determined by grouping capacity and age of each unit and assigning them to the appropriate cluster. This LCOS graphic shows main drivers of cost, namely the charging costs, capital costs, and the Fixed O&M costs. Revenue per dispatch is also plotted, and overlaid with annual profit per dispatch (which is the the simple difference between the LCOS and revenue). Under this assumed Fixed O&M, 0% of the fleet is profitable under the 2030 Uttar Pradesh electricity price scenario.

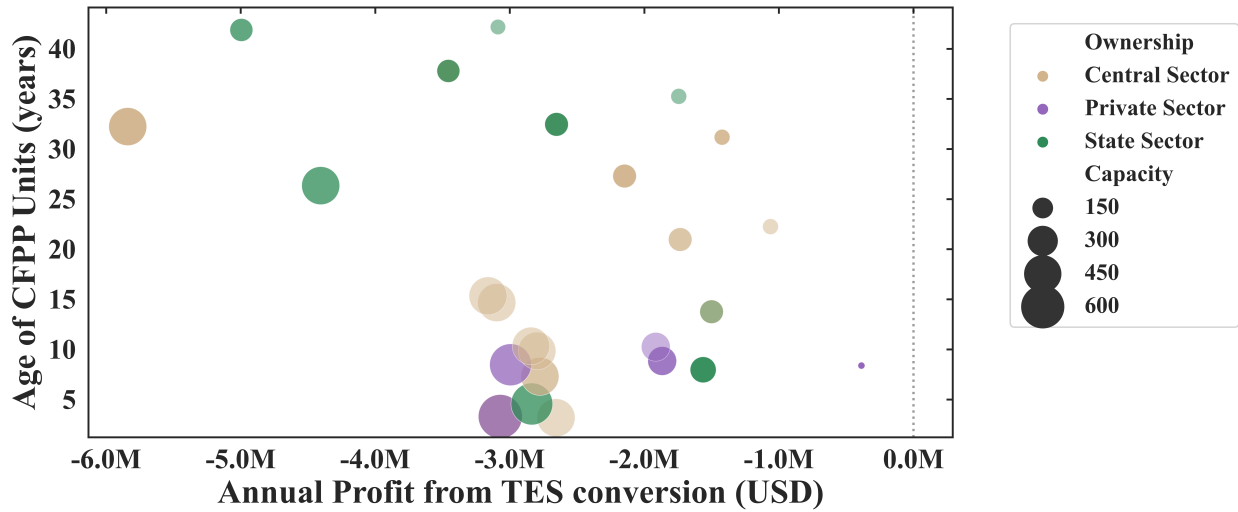


Figure A.8: Annual profit or loss from IDS for each CFPP in Uttar Pradesh, based on the 26 representative units classified by age and capacity. Under this assumed Fixed O&M, 0% of the fleet is profitable under the 2030 Uttar Pradesh electricity price scenario.

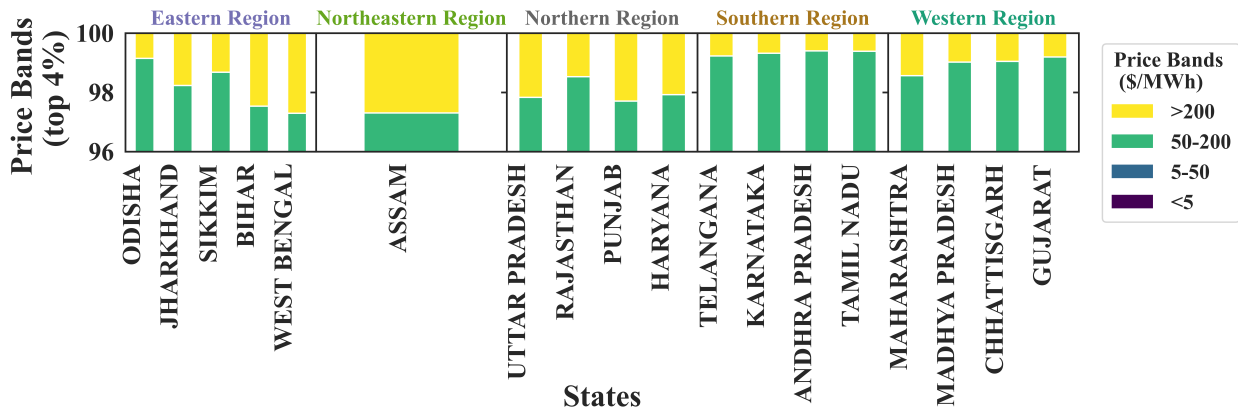


Figure A.9: This plot shows the top 4% of electricity prices per price profile. The bands are grouped into bins of above \$200/MWh and between \$50 and \$200/MWh. The price profiles are the input to the integrated dispatch and optimization model and are made of 23 representative weeks derived from a k-means clustering analysis from the original year-long hourly profile per state.

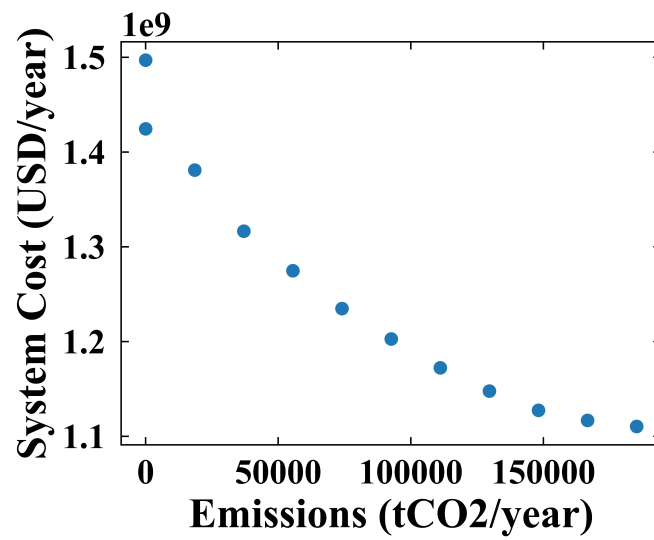


Figure A.10: System emissions and system cost trade-off

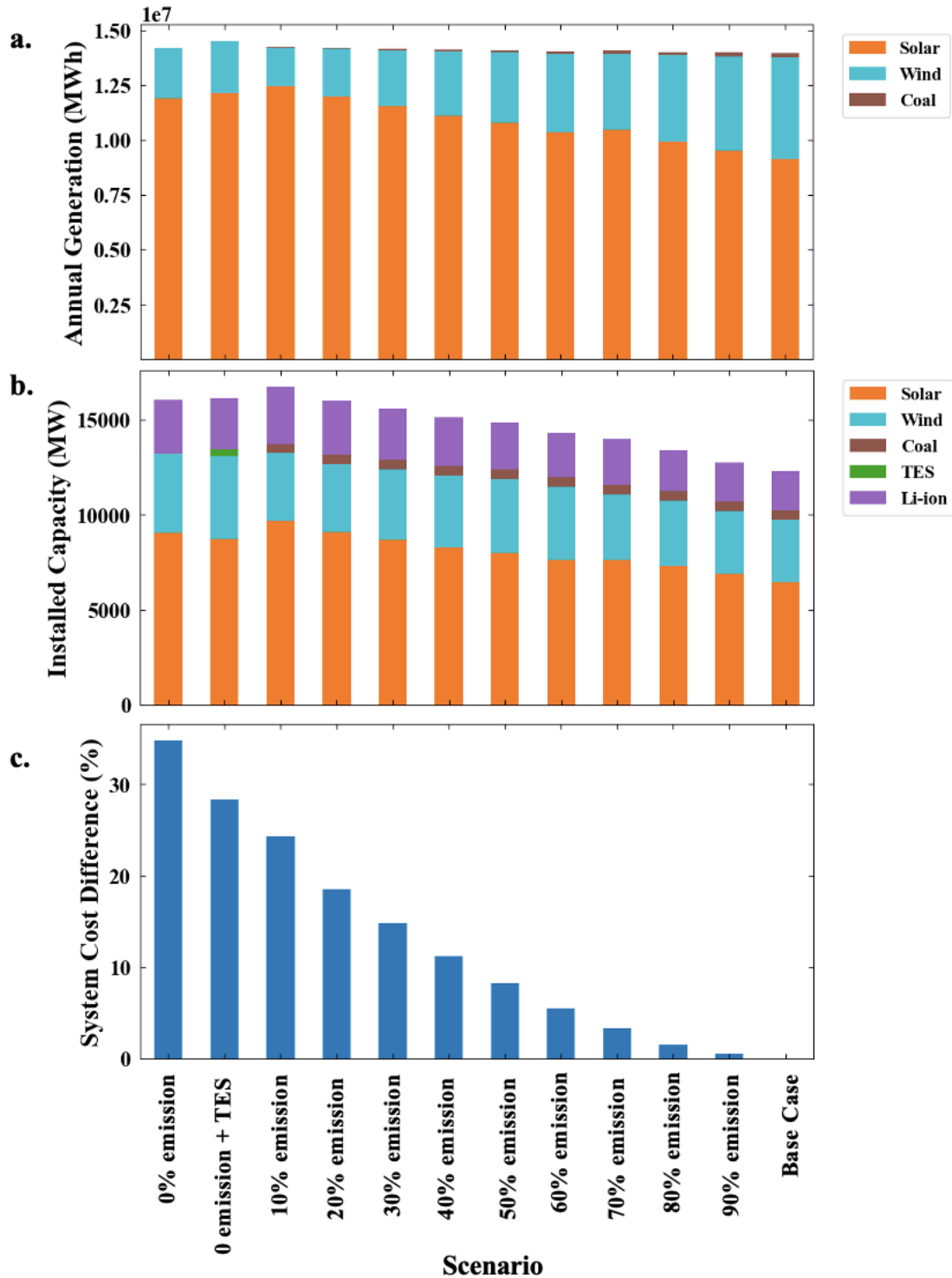


Figure A.11: a. Annual Generation (MWh), b. Installed Capacity (MW), and c. System Cost Difference for Scenarios with emissions constraints. With more stringent emissions constraints, the coal plant capacity factor decreases (as seen in the annual generation plot), the amount of VRE + storage capacity installed increases, and the system cost generally increases from the base case. TES retrofits is optimal to deploy in the zero emissions case, and results in lower system costs than the zero emissions case without TES that simply retires coal. Both zero emissions cases do not have any installed coal capacity.

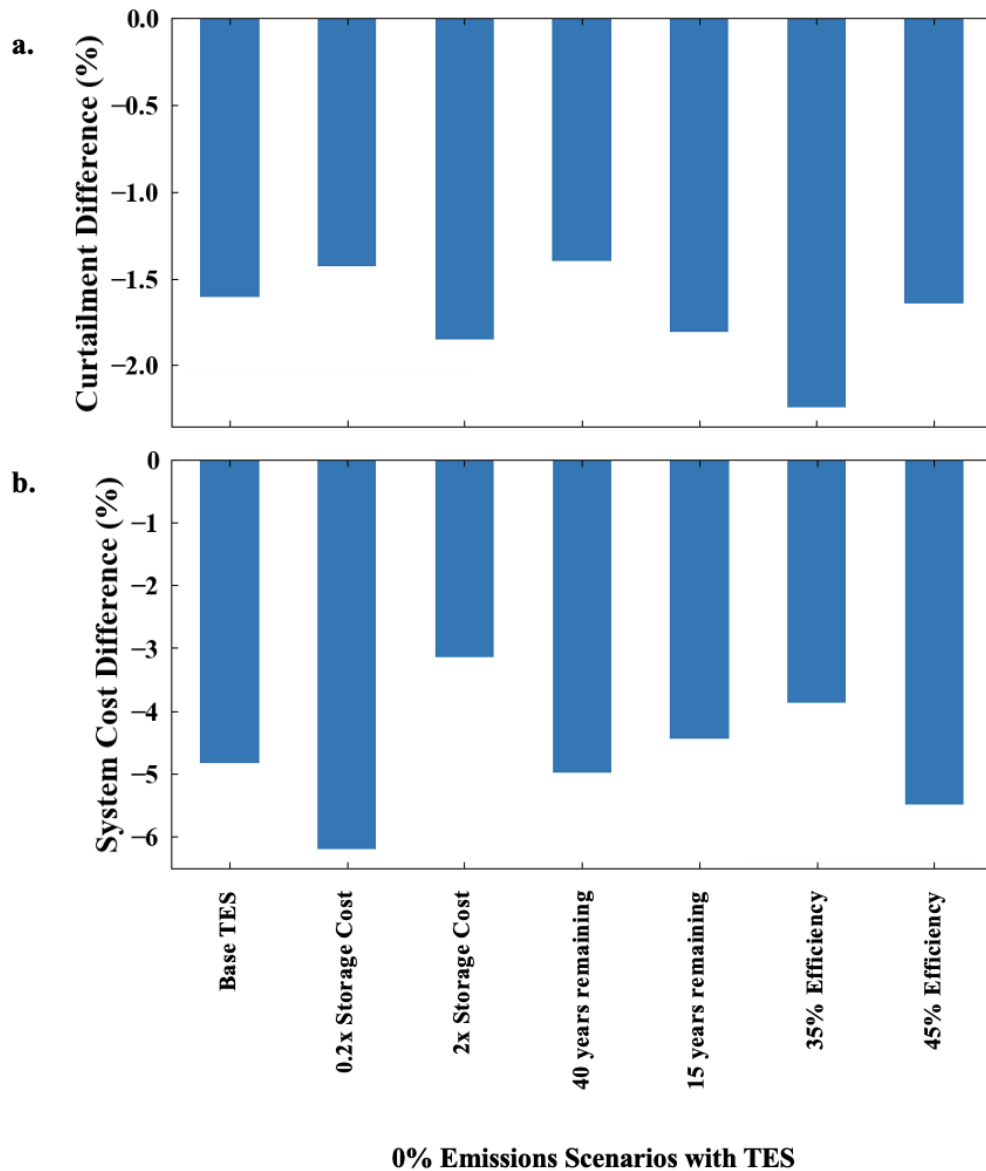


Figure A.12: For the zero-emissions cases, this figure compares the percentage reduction in **a.** curtailment and **b.** system cost from the zero-emissions case with no option to deploy TES retrofits and full coal retirement is the only option. The sensitivities compared exhibit similar trends to the plant-level modeling sensitivities and include: TES storage capacity cost, years remaining, and steam-turbine efficiency, with the storage and efficiency causing the largest range of impacts on system cost.

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