Co-Optimization of Transmission Lines and Energy Storage Systems for Multi-Year Expansion Planning

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***Abstract*—The growing adoption of inverter-based resources introduces planning and operational challenges for transmission system planners. Energy storage systems are seen as key assets for addressing these issues, but they are not well represented in conventional transmission network planning methods. This paper proposes the expansion of a multi-year adaptive robust optimization model for the co-optimization of investments in transmission lines and battery energy storage systems (BESSs). The framework includes a comprehensive BESS model that covers power and duration-dependent capital costs along with fixed operation and maintenance costs. It also defines the inter-temporal operational constraints needed to model BESS energy levels. Comparative case studies on a modified 24-bus IEEE Reliability Test System show that the proposed approach leads to more cost-effective and reliable expansion plans by strategically using BESSs to postpone expensive transmission upgrades and to mitigate network congestion.**

***Index Terms*—transmission network expansion planning, energy storage systems, inverter-based resources, uncertainty, robust optimization**

I. Introduction

The rapidly deepening penetration rate of inverter-based resources (IBRs), such as converter-interfaced generation (CIG) like wind and solar, poses significant challenges for transmission system planners (TSPs). On the one hand, IBRs in general introduce challenges in terms of dynamic performance and frequency stability due to their lack of intrinsic rotational inertia [1], [2]. If not managed properly, this shortfall can lead to dangerous instabilities on the transmission system (TS), especially following a large disturbance such as a sudden loss of generation. On the other hand, TSPs need to deal with the uncertainty surrounding availability of primary resources for CIG [3], since these are heavily dependent on fluctuating meteorological conditions.

Energy storage systems (ESSs) are increasingly viewed as critical network assets capable of mitigating the aforementioned shortcomings of CIG. Specifically, the grid-forming (GFM) control approach for inverters has been developed as a means to enhance the grid-supporting capabilities of IBRs [4], [5]. One specific implementation of GFM control is the virtual synchronous machine (VSM) scheme that emulates the dynamic performance of synchronous generators and can also provide inertia to the grid [6]. However, the provision of inertia from VSM-controlled IBRs is dependent of the availability of sufficient active power *and* energy, which is why such devices need to be paired with ESSs [7]. Energy storage can also contribute to the reliability of wind and solar power by mitigating their inherent variability and enabling these renewable energy sources to behave more like dispatchable resources from the transmission system's perspective [8]. Furthermore, in the context of transmission network expansion planning (TNEP), ESSs can be used to reduce congestion in transmission lines [9] and thereby postpone or even avoid costly TS investments. In fact, it has been shown that battery energy storage systems (BESSs) may virtually increase the transmission capacity of existing transmission lines by effectively distributing energy transfers over time [10]. In other words, construction of utility-scale energy storage facilities may eliminate the need for new lines or enable the deferral of the construction of new lines.

Considering a future TS dominated by IBRs [11], it becomes essential to incorporate ESS design considerations within the TNEP problem. Conventional TNEP primarily focuses on minimizing investment and operation costs while ensuring that the system can meet forecasted peak demands. Nonetheless, the review presented in [12] lists emerging TNEP methods that address the rise in the adoption of IBRs. The review recognizes the current under-utilization of ESSs in TS planning and also recommends that the modeling of uncertainty in renewable generation should be prioritized. In that spirit, a robust TNEP approach is presented in [13] to address the uncertainty of loads and renewable generation. Meanwhile, [14] introduces a stochastic adaptive robust optimization framework to guide generation and transmission investment decisions under deep penetration of CIG. Then, [15] proposes an adaptive robust optimization (ARO) model that considers the non-convex and inter-temporal operational constraints of ESSs. While these methodologies address uncertainty associated with renewable generation, their effective inclusion of ESS technologies within the TNEP problem remains limited.

This paper lays the groundwork for a comprehensive TNEP framework that aims to generate more robust and economical expansion plans in IBR-dominated transmission systems. Thus, the current work proposes the implementation of an ESS cost model integrated in a multi-year ARO framework to optimize the sizing and placement of storage facilities alongside the construction of new transmission lines. The operation and maintenance (O&M) costs, as well as the

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operational constraints of ESSs are also presented. This approach enables ESSs to be considered at par with transmission line investments over a multi-year planning horizon. Indeed, incorporating both transmission lines and ESSs as investment candidates may unlock more economical and robust expansion plans that benefit a TS with large shares of CIG. The paper is therefore organized as follows. The technical background regarding the multi-year ARO model for TNEP is presented in Section II. Then, the ESS model and associated constraints are detailed in Section III. A comparative case study and analyses are provided in Section IV to validate the effectiveness of the proposed method. Finally, the concluding remarks are presented in Section V.

II. Adaptive Robust Optimization Background

The basis for the proposed TNEP methodology is an ARO model developed in [16]. The authors propose a multi-year framework that allows investments in transmission lines to be made in any year during the planning horizon. In addition, this model also accounts for the ramping limits of conventional generation as well as the operational variability and uncertainty associated with deep penetration of renewable generation.

In their multi-year ARO model, displayed below, the authors of [16] define three nested levels. The upper-level, (1a)–(1c) serves to minimize the investment and the operations costs associated with the worst-case realizations of uncertain factors. The middle-level problem (2a), (2b) is cast to determine the worst-case operational costs given the upper-level investment decisions. Finally, the lower-level problem (3a)–(3d) seeks to minimize the cost of operations given the investment decisions and worst-case uncertainty realizations.

$$\min_{\boldsymbol{x}_y, c_y^{\mathrm{O,WC}}} \sum_{y \in \Omega^{\mathrm{Y}}} \frac{1}{(1+\kappa)^{y-1}} \left(\boldsymbol{a}^T \boldsymbol{x}_y + \frac{c_y^{\mathrm{O,WC}}}{1+\kappa} \right) \tag{1a}$$

subject to :

$$\sum_{y \in \Omega^{\mathrm{Y}}} \boldsymbol{A}_y \boldsymbol{x}_y \leq \boldsymbol{b}, \tag{1b}$$

$$\boldsymbol{x}_y \in \{0,1\}^m; \forall y \in \Omega^{\mathrm{Y}}, \tag{1c}$$

$$c_y^{\mathrm{O,WC}} = \Bigg\{ \max_{\boldsymbol{u}_y, c_y^{\mathrm{O}}} c_y^{\mathrm{O}} \tag{2a}$$

subject to :

$$\boldsymbol{u}_y \in \mathcal{U}_y \tag{2b}$$

$$c_y^{\mathrm{O}} = \min_{\boldsymbol{v}_y, \boldsymbol{z}_y} \boldsymbol{d}_y^T(\boldsymbol{u}_y)\boldsymbol{v}_y + \boldsymbol{e}_y^T \boldsymbol{u}_y \tag{3a}$$

subject to :

$$\boldsymbol{B}\boldsymbol{x}_y + \boldsymbol{C}(\boldsymbol{x}_y)\boldsymbol{v}_y + \boldsymbol{D}_y\boldsymbol{u}_y = \boldsymbol{f} : \boldsymbol{\lambda}_y, \tag{3b}$$

$$\boldsymbol{E}\boldsymbol{x}_y + \boldsymbol{F}\boldsymbol{v}_y + \boldsymbol{G}_y\boldsymbol{u}_y + \boldsymbol{H}\boldsymbol{z}_y \geq \boldsymbol{g} : \boldsymbol{\mu}_y, \tag{3c}$$

$$\boldsymbol{z}_y \in \{0,1\}^n\}, \ \forall y \in \Omega^{\mathrm{Y}}, \tag{3d}$$

In this compact formulation of the model, $\boldsymbol{x}_y$ is the vector of investment decision variables for year y in the set Ω^{Y}, and $c_y^{\mathrm{O,WC}}$ is the worst-case operation cost for that same year. Variables representing the uncertainty realizations are contained in the vector $\boldsymbol{u}_y$ belonging to the uncertainty set $\mathcal{U}_y$, and the vectors $\boldsymbol{v}_y$, $\boldsymbol{z}_y$ contain the continuous and binary variables of the lower-level problem, respectively. Here, the index n represents the number of buses in the network and determines the dimensions of $\boldsymbol{z}_y$. Furthermore, $\boldsymbol{a}, \boldsymbol{b}, \boldsymbol{d}_y, \boldsymbol{e}_y$ as well as $\boldsymbol{f}$ and $\boldsymbol{g}$ are vectors of coefficients, while $\boldsymbol{A}_y, \boldsymbol{B}, \boldsymbol{C}, \boldsymbol{D}_y, \boldsymbol{E}, \boldsymbol{F}, \boldsymbol{G}_y$ and $\boldsymbol{H}$ are matrices of coefficients. Then, the vectors $\boldsymbol{\lambda}_y$ and $\boldsymbol{\mu}_y$ contain the Lagrange multipliers for the respective equality and inequality constraints of the lower-level problem.

As mentioned previously, the upper-level problem minimizes the sum of the investment costs and the operation costs associated with the worst-case realization of the uncertain variables $\boldsymbol{u}_y$. Investment decisions can be made at the beginning of any year in the planning horizon and the total costs are annualized with the discount rate κ as seen in (1a). In this model, the investments costs are also bound by a maximum investment budget (1b).

The uncertain variables considered in this model are the generation capacity of conventional and renewable generating units, the peak demand and the marginal operation costs of conventional generating units. Specifically, the model uses a cardinality-constrained uncertainty set which imposes an uncertainty budget. This budget limits the number of uncertain variables which may deviate from their forecast value to their worst-case realization.

Furthermore, data aggregation and clustering methods are used to represent the large amounts of data that model the varying demand and generation from renewable sources. For this purpose, a modified maximum dissimilarity algorithm as well as the priority chronological-time period clustering method [17] are employed to generate reduced sets of representative days (RDs), which are themselves split up into representative time periods (RTPs). This approach allows to significantly reduce computational time while retaining the major trends and particularities in the chronological time data.

The rest of this paper builds on the existing multi-year ARO model presented in this section by incorporating an ESS cost model and operational constraints. The reader is referred to [16] for details regarding the full model definition as well as its solution procedure.

III. Energy Storage Modeling and Constraints

This section introduces the cost model for utility-scale BESSs which includes both investment costs as well as O&M costs. In addition, the relevant modifications to the objective function and operational constraints for the multi-year ARO model are presented.

A. Cost Modeling for Battery Energy Storage Systems

Without loss of generality, the storage technology considered in this study is the lithium-ion BESS, since it remains one of the most well documented storage technologies. Indeed, researchers from the National Renewable Energy Laboratory (NREL) provide a report on the cost projections of utility-scale lithium-ion battery storage [18], which is based on an analysis of multiple recent publications on utility-scale storage costs.

The two major components that define the construction and installation costs of a BESS are the energy and power capacities of the system. The NREL report provides the following per kilowatt cost relationship for BESSs in 2024:

$$M^{\mathrm{B}} = \$240.8/\mathrm{kWh} \times d + \$379.16/\mathrm{kW}, \tag{4}$$

where d is desired the storage duration in hours. Here, the duration d determines the energy capacity; for example, a 100 kW BESS with a 4-hour duration has a rated energy capacity of 400 kWh. Then, depending on the desired duration, the total BESS investment cost can be obtained as

$$C^{\mathrm{B}} = M^{\mathrm{B}}(d) \times P^{B}_{nom}, \tag{5}$$

where P^{B}_{nom} is the nominal power capacity of the BESS in kilowatts.

Evidently, the investment cost of a BESS scales primarily with its duration. As a result, the sizing of the BESS energy capacity should be a crucial design choice in the TNEP problem, as it also determines the ability of the BESS to displace energy that would otherwise require transmission lines.

In addition to the investment costs, the model also includes fixed yearly O&M costs. These costs include BESS maintenance and battery augmentations, which are assumed to be sufficient to keep the system running at its rated capacity during its useful lifetime. Thus, battery degradation is not modeled explicitly. According to [18], these fixed O&M costs can be taken into account by adding 4% of the system's total investment costs for every year of operation.

Finally, it should be noted that the proposed cost model could be expanded to include other storage technologies by sourcing the relevant data on construction and O&M costing.

B. Objective Function and Operational Constraints

The upper-level cost function can be modified to consider BESSs as potential investment decisions alongside transmission lines. The original formulation in (1a) is therefore replaced by

$$\min_{\boldsymbol{x}_y, c^{\mathrm{O,WC}}_y} \sum_{y \in \Omega^{\mathrm{Y}}} \frac{1}{(1+\kappa)^{y-1}} \left(\boldsymbol{a}^T \boldsymbol{x}_y + \frac{c^{\mathrm{O,WC}}_y + c^{\mathrm{O,B}}_{by}}{1+\kappa} \right), \tag{6}$$

where $c^{\mathrm{O,B}}_{by}$ is the fixed yearly O&M cost of BESSs defined as

$$c^{\mathrm{O,B}}_{by} = \sum_{b \in \Omega^{\mathrm{B}}} 0.04 \times C^{\mathrm{B}}_b \tilde{x}^{\mathrm{B}}_{by} \tag{7}$$

and the term $\boldsymbol{a}^T \boldsymbol{x}_y$ is expanded to comprise the investment costs of both transmission lines and BESSs as follows:

$$\boldsymbol{a}^T \boldsymbol{x}_y = \sum_{l \in \Omega^{\mathrm{L}}} C^{\mathrm{L}}_l x^{\mathrm{L}}_{ly} + \sum_{b \in \Omega^{\mathrm{B}}} C^{\mathrm{B}}_b x^{\mathrm{B}}_{by}. \tag{8}$$

In (8), C^{L}_l is the investment cost of line l belonging to the set Ω^{L} and C^{B}_b is the investment cost of BESS b belonging to the set Ω^{B}. The binary decision variables x^{L}_{ly} and x^{B}_{by} determine if line l and is built in year y and if BESS b is built in year y respectively. In addition, the binary variable $\tilde{x}^{\mathrm{B}}_{by}$ in (7) indicates the presence of BESS b in the year it is built and for every subsequent year.

A similar modification is necessary for constraint (1b) which sets a limit on the total investment budget available for the entire planning horizon. As such, the modified constraint becomes

$$\sum_{y \in \Omega^{\mathrm{Y}}} \frac{1}{(1+\kappa)^{y-1}} \left(\sum_{l \in \Omega^{\mathrm{L}}} C^{\mathrm{L}}_l x^{\mathrm{L}}_{ly} + \sum_{b \in \Omega^{\mathrm{B}}} C^{\mathrm{B}}_b x^{\mathrm{B}}_{by} \right) \leq I^{\max}, \tag{9}$$

where $I^{\max}$ is the available investment budget in today's dollars.

Next, two upper-level problem constraints relating to BESS investment binary decision variables are introduced:

$$\sum_{y \in \Omega^{\mathrm{Y}}} x^{\mathrm{B}}_{by} \leq 1; \quad \forall b \in \Omega^{\mathrm{B}}, \tag{10a}$$

$$\tilde{x}^{\mathrm{B}}_{by} = \sum_{\tilde{y}=1}^{\tilde{y}=y} x^{\mathrm{B}}_{b\tilde{y}}; \quad \forall b \in \Omega^{\mathrm{B}}, \forall y \in \Omega^{\mathrm{Y}}, \tag{10b}$$

$$\sum_{y \in \Omega^{\mathrm{Y}}} \sum_{b \in \Omega^{\mathrm{B(n)}}} x^{\mathrm{B}}_{by} \leq 1; \quad \forall n \in \Omega^{\mathrm{N}}. \tag{10c}$$

Constraint (10a) ensures that a given BESS investment can be made in only one year of the planning horizon. Then, the binary variable $\tilde{x}^{\mathrm{B}}_{by}$ in constraint (10b) is required to be equal to 1 for the year in which the BESS was built and for every subsequent year. Finally, $\Omega^{\mathrm{B(n)}}$ is a subset of Ω^{B} which comprises all candidate BESSs at bus n. As such, (10c) ensures that at most one BESS is built at any given bus.

The BESS operational constraints for the lower-level problem also need to be defined. Constraints here are needed for tracking its energy store, energy limits and power limits:

$$e^{\mathrm{B}}_{byth} = e^{\mathrm{B}}_{byth-1} + \left(\eta^{\mathrm{B,C}}_b p^{\mathrm{B,C}}_{byth} - \frac{p^{\mathrm{B,D}}_{byth}}{\eta^{\mathrm{B,D}}_b} \right) \tau_{yth}, \tag{11a}$$

$$e^{\mathrm{B}}_{byt0} = \tilde{x}^{\mathrm{B}}_{by} E^{\mathrm{B}}_{byt0}, \tag{11b}$$

$$\tilde{x}^{\mathrm{B}}_{by} E^{\mathrm{B,min}}_b \leq e^{\mathrm{B}}_{byth} \leq \tilde{x}^{\mathrm{B}}_{by} E^{\mathrm{B,max}}_b, \tag{11c}$$

$$\tilde{x}^{\mathrm{B}}_{by} E^{\mathrm{B}}_{byt0} \leq e^{\mathrm{B}}_{bytH}, \tag{11d}$$

$$0 \leq p^{\mathrm{B,C}}_{byth} \leq \tilde{x}^{\mathrm{B}}_{by} u^{B}_{byth} P^{\mathrm{B,C,max}}_b, \tag{11e}$$

$$0 \leq p^{\mathrm{B,D}}_{byth} \leq \tilde{x}^{\mathrm{B}}_{by} (1 - u^{B}_{byth}) P^{\mathrm{B,D,max}}_b; \tag{11f}$$

$$\forall b \in \Omega^{\mathrm{B}}, \forall y \in \Omega^{\mathrm{Y}}, \forall t \in \Omega^{\mathrm{T}}, \forall h \in \Omega^{\mathrm{H}}.$$

Here, the sets of all RDs and RTPs are comprised in Ω^{T} and Ω^{H}, respectively. The parameter τ_{yth} is the duration of one RTP in hours, whereas $\eta^{\mathrm{B,C}}_b$ and $\eta^{\mathrm{B,D}}_b$ are the respective charging and discharging efficiencies of BESS b. The upper and lower limits on the BESS energy are $E^{\mathrm{B,min}}_b$ and $E^{\mathrm{B,max}}_b$ respectively, while E^{B}_{byt0} is the energy level of BESS b at the start of RD t. Then, $P^{\mathrm{B,C,max}}_b$ and $P^{\mathrm{B,D,max}}_b$ are the maximum charging and discharging power capacities of BESS b. Regarding the continuous variables, e^{B}_{byth} is the instantaneous energy level of BESS b for for $h \geq 1$, whereas e^{B}_{byt0} is the initial value of energy. The instantaneous charging and discharging

TABLE I
CANDIDATE BESS PARAMETERS

Buses	Power (MW)	Duration (h)	Investment Cost ($)
1, 6, 10,	100	4	134,200,000
12, 13, 15,	100	6	182,200,000
19 & 22	100	8	230,500,000

power levels of a BESS are represented by $p^{\mathrm{B,C}}_{byth}$ and $p^{\mathrm{B,D}}_{byth}$ respectively. Finally, u^{B}_{byth} is a binary variable that prevents both the charging and discharging powers from being greater than zero at the same time. The reader may refer to [16] for a comprehensive notation table of the original problem shown in Section II.

Constraint (11a) calculates the instantaneous energy level in a BESS while (11b) specifies that the initial value of the energy in BESS b should be equal to the parameter E^{B}_{byt0} only if the BESS exists. Next, (11c) sets the upper and lower limits on energy and (11d) ensures that the energy level at the last RTP is no less than E^{B}_{byt0}. The last two constraints (11e) and (11f) set upper and lower limits on the charging and discharging powers of a BESS. In these constraints, the binary variable $\tilde{x}^{\mathrm{B}}_{by}$ activates the BESS operational limits, ensuring that energy, e^{B}_{byth}, and charging and discharging powers $p^{\mathrm{B,C}}_{byth}$, $p^{\mathrm{B,D}}_{byth}$ are non-zero only for BESSs that have already been constructed.

The nonlinear product of binary variables $\tilde{x}^{\mathrm{B}}_{by} u^{B}_{byth}$ in (11e) and (11f) is linearized as in [19] by replacing it with auxiliary variable $\alpha^{\mathrm{B}}_{byth}$, which is defined as follows:

$$\alpha^{\mathrm{B}}_{byth} \leq \tilde{x}^{\mathrm{B}}_{by}, \tag{12a}$$
$$\alpha^{\mathrm{B}}_{byth} \leq u^{B}_{byth}, \tag{12b}$$
$$\alpha^{\mathrm{B}}_{byth} \geq \tilde{x}^{\mathrm{B}}_{by} + u^{B}_{byth} - 1. \tag{12c}$$

The resulting formulation is therefore recast as a more tractable mixed-integer linear programming (MILP) problem.

IV. CASE STUDIES AND NUMERICAL RESULTS

In this section, the proposed model is applied to a modified version of the IEEE 24-bus Reliability Test System [20] with large shares of renewable generation and long transmission lines. The input data used in this section is largely adapted from [21]. This includes the uncertain parameters for loads, conventional and renewable generation as well as data on existing and candidate transmission lines. The current implementation does not include uncertain parameters for BESS costs or availability. All chronological data is aggregated into 10 RDs, each composed of 8 RTPs. It should be noted that constraint (11d) imposes a minimum BESS energy level at the end of each RD that is at least equal to the initial energy stored. The reader is referred to [21] for further details regarding the weights, durations and capacity factors of each RD and RTP. To complete this data, a set of candidate BESSs is introduced for the proposed model as shown in Table I.

Three discrete BESS sizes of 4, 6 or 8 hours in duration and with equal nominal power, are considered for construction at each of the candidate buses. Furthermore, the model limits the number of BESSs at each bus to one, meaning that both the locations and the discrete sizes of BESSs are determined by the optimization.

TABLE II
INVESTMENT DECISIONS OVER THE PLANNING HORIZON

	Medium Uncertainty Budget		High Uncertainty Budget	
	Base	Proposed	Base	Proposed
Y1	L6-12 (x2)	L6-12 B6 (6h)	L6-12 (x2) L6-13 L7-8	L6-12 (x2) L7-8 B6 (6h)
Y2	L7-8	L7-8	L13-19	
Y3	L13-19	B10 (4h)		
Y4	L10-13		L6-13 L13-19	
Y5				B10 (6h)
Y6	L13-19	L10-13		
Y7		L13-19		B13 (4h)

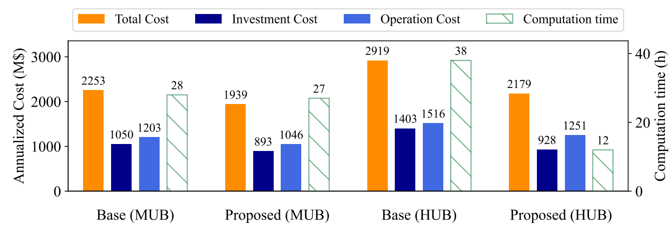

Fig. 1. Comparison of costs and computation times for the medium uncertainty and high uncertainty budget cases.

Therefore, a comparative study between the base model in Section II and the proposed model that considers investments in BESSs is conducted for the medium uncertainty budget (MUB) and high uncertainty budget (HUB) cases as defined in [16]. The discount rate κ is set to 10% and the total investment budget $I^{\max}$ is limited to $1,500,000,000 for a 10-year planning horizon. Numerical results were obtained on a computer with an Intel i7-14700 processor and 64 gigabytes of memory. The solver used was CPLEX 22.1.2.0 running under version 1.16.0 of the GAMSPy library in Python 3.13. As shown in Fig. 1, computation times ranged between 12 and 38 hours depending on the case.

The investment plans produced by the base and proposed models for both uncertainty budgets are presented in Table II. The economic repercussions of these investment plans are depicted in Fig. 1, where annualized investment and operation costs are compared. As expected, the investment costs for the base model are higher since more lines are built earlier on in the planning horizon. The proposed model minimizes the number of investments at year 1, and postpones the construction of BESSs until they are truly needed. Overall BESS construction costs are further diminished by the model's selection of storage durations based on operational needs. Furthermore, the HUB case requires a higher number of investments for both the base and proposed models, which results in overall higher costs when compared to the MUB case.

Operational costs are also found to be lower for the proposed model. Focusing on the HUB case, Fig. 2 provides a

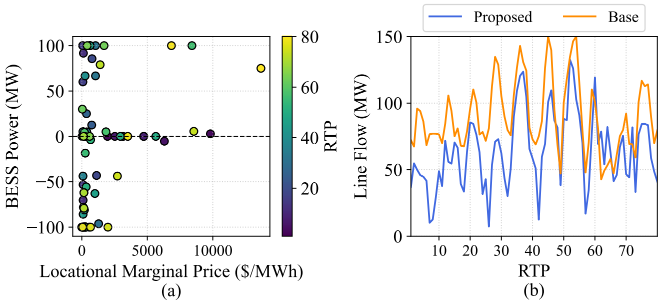

Fig. 2. (a) BESS power in relation to the locational marginal price at bus 6 and (b) comparison of power flow on line 6-10 for the HUB case.

visualization of how BESSs are helping bring down operation costs. Subplot (a) shows, for every RTP of year 6, the discharging (positive) and charging (negative) powers of the BESS at bus 6 with respect to the locational marginal price (LMP) at that same bus. To ensure the most cost-effective operation, the BESS should be charging mostly when the LMP is low and discharging mostly when the LMP is high. While the charging of the BESS seems to follow this behavior, the plot also displays multiple instances of discharging at low LMP values. This might indicate that BESS is being utilized to solve a line congestion problem. Indeed, the investment plans in Table II show that two lines are built between buses 6 and 12, suggesting that this is a highly congested transmission corridor. Thus, the BESS discharging to serve the local load and to relieve congestion in adjacent lines may become the most economical solution, even when the LMP is low. This behavior is corroborated by subplot (b), which shows the comparison of power flows in line 6-10 during year 6. Indeed, the line flows are almost always lower for the proposed model since the BESSs on buses 6 and 10 are reducing congestion.

V. Conclusion

In this paper, a multi-year ARO framework for TNEP is expanded to co-optimize investments in transmission lines and ESSs. The proposed methodology integrates the formulation of power and and duration-dependent BESS capital costs and fixed annual O&M costs. Furthermore, the necessary inter-temporal operational constraints for BESSs are introduced and linearized to preserve the model's MILP structure. The numerical results demonstrate that the proposed model yields more economical expansion plans by deploying BESSs over the planning horizon and avoiding costly line construction. Moreover, operational analysis of the BESS power dispatch revealed that strategic placement of energy storage may provide critical congestion relief in addition to energy arbitrage, thereby lowering total operation costs. Future works will focus on adding uncertain parameters for ESS availability and costs, modeling other ESS technologies and incorporating frequency stability constraints to the TNEP framework.

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