Assessing the Economic Value of Co-Optimized Grid-Scale Energy Storage Investments in Supporting High Renewable Portfolio Standards

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Abstract

Worldwide, environmental regulations such as Renewable Portfolio Standards (RPSs) are being broadly adopted to promote renewable energy investments. With corresponding increases in renewable energy deployments, there is growing interest in grid-scale energy storage systems (ESS) to provide the flexibility needed to efficiently deliver renewable power to consumers. Our contribution in this paper is to introduce a unified generation, transmission, and bulk ESS expansion planning model subject to an RPS constraint, formulated as a two-stage stochastic mixed-integer linear program (MILP) optimization model, which we then use to study the impact of co-optimization and evaluate the economic interaction between investments in these three classes of assets in achieving high renewables penetrations. We present numerical case studies using the 24-bus IEEE RTS-96 test system considering wind and solar as available renewable energy resources, and demonstrate that up to \$180 million/yr in total cost savings can result from the co-optimization of all three assets, relative to a situation in which no ESS investment options are available. Surprisingly, we find that co-optimized bulk ESS investments provide significant economic value through investment deferrals in transmission and generation capacity, but very little

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cost savings in operational cost. Finally, we observe that planning transmission and generation infrastructure first and later optimizing ESS investments—as is common in industry—captures at most 1.7% (\$3 million/yr) of the savings that result from co-optimizing all assets simultaneously.

Keywords: Energy storage, Renewable portfolio standards, Transmission expansion planning

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1. Introduction

The electricity industry is undergoing significant transformation due to increasing renewables generation. At the end of 2014, renewables represented nearly 60% of global generation capacity additions, reaching a total installed capacity of 1,712 GW [1]. To continue reducing emissions and promoting investment in new renewable generation (from wind and solar), environmental regulators are increasingly relying on new integration technologies, such as energy storage systems (ESS), and incentives, such as Renewable Portfolio Standards (RPSs), Feed-In Tariffs (FITs), and Investment and Production Tax Credits (ITCs and PTCs) [2]. To date, more than 150 countries have implemented renewable policy targets [1]. In this article, we focus on the interaction between RPS-type policies and generation, transmission, and ESS investments; however, our model can be extended to study interactions with other renewable environmental policies.

In contrast to other incentives that pay a fixed price for renewable generation or investment, an RPS incentivizes generators within a region to produce a minimum fraction of electricity from qualifying renewable resources via a market mechanism. Under an RPS, qualifying renewable energy is linked to a tradable Renewable Energy Certificate (REC), with generators meeting the mandate by holding the equivalent number of RECs. A market provides flexibility for generators to trade these RECs to meet RPS requirements, creating economic incentives for innovative and cost-effective renewable production.

While there is no federal-level RPS in the US, 33 states have introduced individual mandates ranging from as low as 10% to as high as 50% (California) and 100% (Hawaii) [2, 3]. Other countries that also have similar binding renewable mandates with tradable RECs include Australia (20% by 2020), Chile (20% by 2025), Denmark (50% by 2020), France (27% by 2020), Japan (20% by 2030), Malaysia (15% by 2050), Spain (38.1% by 2020), South Africa (9% by 2030), and Ukraine (20% by 2030) [1]. Across these countries, REC markets can vary significantly in the definition of obligations and eligibility, resource-specific set-asides and multipliers, cost caps, and available flexibility mechanisms (e.g., banking and borrowing of RECs) [4, 5]. In the US, several studies find that states that have implemented this policy effectively increased renewable investment relative to neighboring states without RPS goals [5, 6]. Other international studies find that RPSs are either about the same or marginally less effective than alternatives such as FITs [7, 8, 9].

With increasingly stringent RPS requirements come integration challenges that must be accounted for when making planning decisions. In particular, resource intermittency for wind and solar deployment can leave to over-generation and steep ramps during peak hours, as illustrated by the California ISO’s now-famous “duck curve” plot for net system demand [10]. To balance intermittent generation, operators will need to cycle thermal generators more often and deploy new flexibility resources, such as demand-side management, sub-hourly dispatch, regional coordination. Several studies argue that these operational resources represent the best value for renewables integration below 50% [11, 12]; however, it is clear that operational changes alone cannot achieve the balancing needed at very high RPS levels and that investment into new network infrastructure will need to be considered.

While pumped-hydro storage remains one of the lowest cost bulk ESS technologies in terms of MWh stored, faster-responding technologies such as flywheels, super capacitors, and batteries (e.g., lithium-ion, vanadium redox flow, zinc-air, and sodium-sulfur) can provide power and ancillary services that reinforce grid stability [13]. Third party investment has also been boosted by Federal

Energy Regulatory Commission Order No. 755 and subsequent Order No. 784,
 55 which require creation of a market for “fast and accurate” frequency regulation
 services for third party merchants, which is favorable for fast-responding ESS
 technologies [14, 15]. In this paper, however, we focus specifically on bulk en-
 ergy storage services, which include load shifting, peak shaving, and generation
 and transmission investment deferrals [16].

60 Currently, the PJM Interconnection (US) has invested in over 100 MW of
 battery energy storage for frequency regulation, while the Sistema Interconec-
 tado del Norte Grande (Chile) has installed over 30 MW for the similar use
 [17]. Further, the California Public Utilities Commission has mandated that the
 state’s three major utilities invest in a combined 1,325 MW of energy storage
 65 capacity by 2020 [18]. The specific justification for this mandate is that energy
 storage can improve the cost-effectiveness of integrating increasing amounts of
 renewables to meet the state’s RPS goals—and with lower carbon emissions
 [19]—through 1) load shifting; 2) generation, transmission, and distribution
 support and upgrade deferrals; and 3) ancillary grid services [20].

70 While lawmakers and system planners agree that ESS investment is key
 to achieving high RPS targets, we find that no existing studies focus on the
 co-optimization of generation, transmission, and ESS investments in the face of
 such requirements. To address this, this paper analyzes the economic interaction
 between investments in these three asset categories on a synthetic transmission
 75 network for a wide range of RPS targets. We formulate our model as a two-stage
 stochastic mixed-integer linear program (MILP) based on standard economic
 dispatch and transmission expansion planning models, coupled with a generic
 ESS operations model. We then obtain insight into the value of ESS investments
 relative to other assets in achieving RPS compliance in a cost-effective manner.

80 Using a 24-bus test-case we find that co-optimizing generation, transmission,
 and ESS investments can save up to \$180 million/yr or 9.1% of total system cost
 with respect to a co-optimization model that does not considers ESS. Further-
 more, we compare the benefits of considering ESS when optimizing transmission
 and generation infrastructure versus planning ESS investments after transmis-

85 sion and generation infrastructure has already been selected. These savings are
of (at most) \$3 million/yr instead of \$180 million/yr. Although the magni-
tude of these savings is not general and depends on the specific application, our
results highlight that:

a) the savings that result from considering ESS investments can be significant
90 and are primarily a result of deferrals in new generation and transmission
infrastructure,

b) optimizing ESS investments after planning generation and transmission in-
frastructure only captures energy arbitrage value, which is a small percentage
95 of the potential economic benefits of ESS in meeting RPS policies, and

c) co-optimization models and/or more coordination between transmission plan-
ners and investors in generation and ESS could reduce the cost of meeting
RPS policies.

100 The rest of the paper is organized as follows. Section 2 summarizes the
relevant literature on generation, transmission, and storage investment planning
and in co-optimization models. In Section 3, we propose a planning model that
co-optimizes generation, transmission, and ESS investments. Section 4 describe
the test-case and data assumptions. In Section 5 we present an analyze our
105 numerical experiments. Finally, in Section 6, we conclude and discuss the policy
implications.

2. Literature Review

Optimal generation and transmission investment planning has received in-
creasing attention in the last two decades [21, 22]. Transmission planning, in
110 particular, is a challenging problem given the combinatorial nature of the prob-
lem and the size of real-world transmission networks. Some proposed models in-
clude linearized DC mixed-integer linear formulations [23, 24], non-linear models

with DC power flows that take into account transmission losses [25], and non-linear models with AC power flows [26, 27]. In the context of power system economics, previous studies have analyzed the interaction between RPS goals, the representation of transmission constraints, and the “lumpiness” of real transmission investments, finding significant deviations in decision-making when the physical and economic constraints are considered [28, 29, 30]. In our research we work with a linearized DC formulation, which provides a good balance between solution accuracy and computational complexity.

The majority of the investment planning models reported in the academic literature seek to minimize total system cost, assuming that the planning is done by a vertically integrated utility. However, there is another class of planning tools that fall into the category of equilibrium models. These include generation equilibrium [31], transmission-generation leader-follower schemes [32, 33], and equilibrium models with risk-averse agents [34, 35]. In this article, however, we focus on Integrated Resource Planning (IRP) approaches that can be formulated as either linear or mixed-integer linear programs. Note that if transmission is centrally planned and anticipative,¹ and there is perfect competition among generation firms, then the solution found using an IRP approach is equivalent to the one obtained from an equilibrium model.²

With increasing interest in ESS, various studies have attempted to quantify the operational benefits of ESS on transmission networks. Both [16] and [36] find that ESS can provide significant operational savings with respect to unit commitment and cycling costs. The authors of [37] extend this co-optimization model to include N-1 security criteria in a two-stage stochastic framework, finding that lower-cost investments in ESS may be favored over expensive transmission upgrade commitments. Previous work has also considered the impact

¹A proactive or anticipative transmission planner makes transmission investments taking into account the effect of these upgrades on generation investments and, ultimately, on total system cost or social welfare [32].

²This is true for perfectly competitive markets with risk-neutral agents. An extension of this result for risk-averse agents is proposed in [34].

of ESS to enforce N-1 reliability criteria [36]. Finally, [38] and [39] find that
140 ESS co-located with renewable generation can increase transmission utilization
by reducing the variability of renewables output. However, [38] finds that ESS
can provide increased economic value by co-location with load. While in many
cases adding ESS can increase social welfare, [40] demonstrate situations in
which adding ESS to an imperfect market may actually decrease social welfare.

145 Looking toward long-term investments, optimal ESS allocation becomes an
integral component of the transmission and generation expansion planning prob-
lem. Various studies have demonstrated economic benefits from load shifting
and transmission investment deferrals, the degree being dependent on the capi-
tal cost of ESS [41, 42, 43]. The authors of [39] further extend this research by
150 studying the economic value of ESS for sub-hourly dispatch, analyzing power
and energy services provided by fast-responding ESS. Another study notes that
the opportunity to recover investment costs through energy arbitrage alone is
limited, by analyzing a model that considers both energy and ancillary services
[44]. This particular study demonstrates that investment in bulk ESS can pro-
155 vide savings in a unit commitment context through reduced thermal cycling,
flattening of locational marginal prices (LMPs), and the possibility of cross-
market arbitrage (between energy and ancillary service). In [45] the authors
also look at the value of energy arbitrage for ESS in European markets, conclud-
ing that this technology can provide more economic benefits in less integrated
160 electricity markets.

However, to the best of our knowledge, there is no existing study on the
interaction between generation, transmission, and ESS investments and RPS
policies. More specifically, no one has assessed the value of optimizing all these
assets simultaneously versus optimizing them sequentially.

165 3. Methodology

3.1. Nomenclature

We now present the nomenclature for our stochastic expansion planning model with ESS.

3.1.1. Sets and Indices

$\mathcal{T}$	Hours in a day, indexed by t
$\mathcal{B}$	Buses, indexed by b, b'
$\mathcal{G}$	All generators, indexed by g
$\mathcal{E}$	Existing generators, $\mathcal{E} \subseteq \mathcal{G}$, indexed by e
$\mathcal{N}$	New generators, $\mathcal{N} \subseteq \mathcal{G}$ and $\mathcal{N} = \mathcal{E}^c$, indexed by n
$\mathcal{R}$	New renewable generators, $\mathcal{R} \subseteq \mathcal{N}$, indexed by r
$\mathcal{L}$	All transmission lines, indexed by l
$\mathcal{J}$	New transmission lines, $\mathcal{J} \subseteq \mathcal{L}$, indexed by j
$\mathcal{S}$	Joint load and renewables production scenarios, indexed by s

170 3.1.2. Parameters

C_n^{inv}	Generator investment cost [\$/MW-yr]
C_g^{fom}	Generator fixed O&M cost [\$/MW installed]
C_g^{vom}	Generator variable O&M cost [\$/MWh]
C_g^{fuel}	Fuel cost [\$/MMBtu]
HR_g	Heat rate [MMBtu/MWh]
P_g^{max}	Generator capacity upper bound [MW]
$P_{r,t}^{max}$	Hourly renewable resource: production upper bound [MW]
C^{es}	ESS capacity investment cost [\$/MWh-yr]
C^{pc}	ESS power conversion investment cost [\$/MW-yr]
$C^{om,es}$	ESS fixed O&M cost [\$/MW installed]
C^d	ESS discharge cost [\$/MWh]
η	Roundtrip efficiency for ESS
C_j^{inv}	Transmission investment cost [\$/yr]
F_l^{max}	Line real power flow capacity [MW]

B_l	Susceptance on line [p.u.]
$P_{b,t,s}^d$	Demand at bus [MW]
C^{ue}	Cost penalty for unserved energy [\$/MWh]
RPS	Renewable Portfolio Standard target [%]
C^{nc}	RPS noncompliance penalty [\$/MWh]
M	Big M parameter for disjunctive constraints
σ_s	Probabilistic weighting of a scenario

3.1.3. Investment (First Stage) Variables

k_b^{es}	Integer investment for storage capacity
k_b^{pc}	Integer investment for power conversion
$x_{n,b}^g$	Integer variable indicating thermal generator builds
$x_{r,b}^r$	Continuous variable indicating renewable generator builds
x_j	Binary variable indicating transmission line builds

3.1.4. Operational (Second Stage) Variables

$p_{g,b,t,s}$	Generator dispatch at bus [MW], ≥ 0
$p_{b,t,s}^{ue}$	Load shed at bus [MW], ≥ 0
$f_{l,t,s}$	Flow on line [MW]
$\theta_{b,t,s}$	Phase angle at bus [radians]
$s_{b,t,s}$	Energy level in ESS at bus [MWh], ≥ 0
$r_{b,t,s}^c$	Charging of ESS at bus [MW], ≥ 0
$r_{b,t,s}^d$	Discharging of ESS at bus [MW], ≥ 0
$b_{b,t,s}^r$	Binary variable indicating ESS mode
p^{nc}	RPS noncompliance [MWh], ≥ 0

3.2. Model Formulation

We now introduce our co-optimization model considering a centralized planner, capturing investment in thermal and renewable generators, ESS, and trans-

175

mission lines.³ This model reflects a two-stage decision process, in which investment decisions are made in the first stage. Second stage decisions are then based on economic dispatch, where the investment decisions from the first stage are tested against operating conditions representing different days.

180 We use a generic representation of an ESS, with the energy capacity (MWh stored) and power conversion (MW input/output) components decoupled. This approach allows the model to determine the optimal power-to-energy ratio for the system, similar to the formulation introduced in [47]. Such a representation is sufficiently flexible to enable specification of a broad portfolio of real ESS,
185 including pumped-hydro storage, compressed air storage, and batteries.

Total system costs are broken into first stage costs (C^{fs}), which include costs associated with investment in new generators, transmission lines, and ESS, and second stage costs (C^{ss}), which include operational costs associated with all assets, in addition to penalties associated with RPS non-compliance and
190 unserved energy. Formally, these costs are computed as follows:

$$\begin{aligned}
C^{fs} &= \sum_{n \in \mathcal{N}, b \in \mathcal{B}} C_n^{inv} x_{n,b}^g + \sum_{j \in \mathcal{J}} C_j^{inv} x_j + \sum_{b \in \mathcal{B}} (C^{es} k_b^{es} + C^{pc} k_b^{pc}) \\
C_s^{ss} &= \sum_{g \in \mathcal{G}, b \in \mathcal{B}, t \in \mathcal{T}} (C_g^{fuel} HR_g + C_g^{vom}) p_{g,b,t,s} \\
&\quad + \sum_{e \in \mathcal{E}} C_e^{fom} P_e^{max} + \sum_{n \in \mathcal{N}, b \in \mathcal{B}} C_n^{fom} P_n^{max} x_{n,b}^g \\
&\quad + \sum_{b \in \mathcal{B}, t \in \mathcal{T}} C^{d,r}_{b,t,s} + \sum_{b \in \mathcal{B}} C^{om,es} k_b^{pc} + \sum_{b \in \mathcal{B}, t \in \mathcal{T}} C^{ue} p_{b,t,s}^{ue} + C^{mc} p^{nc}
\end{aligned}$$

³As discussed in [46], this is equivalent to a decentralized market model with perfect competition and nodal pricing. However, more realistic assumptions can be made. For instance, the model could be modified to consider market power of generation firms and ESS investors. Existing formulations that consider these features have been proposed in [31, 32, 33]. Furthermore, as Sioshansi points out, ownership of ESS and market structure can affect the competitive equilibrium and social welfare [40]. However, modeling a market where generators have market power would require a much more complicated model than the one used in this article, whose implementation is beyond the scope of our research.

Our optimization model is then given by:

$$\min C^{fs} + 8760 \sum_{s \in \mathcal{S}} \sigma_s C_s^{ss} \quad (1)$$

subject to

$$\begin{aligned} \sum_{l(\cdot, b) \in \mathcal{L}} f_{l,t,s} - \sum_{l(b, \cdot) \in \mathcal{L}} f_{l,t,s} + \sum_{g \in \mathcal{G}} p_{g,b,t,s} \\ + (r_{b,t,s}^d - r_{b,t,s}^c) + p_{b,t,s}^{ue} = P_{b,t,s}^d \quad \forall b \in \mathcal{B}, t \in \mathcal{T}, s \in \mathcal{S} \end{aligned} \quad (2)$$

$$p_{e,b,t,s} \leq P_e^{max} \quad \forall e \in \mathcal{E}, b \in \mathcal{B}, t \in \mathcal{T}, s \in \mathcal{S} \quad (3)$$

$$|f_{l,t,s}| \leq F_l^{max} \quad \forall l \in \mathcal{L}, t \in \mathcal{T}, s \in \mathcal{S} \quad (4)$$

$$f_{l,t,s} = B_l (\theta_{b,t,s} - \theta_{b',t,s}) \quad \forall l(b, b') \in \mathcal{L}, t \in \mathcal{T}, s \in \mathcal{S} \quad (5)$$

For new generators $\mathcal{N} \subseteq \mathcal{G}$ and transmission lines $\mathcal{J} \subseteq \mathcal{L}$, (3) and (5) are modeled as disjunctive constraints, as in [48]. We define capacity (7) based on the solar or wind resources available in each time period, $P_{r,t}^{max}$, in contrast to the time-independent P_g^{max} for new thermal generators:

$$p_{n,b,t,s} \leq x_{n,b}^g P_g^{max} \quad \forall n \in \mathcal{N} \setminus \mathcal{R}, b \in \mathcal{B}, t \in \mathcal{T}, s \in \mathcal{S} \quad (6)$$

$$p_{r,b,t,s} \leq x_{r,b}^r P_{r,t}^{max} \quad \forall r \in \mathcal{R}, b \in \mathcal{B}, t \in \mathcal{T}, s \in \mathcal{S} \quad (7)$$

$$|f_{j,t,s} - B_l (\theta_{b,t,s} - \theta_{b',t,s})| \leq M(1 - x_j) \quad \forall j(b, b') \in \mathcal{J}, t \in \mathcal{T}, s \in \mathcal{S} \quad (8)$$

Next, we add ESS modeling components. Response times for ESS, which range from milliseconds to many minutes depending on specific technology, are not considered in our formulation. In the formulation of ESS, we use a binary variable $b_{b,t,s}^r$ to indicate whether the ESS unit is charging or discharging. However, including such binary variables increases the computational difficulty of our model, which may not be desirable for larger case studies. In Appendix A, we investigate the impact of not including such binary variables. We assume that roundtrip efficiency is evenly distributed across charging and discharging

modes, with $\eta^c = \eta^d = \sqrt{\eta}$. Our ESS model is then given as:

$$s_{b,t,s} = s_{b,t-1,s} + \Delta t (\eta^c r_{b,t,s}^c - r_{b,t,s}^d / \eta^d) \quad \forall b \in \mathcal{B}, t \in \mathcal{T}, s \in \mathcal{S} \quad (9)$$

$$s_{b,t,s} \leq k_b^{es} \quad \forall b \in \mathcal{B}, t \in \mathcal{T}, s \in \mathcal{S} \quad (10)$$

$$r_{b,t,s}^c \leq k_b^{pc} \quad \forall b \in \mathcal{B}, t \in \mathcal{T}, s \in \mathcal{S} \quad (11)$$

$$r_{b,t,s}^d \leq k_b^{pc} \quad \forall b \in \mathcal{B}, t \in \mathcal{T}, s \in \mathcal{S} \quad (12)$$

$$r_{b,t,s}^c \leq M \cdot b_{b,t,s}^r \quad \forall b \in \mathcal{B}, t \in \mathcal{T}, s \in \mathcal{S} \quad (13)$$

$$r_{b,t,s}^d \leq M \cdot (1 - b_{b,t,s}^r) \quad \forall b \in \mathcal{B}, t \in \mathcal{T}, s \in \mathcal{S} \quad (14)$$

We make our model separable by day by modifying (9), so that the last hour of each representative day coincides with the first hour of the same day rather than that of the following day. We do this because our load data only provides days that are representative of “typical” loads across the sampled years (see Section 4), so five sampled days are not actually consecutive in time. We also note that, because daily over-production is the key challenge for renewable integration, intraday load shifting via ESS is seen as more important than inter-day shifting [12]. A similar formulation is presented in [37]:

$$s_{b,t=1,s} = s_{b,t=T,s} + \Delta t (\eta^c r_{b,t=1,s}^c - r_{b,t=1,s}^d / \eta^d) \quad \forall b \in \mathcal{B}, s \in \mathcal{S} \quad (15)$$

Finally, we have the RPS constraint, which enforces a lower bound on the amount of annual energy production that is met by qualifying renewables [46]:

$$\sum_{\substack{r \in \mathcal{R}, b \in \mathcal{B}, \\ t \in \mathcal{T}, s \in \mathcal{S}}} \sigma_s p_{r,b,t,s} + p^{nc} \geq RPS \sum_{\substack{g \in \mathcal{G}, b \in \mathcal{B}, \\ t \in \mathcal{T}, s \in \mathcal{S}}} \sigma_s p_{g,b,t,s} \quad (16)$$

Due to the long-term planning nature of this model, we do not include features such as unit commitment variables and constraints, forced outage rates, ramp rates, and lower limits on power output. We acknowledge that these assumptions limit our conclusions, because it is well known that both the inter-
195 mittency and unpredictability of renewables present operational challenges that can only be captured when considering the features mentioned above [10]. However, a model with such a level of detail would result in a much more challenging

optimization problem than the one we consider in this study.⁴ Furthermore, such a model would likely require the utilization of a more sophisticated solution
200 technique for large-scale problems than the one we use in this article, such as Benders decomposition [51] or Progressive Hedging [52].

Other promising solution approaches for large-scale or nonlinear applications are heuristics. Some of the most popular heuristics applied to planning problems include particle swarm optimization [53, 54], greedy randomized search
205 [55], sensitivity analysis [56], and genetic algorithms [57]. Although there is no guarantee that these heuristics will indeed find a global optimum, they often provide high quality solutions that could suffice for industrial applications in much shorter times than an algorithm such as branch and cut. For instance, AC transmission planning is a clear example of a highly nonlinear and non-
210 convex problem where a heuristic might perform much better than an interior point method [27]. However, the application of decomposition techniques or solution heuristics is beyond the scope of this paper, and we leave it as a subject of future research. Further, our objective in this paper is to first fully quantify the impact of co-optimization, which requires an exact solution method.

215 We implement the above model using the Pyomo 4.2 algebraic modeling language and library [58]. All experimental instances are solved using Gurobi 6.5.0 on an quad-core workstation with 16 GB of RAM. The two-stage stochastic MILP is solved to a 0.1% optimality gap, unless otherwise noted. All discrete decision variables in the model are then fixed, and the model is re-solved as a
220 linear program (LP) to recover dual information, i.e., locational marginal prices (LMPs) and REC prices.

⁴Previous studies have discussed the tradeoffs associated with excluding different operating constraints in generation planning models [49, 50]. The authors of [49] find a 0.02% error in cost for models considering thermal generators when relaxing unit commitment variables and constraints.

4. Data

We now describe the test network and associated data used for the numerical case study presented in Section 5.

Figure 1: Diagram of the 24-bus IEEE Reliability Test System. The six buses available for renewable investment are highlighted in blue, each with different renewable resource profiles. The three transmission corridors with reduced line limits are also highlighted, in red. (Adapted from [59].)

225 *Network.* Our experimental results are based on the 24-bus IEEE Reliability
 Test System (RTS-96), which consists of 24 buses, 34 transmission lines, and
 32 existing generators with an aggregate installed capacity of 3,405 MW [60].
 Existing generators are partitioned into nine groups, based on fuel type and
 generation technology. The system is divided into two voltage areas. Following
 230 [59], we allow renewables to be sited at six buses (3,5,7,16,21,23); [59] only
 considers wind generation, while we consider both wind and solar. To induce

congestion, thermal limits along the three transmission corridors connecting bus pairs (15,21), (14,16), and (13,23) are reduced to 400 MW, 250 MW, and 250 MW, respectively. A modified network schematic is shown in Figure 1.

235 *Demand and Renewable Profiles.* Hourly demand, wind, and solar PV profiles were obtained from Munoz and Mills [61]. These profiles are based on five years of utility data, normalized for demand growth. Wind and solar profiles provide maximum hourly output from a given unit of renewable capacity, though both wind and solar generators can be curtailed when needed. Each of the
240 six buses with renewable generation are prescribed different wind and solar profiles to mimic spatial variability. We select the number of days to sample in advance. Following [61], we then identify the sample from 10,000 replicates that minimizes the sum of the square differences of the means, standard deviations, and correlations between the replicate and the full dataset. The authors of
245 [61] argue that at least 50 representative days are necessary to capture the behavior of the original system. However, for our purposes using the synthetic RTS-96 test case, we only consider five representative days in order to maintain computational tractability.

Gen. Group	P_e^{max} [MW]	C_e^{fuel} [\$/MMBtu]	C_e^{fom} [\$/MW-yr]	C_e^{vom} [\$/MWh]	HR_e [MMBtu/MWh]
U12	12	11.47	13,170	3.6	12,000
U20	20	16.53	7,040	15.5	14,500
U50	50	–	14,800	2.65	–
U76	76	2.26	51,400	7.22	12,000
U100	100	11.47	13,170	3.6	10,000
U155	155	2.26	51,400	7.22	9,700
U197	197	11.47	13,170	3.6	9,600
U350	350	2.26	51,400	7.22	9,500
U400	400	0.72	93,300	2.14	10,000

Table 1: Existing generator operational cost parameters

Cost Data. Operations costs for existing generators are shown in Table 1, and
250 were derived using current fuel and O&M cost data obtained from the U.S.

Gen. Type	P_n^{max} [MW]	C_n^{fuel} [\$/MMBtu]	C_n^{fom} [\$/MW-yr]	C_n^{vom} [\$/MWh]	HR_n [MMBtu/MWh]	C_n^{inv} [\$/MW-yr]
CC	620	4.38	13,170	3.6	7.05	59,650
CT	85	4.38	7,040	15.45	10.85	43,970
Nuc.	2,234	0.72	93,280	2.14	9.612	292,100
IGCC	600	2.26	62,250	31.7	8.7	232,400
PV	0-1,500	–	24,690	–	–	251,900
Wind	0-1,000	–	39,550	–	–	144,000

Table 2: New generator investment and operations cost parameters

Energy Information Agency [62, 63]. Capacities and costs for new generators are compiled from the same data and are shown in Table 2. Investments in new transmission lines are limited to the 34 existing corridors of the RTS-96 test case. Transmission investment costs are derived from the line lengths specified in the IEEE RTS-96 [60], with a cost of \$450,000/mile-yr for 138 kV lines and \$950,000/mile-yr for 230 kV lines from [64].

ESS Data. ESS component costs can vary significantly, depending on the specific storage technology. Several surveys have compiled cost estimates and discuss the technical use cases for different technologies [13, 65]. These costs have been annualized based on a 20 year lifespan, with a 5% discount factor. While traditional ESS such as pumped-hydro storage provide a cheap means of storing energy, they incur relatively high power conversion investment costs and low roundtrip efficiencies. In contrast, newer battery ESS technologies tend to have relatively high energy capacity investment costs and high roundtrip efficiencies. We begin to address this contrast with a sensitivity analysis in Appendix B.2; however, the main results presented in Section 5 will be based on our base ESS case with the parameters described in Table 3.

C^{es} [\$/MWh-yr]	C^{pc} [\$/MW-yr]	$C^{om,es}$ [\$/MW-yr]	C^d [\$/MWh]	η [%]
4,000	80,000	5,000	5	81%

Table 3: Parameterization for base ESS case.

In the experiments presented in this paper, we limit ESS capacity to 1,000 MWh/bus and only consider one ESS device type in a given experiment. However, we suggest that future studies incorporate a portfolio of ESS technologies, which can be straightforwardly represented in our model. Such optimal ESS portfolio investments (without generation and transmission expansion planning) have been studied in [39].

5. Results and Discussion

We compare results obtained from a generation-and-transmission-expansion only (GTEP-only) model with those obtained from our fully co-optimized ESS model, to analyze the economic value of ESS co-optimization. We further compare these results to a sequential investment model—where generation and transmission expansion decisions are made first, then ESS decisions are made once these expansions decisions have been fixed.

In Section 5.1, we show that a significant proportion of the benefit from ESS investments in a bulk energy context come from generation and transmission investment deferrals, increasing the utilization of existing network assets. In contrast, operational savings results from arbitrage (load shifting and peak shaving) provide comparatively small benefits, most clearly demonstrated in our comparison with a sequential investment framework. We analyze the ESS sizing decisions in Section 5.2, deriving average ESS unit costs on the network. Section 5.3 analyzes the endogenously derived REC prices to show the benefit of bulk ESS to meet increasing RPS targets. Finally, in Section 5.4, we present a system-level hourly dispatch to show the behavior of bulk ESS.

A sensitivity analysis on fuel price, system demand, and ESS parameterization is presented in Appendix B to support these results.

5.1. Total System Cost

Our experiments indicate that the added option to invest in ESS in the fully co-optimized model significantly reduces annualized system cost for high RPS

Figure 2: Annualized cost, showing the value of co-optimization of all three assets in comparison to a sequential investment framework (where generation and transmission decisions are made first followed by ESS investments) and the traditional GTEP-only decisions, over various RPS targets.

targets relative to either the GTEP-only or sequential investment decisions. Figure 2 breaks down the change in system costs, showing that the base ESS case saves up to \$180 million/yr in total system costs (9.1% of GTEP-only costs) in the 75% RPS case, with correspondingly lower savings at lower RPS levels. In

low RPS regimes, we see that there is little value for bulk energy services from co-optimized ESS. It is only at higher RPS levels, above 40% penetration, where co-optimized ESS comes into the market. In these cases, we see relative reductions in renewable capacity investments due to higher utilization of that capacity to meet the same penetration targets. In the 67% and 75% RPS targets, we also

see transmission investment deferrals from co-optimized ESS. Since the IEEE RTS-96 network is relatively well-connected with limited congestion, we expect greater ESS value to be found in systems with tighter transmission constraints, as in [38].

In the sequential investment situation, ESS would provide value solely through operational savings (e.g. load shifting, balancing, and reductions in generator O&M) [16, 36, 39]. In Figure 2, the direct cost of sequential ESS investments are barely visible at any RPS target; however, we can see the indirect, operational cost savings at RPS targets above 60%, where thermal O&M costs begin to fall below the GTEP-only solution. In total, the savings from sequential ESS investments imply only \$3 million/yr in value from bulk energy services in this case study. Thus, the sequential model captures at most 1.7% of the \$180 million/yr savings from fully co-optimized bulk ESS.

5.2. ESS Sizing and Siting

RPS [%]	Co-Optimized			Sequential		
	[MW]	[MWh]	Buses	[MW]	[MWh]	Buses
0	–	–	–	–	–	–
10	–	–	–	–	–	–
25	–	–	–	–	–	–
33	–	–	–	–	–	–
40	100	850	13,23	–	–	–
45	300	2,500	7,8,15,17,23	–	–	–
50	300	2,950	13-15,21,23	–	–	–
60	650	3,900	1,7,11,13,15,20,21	50	300	14
67	900	4,750	3,7,10,13,21,23,24	50	450	14
75	1,250	7,250	1,3,5,7-10,13, 14,19,23,24	100	600	14

Table 4: Built ESS capacity in each RPS scenario for the fully co-optimized model v. sequential investment framework.

In our co-optimization findings, we observe that the mean power-to-energy ratio across RPS targets is 1:6.3, with a mean annualized installed cost of \$110,000/MW-yr or \$15,000/MWh-yr. These installed costs are very competitive with the generation and transmission investment costs prescribed in Section 4. Table 3 shows how ESS investments quickly increase with RPS targets, growing to 33% of peak system demand (MW) in the 75% target. At 75% RPS,

325 ESS investments are made across half the buses in the system due to the con-
 straint that no more than 1,000 MWh of ESS be sited at any location. In the
 presented case study, ESS investments are often made near or co-located with
 renewable generation. Further, co-optimized ESS is never co-located with new
 thermal generation (though sometimes with existing thermal), indicating that
 330 ESS and thermal generators provide redundant services in the face of significant
 renewables in terms balancing. However, we also note the limitations of the con-
 clusions from this case study given the relatively homogenous test network and
 the lack of transmission losses in our model formulation.

In contrast, sequential ESS investments are very limited in both size and
 335 location across RPS targets. In these cases, ESS is only sited at bus 14, which
 is connected to renewable resources at bus 16 by one of the reduced transmission
 lines (see Figure 1) and relatively far from other generators). In contrast to the
 co-optimized solution, new combustion turbine (CT) generators are co-located
 with the sequential ESS investments at bus 14, indicating that the installed CT
 340 units are of relatively low value, and ESS is providing an additional balancing
 service at this bus.

5.3. REC Pricing

Our original motivation in this research was to investigate the contribution
 of ESS to meeting RPS requirements. Previous sections have discussed ESS
 345 investments and how they reduce overall system cost at various renewable pen-
 etration levels. We now focus on how ESS can specifically influence REC pricing
 associated with a desired renewable penetration level. REC prices correspond
 to the marginal cost of meeting an RPS target, which we compute as the change
 in total system cost that results from increasing the renewable target by one
 350 MWh.⁵ Figure 3 shows the evolution of the REC price at increasing RPS levels.

⁵In a convex model (e.g. a linear program), the REC prices are simply the dual variables
 associated with constraint (16). However, because our model includes binary variables, we
 estimate the REC prices using the definition of a shadow price [29].

We observe the non-convexity of the REC price as a function of RPS targets, due to the lumpy nature of the investments.

Figure 3: Endogenously derived REC prices for various RPS targets on the RTS-96 test network for the GTEP-only and the fully co-optimized solutions. The REC price describes the marginal increase in system cost to meet an incremental increase in the RPS target. Tick marks on the x-axis correspond to RPS targets tested.

At renewable targets below 50%, we do not see a significant reduction in the REC price due to the introduction of co-optimized ESS investments. We see a marginal decrease in REC prices at the 40% RPS target, but the gap closes at 45% and 50% before increasing again at very high RPS targets due to non-convexities in investment decisions. For the RPS targets of 60% and higher, we begin to see significant REC price reductions, consistent with our observations in Section 5.1 that co-optimized ESS leads to significant generation and transmission investment deferrals in addition to operational savings.

In the context of the marginal value of renewable capacity, Figure 4 shows the aggregate impact of co-optimized ESS investments on renewable dispatchability, which is directly related to the incremental cost of meeting renewable targets (i.e. the REC price). Only a very small fraction of renewable are curtailed below 50% penetrations. However, curtailment in the GTEP-only solution grows quickly with renewable penetration, leading to an increasing marginal cost to supply energy into the market. At very high RPS targets, we observe that sequential ESS investments provide almost no incremental benefit over the

GTEP-only solution in terms of total energy dispatched from renewables. At
 370 75% RPS, we see that the GTEP solution curtails 33% of total renewables (25%
 of available wind and 42% of available solar), and the sequential solution also
 curtails 33% of total renewables (33% of each type). In contrast, co-optimized
 ESS leads to lower overall renewable capacity investments as well as lower cur-
 tailment, curtailing only 20% of installed resources (15% and 25% in wind and
 375 solar, respectively).

Figure 4: Available wind and solar resources dispatched and curtailed at various high RPS levels. In the sequential ESS solution, the available renewable resources (i.e. installed capacities) are equal to the GTEP-only solution, with marginal differences in dispatched renewables, since generation investments are fixed. In contrast, both capacity and total dispatch decisions differ significantly in the fully co-optimized solution.

5.4. Hourly Dispatch

Figure 4 highlighted the aggregate impact of co-optimized ESS on renewable energy: now, Figure 5 demonstrates how ESS behaves in each hour in the face of significant renewables. Here, the flexibility provided by co-optimized ESS
 380 allows the system operator to capture and shift significant renewable energy

across time. The co-optimized dispatch clearly shows how spikes in renewable production are covered by ESS flexibility and moved to hours of low renewables. In contrast, only 50 MW of ESS capacity are available in the sequential ESS solution, resulting in only marginal load shifting.

385 Further, and implicitly, ESS can be seen to assist thermal generators with load following services. With co-optimized ESS, ramps are not fully eliminated, but are reduced when there is excess renewable production early in the day to be discharged in the peak periods. In the second representative day in Figure 5 (a relatively high load day), the thermal ramp with co-optimized storage is
390 still steep owing to the limited amount of renewables earlier in the day. In the third representative day, a low-demand day, there is a significant drop-off in wind production that requires thermal generators to ramp up for only a few hours to provide balancing services in the GTEP-only and sequential solutions; however, the co-optimized ESS is able to capture a spike in renewables early in
395 the day (that would otherwise be curtailed without ESS) to provide balancing. Since our model formulation does not explicitly model generator ramping or unit commitment constraints, we expect that the value of ESS for providing balancing services to be consistently higher in real systems subject to these technical constraints.

400 6. Conclusions and Policy Implications

Our results indicate that co-optimizing ESS investments can be a cost-effective investment mechanism to achieving compliance with high RPS targets. We demonstrate that ESS investments can economically provide bulk energy services to systems with increasing renewables penetration levels, including load
405 shifting/peak shaving, and can facilitate investment deferrals. Our numerical experiments show savings of up to \$180 million/yr (9.1%) in total system costs for the highest RPS target considered when co-optimizing ESS. The introduction of co-optimized ESS increases operational flexibility and enables better energy balancing across the network, lowering REC prices for RPS compliance and re-

Figure 5: Hourly production over five sampled days for a 67% RPS level in our GTEP-only model (left), sequential ESS investments (middle), and fully co-optimized ESS (right). ESS investments made in the sequential setting provide only marginal dispatchable power, while fully co-optimized ESS capacity is able to provide significant load shifting across all representative days.

410 ducing renewable curtailment. However, the vast majority of the value of our
 co-optimization framework is derived from investment deferrals. In contrast,
 we find that making ESS investment decisions after generation and transmis-
 sion investments have been fixed results in just \$3 million/yr in cost savings
 via operational benefits. Plainly, we find that it is only by considering genera-
 415 tion, transmission, and ESS simultaneously that we are able to extract the full
 value of bulk ESS investments. These findings are contrary to [16, 36, 39], who
 find sufficient operational savings to induce beneficial ESS investments in cases
 where generation and transmission capacities are considered fixed.

We also find that the incremental need for ESS capacity grows quickly at
 420 high RPS levels. The optimal bulk ESS capacity reaches 1.25 GW at 75% RPS
 levels on our test network, corresponding to 33% of peak system demand and
 21% of total renewables capacity. Such ESS penetration levels pose a challenge
 in practice, as just 60 MW of ESS capacity was installed in the U.S. market
 (where non-coincidental peak demand is on the order of 700 GW [66]) in Q3
 425 2015, though it is estimated that ESS deployments could scale to over 1 GW/yr
 by 2020 [67].

Although our model ignores important features that become particularly relevant at high renewable targets, such as unit commitment state, unit ramping limits, and the stochastic nature of wind and solar production, our results highlight the need for models that explicitly and concurrently consider the capacities of all generation, transmission, and storage assets in the system as variables—as is the case in real-world power systems. Such co-optimization models are necessary for appropriately gauging the full economic value of bulk energy services from various energy storage technologies.

A direct application of the planning framework proposed in this article is in vertically integrated utilities, where a single planning authority makes all investment decisions. Some examples of these include the Bonneville Power Administration and the Tennessee Valley Authority in the US. Customers served by these utilities could greatly benefit if planners selected infrastructure to meet renewable targets co-optimizing all assets simultaneously, instead of sequentially as they do in practice.

In deregulated markets, such as the California ISO, the PJM Interconnection, and the New England ISO in the US, as well as the power sectors in Australia, Korea, Japan, Scandinavia, Chile, New Zealand, and Spain, the planning of generation, transmission, and ESS investments is done by separate entities. For those markets, the results from the co-optimization model proposed would only provide an upper bound on the cost savings that could be attained if transmission planners and private investors in generation and ESS worked collaboratively. Another potential application is in deregulated markets where there is nearly perfect competition and nodal pricing. In those markets, a proactive or anticipative transmission planner could utilize our co-optimization model to select transmission investments taking into consideration the response of private investors in generation and ESS capacity.

Finally, a challenge that remains open is the application of the proposed framework to larger and more realistic networks. Further work will go into applying this stochastic modeling framework in a high performance computing environment to test more representative days and larger networks.

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Appendix A. ESS Charging State Indicator Variables

Similar to [41], our formulation explicitly prevents ESS at each bus from simultaneously charging and discharging in constraints (13) and (14) through the use of the binary variables $b_{b,t,s}^r$. This phenomenon can occur in models that do not track charging and discharging state when there are sufficiently negative LMPs, resulting in excess energy being “burned off” through ESS inefficiency. However, in practice such operational behavior is unrealistic, and if such behavior is not explicitly prevented, we expect that an optimization model would over-estimate the value of downward flexibility provided by ESS.

Negative prices are increasingly a reality in operations, due to regulatory incentives such as Production Tax Credits (PTCs), Feed-In Tariffs (FITs), or as is the case with our study, RECs associated with RPS requirements. Due to the favored position of renewables, in low demand–high solar/wind availability situations, operational revenue can be increased by keeping renewables online and consequently receiving credit for renewable generation toward PTCs, FITs, or RECs, suppressing the price of electricity [68]. While ESS can provide some flexibility in the system by absorbing excess generation (thereby reducing the likelihood of negative prices), in scenarios with significant RPS requirements and very high REC prices, negative locational marginal prices may be unavoidable.

A potentially significant impediment to inclusion of binary variables to model charge/discharge state is the resulting increase in computational burden. However, as shown in Figure A.6, the impact of excluding the charging mode binary indicator variables is insignificant for the case study considered in this paper. In the solution without binaries, we observe a 8% increase in energy production due to simultaneous charging/discharging, associated with \$8 million/yr in extra O&M costs but more than offset by \$20 million/yr decrease in investment costs. The overall result is an extra 0.6% in expected cost savings over the base co-optimized ESS result, which we deem insignificant in relation to the overall system. This result yields an advantage from an algorithmic perspective, as solving the extensive form of our planning model for a realistic network will be

Figure A.6: Comparison of total costs for our base ESS case optimization model with and without charging mode indicators, $b_{b,t,s}^r$, showing only marginal impacts on total cost in all RPS targets for the case study presented in this paper. The higher ESS O&M costs are associated with simultaneous charging/discharging behavior.

computationally intensive. Being able to relax the binaries variables could allow direct application of decomposition algorithms that require convexity of the operations (second-stage) problem, such as [51]. In cases where the relaxation could result in significant errors, an alternative decomposition method that does not require convexity could be employed, such as [52].

Appendix B. Sensitivity Analyses

In this section, we present various sensitivity analyses on both system-level and ESS-specific parameters. While these findings are not a comprehensive analysis of all possible system parameters, they serve to support the key findings presented in Section 5.

Figure B.7: Sensitivity analysis for fuel price (left) and demand (right) at 75% renewables penetration. Fuel price has only a minor impact on system cost, while varying demand noticeably changes system cost. However, across all sensitivities, co-optimized ESS shows significant cost savings over GTEP-only and sequential ESS investments.

Appendix B.1. Fuel Price and Peak Demand

Here, we present a sensitivity study for two key system parameters: fuel price, C_g^{fuel} , and demand, $P_{b,t,s}^d$. We vary fuel prices by $\pm 30\%$ from the base values in Tables 1 and 2. For peak demand, we vary demand by $\pm 15\%$ from the 4,600 MW peak in the base case. While both cases were performed across the original range of renewable penetrations (0% to 75%), for the sake of conciseness, we present numerical results for only the highest case, 75%. In both sensitivities, co-optimized ESS continues to provides significant savings over either the GTEP-only or sequential investment framework, in each case saving close to 9% in total system costs at renewables level of 75%—in line with our main results.

In the case of fuel price, Figure B.7 shows that a 30% fluctuation in fossil fuel prices has a minimal effect on total cost, due to the low share of thermal generators on the system. REC prices for the 30% fuel price sensitivities were within \$10/MWh of the base case values plotted in Figure 3. We observe a direct relationship between system demand and system cost. A 15% change

in demand leads to approximately 15% changes in annualized cost. In the
525 sensitivity on demand, we further observe that co-optimized ESS provides a
cushion against the marginal cost of meeting stringent renewables targets. In the
face of varying system demand, REC prices for the GTEP-only and sequentially-
invested ESS vary by over \$40/MWh, while REC prices for the co-optimized
ESS vary by less than \$5/MWh. Based on our main findings as in Figure 4,
530 lower renewables curtailment likely explains a significant portion of these savings
from co-optimization.

Appendix B.2. “Battery” ESS Parameters

In this section, we present a second parameterization of the ESS units as a
brief sensitivity of ESS costs depending on the technology considered. In the
535 “battery” ESS case, we mimic a higher efficiency, higher power-to-energy ratio
technology, such as lithium-ion batteries that have become increasingly popular
for grid-scale storage, with the characteristics described in Table B.5. In this
case, the investment cost of the energy component is much higher relative to
the power conversion equipment, as described in [13, 65].

C^{es}	C^{pc}	$C^{om,es}$	C^d	η
[\$/MWh-yr]	[\$/MW-yr]	[\$/MW-yr]	[\$/MWh]	[%]
56,000	16,000	5,000	7	95%

Table B.5: Parameterization for “battery” ESS case.

540 With higher investment and O&M costs associated with the “battery” pa-
rameterization, we see a significantly lower investment in ESS capacity, as shown
in Table B.6. In this case, ESS investments are most often co-located with re-
newable generation with a higher power-to-energy ratio of 1:1.9, suggesting a
shift toward power services rather than bulk energy shifting. Figure B.8 shows
545 the relative cost savings over the standard GTEP model and compares these sav-
ings to the co-optimize solution in our base ESS case first presented in Section
5.1. The result is lower cost savings when compared to our base co-optimization
solution, up to 2.6% of the GTEP-only system cost (versus up to 9.1% in the

RPS [%]	Battery ESS		
	[MW]	[MWh]	Buses
0	–	–	–
10	–	–	–
25	–	–	–
33	–	–	–
40	–	–	–
45	–	–	–
50	–	–	–
60	150	150	13,14
67	250	500	5,7,14
75	600	1,350	3,5,7,14

Table B.6: Built ESS capacity in each RPS scenario, for co-optimized “battery” ESS case.

base case). However, the co-optimized solution values battery ESS higher than
550 the sequential framework, which does not invest in any ESS for any RPS target
due to the high cost. We again observe that the majority of cost savings is
associated with investment deferrals. Further, we observe that the “battery”
ESS is still able to noticeably decrease the REC prices associated with different
RPS targets, as shown in Figure B.9 below.

555 As our co-optimization formulation deals only in bulk energy services, fast-
responding technologies will be consistently undervalued because other value
streams, such as power and ancillary services, are not captured at the hourly
timescale. However, we show that our conclusions for benefits of co-optimized
ESS discussed in Section 5 are still applicable to ESS technologies with different
560 characteristics.

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Figure B.8: Relative cost savings over GTEP-only solution, comparing impact of “base” and “battery” ESS parameterizations. Due to significantly higher investment and operating costs, less “battery” ESS capacity is built; however, there is still significant benefit derived by co-optimizing expensive ESS for bulk services, especially for high RPS targets.

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