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Authors

Wu, Kevin
Haider, Rabab
Van Hentenryck, Pascal

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Kevin Wu[1], Rabab Haider[2], Pascal Van Hentenryck[1]

[1] *Georgia Institute of Technology* [2] *University of Michigan*

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Trust-Region Benders for Scalable Multiperiod Expansion Planning for Transmission and Storage

Kevin Wu[†], Rabab Haider[‡], Pascal Van Hentenryck[†]

***Abstract*—Transmission expansion planning (TEP) seeks to identify cost-effective investment strategies that enable power systems to reliably meet future demand, while accounting for the location, timing, and operational impacts of infrastructure upgrades. As demand grows and renewable penetration increases, there is growing interest in jointly modeling energy storage investments to enhance operational flexibility. This work presents a multiperiod formulation that co-optimizes transmission reconductoring and energy storage installation across multiple planning periods. To solve the resulting large-scale problem efficiently, a Benders decomposition with per-period trust-region stabilization and a relaxation-based warm-start procedure is proposed. The approach is demonstrated on a 2,000-bus Texas system, producing an investment plan spanning 2030–2045 with optimality gap below 1.0%, and is compared against a rolling-horizon approach to highlight the benefits of multiperiod coordination.**

***Index Terms*—transmission expansion planning, storage planning, multiperiod, PTDF, co-optimization**

NOMENCLATURE

a) Sets:

$\mathcal{N}$	Set of buses; $\mathcal{N} = \{1, ..., N\}$; indexed by i
$\mathcal{E}$	Set of branches; $\mathcal{E} = \{1, ..., E\}$; indexed by ij
$\mathcal{R}$	Set of days; $\mathcal{R} = \{1, ..., R\}$; indexed by r
$\mathcal{Y}$	Set of periods; $\mathcal{Y} = \{1, ..., Y\}$; indexed by y
$\mathcal{T}$	Set of hours; $\mathcal{T} = \{1, ..., T\}$; indexed by t

Unless otherwise specified, all parameters and operational variables are indexed by (y, r, t), denoting planning period y, representative day r, and hour t.

b) Parameters:

$\mathbf{p}^{\mathrm{d}}_{i,y,r,t}$	Load at node i
$\underline{\mathbf{p}}^{\mathrm{g}}_{i,y,r,t}$	min output of generator i
$\bar{\mathbf{p}}^{\mathrm{g}}_{i,y,r,t}$	max output of generator i
c^{rec}_{ij}	Annualized reconductoring cost of edge ij
c^{stor}_{i}	Annualized storage installation cost at node i
$c^{\mathrm{G}}_{i}(\cdot)$	Production cost function of generator i
$c^{\mathrm{S}}_{i}(\cdot)$	Storage charge/discharge cost of node i
$\Omega_{\mathcal{R}}(\cdot)$	Probability mass function for set of days $\mathcal{R}$
λ	Load shedding penalty cost
Δ^{c}_{ij}	Reconductoring capacity increment of branch ij
$\bar{\mathbf{p}}^{\mathrm{f}}_{ij}$	Thermal limit of branch ij
α	Interest rate

[†]Kevin Wu and Pascal Van Hentenryck are with the H. Milton Stewart School of Industrial and Systems Engineering, Georgia Institute of Technology, Atlanta, GA, United States. Email: {kwu381, pvh}@gatech.edu

[‡]Rabab Haider is with the Civil and Environmental Engineering, University of Michigan, Ann Arbor, MI, United States. Email: rababh@umich.edu

c) Variables:

$\gamma_{ij,y}$	Reconductoring of branch ij by year y
$\sigma_{i,y}$	Installed storage energy rating at node i by year y
$\mathrm{soc}_{i,y,r,t}$	Storage SoC at node i
$\mathrm{ch}_{i,y,r,t}$	Storage charge at node i
$\mathrm{dis}_{i,y,r,t}$	Storage discharge at node i
$\mathbf{p}^{\mathrm{g}}_{i,y,r,t}$	Output of generator i
$\mathbf{p}^{\mathrm{f}}_{ij,y,r,t}$	Power flow on branch ij
$\xi_{i,y,r,t}$	Load shed at node i

I. INTRODUCTION

Power grids in the U.S. are rapidly decarbonizing to address climate challenges while expanding to meet increasing demand driven by electrification, manufacturing, and computing. Infrastructure expansion is required to ensure the reliable delivery of power to load centers and sufficient operational flexibility to accommodate diverse load patterns and intermittent renewable generation, posing unprecedented challenges for system planners tasked with solving transmission expansion planning (TEP) problems.

TEP is typically formulated as a mixed-integer program (MIP) and is computationally challenging to solve due to discrete investment decisions and the need to capture high spatial, temporal, and operational resolutions. Given the need for operational flexibility [1], there is growing interest in TEP formulations that also model storage investment and operation. The TEP+Storage model jointly considers multiple planning periods and coupled hourly operational decisions, where the location, timing, and operation of investments must be co-optimized, dramatically increasing problem scale. In this paper, the term *multiperiod* refers to planning decisions across multiple investment planning periods.

TEP+Storage formulations differ with respect to investment timing, network representation, temporal resolution, and decomposition strategy. The discussion below focuses on the subset of studies most closely related to the present work, namely multiperiod planning formulations with explicit investment timing decisions and high-resolution network representations.

Existing multiperiod transmission and capacity expansion planning models are often evaluated on relatively low-dimensional test systems (e.g., < 30 regions). For example, [2] introduces a multiperiod Benders decomposition framework but does not explicitly model storage, while [3] and [4] incorporate storage investment but consider a single-node system and a four-region system, respectively. Similarly, [5] propose and evaluate a regularized Benders approach for multiperiod capacity expansion planning problem on a 26-zone contiguous US model. These studies focus on algorithmic development but do not test the viability of these approaches to large-scale networks. The aggregated spatial representations cannot capture high-resolution network effects such as congestion patterns and storage–transmission interactions.

Several recent studies addressing high spatial resolution TEP+Storage employ decomposition techniques such as Benders decomposition or progressive hedging, but are limited to a single planning period [6], [7], or rely on myopic rolling-horizon approximations for multiperiod investment planning [8]. In contrast, large-scale multiperiod expansion models typically adopt aggregated or transport-based transmission representations that relax network physics [9]. While such approaches improve tractability, they impact decisions on siting, costs, and operations. Models with low spatial resolution lack the locational accuracy to sufficiently inform decision making [10], [11].

This work addresses these challenges by extending the trust-region Benders (TR-Benders) decomposition framework of Wu et al. [8] to a multiperiod transmission and energy storage expansion planning problem with intertemporal investment coordination. The proposed formulation jointly optimizes transmission and storage investments across multiple planning periods while preserving DC power flow at hourly operational resolution. To efficiently solve the resulting problem, the TR-Benders framework is extended to leverage the additional decomposition structure introduced by the multiperiod formulation, enabling parallel solution across both planning periods and representative operating days. The approach further incorporates per-period trust-region constraints and a relaxation-based warm-start to improve convergence. The methodology is demonstrated on a high-resolution 2000-bus Texas grid model, producing an investment plan for 2030-2045 with hourly operational decisions and a final optimality gap $< 1.0\%$.

II. FORMULATION

The all-years multiperiod (AY) TEP+Storage model is formulated as a two-stage optimization program. The first stage determines the timing and location of investment decisions, including transmission upgrades and storage installations, to minimize capital expenditures $c^{\text{cap}}(\cdot)$. The second stage resolves hourly operational decisions to minimize operational costs $c^{\text{op}}(\cdot)$. The formulation extends the single-period planning framework [8] to a multiperiod setting in order to capture the delayed value of investments, and is summarized in Model 1.

A. Investment Decisions and Variables

Transmission upgrades are modeled as reconductoring of pre-existing transmission lines, which has been shown to be frequently favored over new line construction due to its cost-effectiveness [12]. The cumulative upgrade of branch ij in period $y \in \mathcal{Y}$ is denoted by binary variable $\gamma_{ij,y}$, which equals 1 if the branch is reconductored, and 0 otherwise. Each upgrade corresponds to a Δ^c_{ij} MW increase in capacity.

Energy storage is modeled as short-duration lithium-ion battery technology, given its technological maturity and widespread adoption in power systems [13]. Cumulative storage investment at node i in period y is denoted by decision variable $\sigma_{i,y}$, representing the installed energy capacity (MWh). Batteries are modeled as four-hour duration, with maximum charge/discharge power of $\sigma_i/4$.

For notational convenience, let γ_y denote the vector of transmission upgrade decisions across all branches in period y, and σ_y denote the vector of storage investment decisions across all nodes in period y. Let $\gamma := (\gamma_y)_{y\in\mathcal{Y}}$ and $\sigma := (\sigma_y)_{y\in\mathcal{Y}}$ denote the concatenation of these decisions across all planning periods. The full vector of investment decisions is denoted by $x := (\gamma, \sigma)$, and $x_y := (\gamma_y, \sigma_y)$ denotes the corresponding investment decisions in period y.

B. Objective

The objective of the AY TEP+Storage problem is to minimize the sum of capital and operational expenditures across all planning periods. The delayed value of investments is modeled using an annual discount factor $d_y := (1+\alpha)^{-p(y)}$, where α is the annual interest rate and $p(y)$ denotes the number of years elapsed since the reference year for the start of planning period y, with $p(1) = 0$. For example, with 5-year planning periods, $p(2) = 5$, $p(3) = 10$, and so on. Capital investment costs for line reconductoring, c^{rec}_{ij}, and storage, c^{stor}_i, are expressed as annualized costs. The resulting capital expenditure is a linear function of the cumulative line reconductoring decisions γ and storage investment decisions σ made by each planning period y. Both investment variables are initialized to zero in the baseline period $y = 0$.

$$c^{\text{cap}}(\gamma,\sigma) := \sum_{y\in\mathcal{Y}} d_y \Bigg[\sum_{ij\in\mathcal{E}} c^{\text{rec}}_{ij}\big(\gamma_{ij,y} - \gamma_{ij,y-1}\big) + \sum_{i\in\mathcal{N}} c^{\text{stor}}_i\big(\sigma_{i,y} - \sigma_{i,y-1}\big)\Bigg]. \quad (1)$$

Given planning decisions $x_y := (\gamma_y, \sigma_y)$ for period y, the operational expenditure incurred in planning period y on representative day $r \in \mathcal{R}$ is denoted by $c^{op}_{y,r}(\cdot)$. The operating cost includes generation costs, storage charging and discharging costs, and a penalty on load-shed slack variables ξ.

$$c^{\text{op}}_{y,r}(x_y) := \sum_{i\in\mathcal{N}}\sum_{t\in\mathcal{T}} \Big[c^{\text{G}}_i\big(p^g_{i,y,r,t}\big) + c^{\text{S}}_i(\text{ch}_{i,y,r,t} + \text{dis}_{i,y,r,t}) + \lambda\, \xi_{i,y,r,t}\Big].$$

The operational costs are also annualized to maintain consistent units with the annualized investment costs. Specifically, the operational cost for planning period y is computed as the probability-weighted sum over representative days and scaled by 365 days per year:

$$c^{\text{op}}_y(x_y) := 365 \textstyle\sum_{r\in\mathcal{R}} \Omega_{\mathcal{R}}(r)\; c^{\text{op}}_{y,r}(x_y)$$

The aggregate operational cost in the AY formulation is then obtained by summing across all planning periods, given the full vector of investments across all periods x.

$$c^{\text{op}}(x) := \textstyle\sum_{y\in\mathcal{Y}} d_y\; c^{\text{op}}_y(x_y) \quad (2)$$

Model 1 Multiperiod TEP+Storage Formulation

$$\begin{aligned}
\min \quad & (1) + (2) \\
\text{s.t.} \quad & (3) - (4), \quad \forall y \in \mathcal{Y}, r \in \mathcal{R}, t \in \mathcal{T} \\
& (5), \quad \forall ij \in \mathcal{E}, y \in \mathcal{Y}, r \in \mathcal{R}, t \in \mathcal{T} \\
& (6), \quad \forall i \in \mathcal{N}, y \in \mathcal{Y}, r \in \mathcal{R}, t \in \mathcal{T} \\
& (7) \quad \forall i \in \mathcal{N}, y \in \mathcal{Y}, r \in \mathcal{R}, t \in \{2, ..., T\} \\
& (8) - (9), \quad \forall i \in \mathcal{N}, y \in \mathcal{Y}, r \in \mathcal{R} \\
& (10) - (12), \quad \forall i \in \mathcal{N}, y \in \mathcal{Y}, r \in \mathcal{R}, t \in \mathcal{T} \\
& (13), \quad y \in \mathcal{Y}
\end{aligned}$$

C. Constraints

A DC power flow is used, via the Power Transfer Distribution Factor (PTDF) matrix Φ, which maps net nodal injections to transmission line flows $\mathbf{p}^{\mathrm{f}}$. For each planning period y, representative day r, and hour t, the vector of net nodal injections is

$$\begin{aligned}
\mathrm{inj}^{y,r,t} := \big[&\mathbf{p}^{\mathrm{g}}_{i,y,r,t} + \mathrm{dis}_{i,y,r,t} \\
&- \mathbf{p}^{\mathrm{d}}_{i,y,r,t} - \mathrm{ch}_{i,y,r,t} + \xi_{i,y,r,t}\big]_{i=1}^{N}
\end{aligned}$$

The operational constraints are as follows:

$$[\mathbf{p}^{\mathrm{f}}_{ij,y,r,t}]_{ij=1}^{E} = \Phi \times \mathrm{inj}^{y,r,t} \tag{3}$$

$$\mathbf{1}^{\top}\mathrm{inj}^{y,r,t} = 0 \tag{4}$$

$$-\bar{\mathbf{p}}^{\mathrm{f}}_{ij} - \gamma_{ij,y}\Delta^{c}_{ij} \leq \mathbf{p}^{\mathrm{f}}_{ij,y,r,t} \leq \bar{\mathbf{p}}^{\mathrm{f}}_{ij} + \gamma_{ij,y}\Delta^{c}_{ij} \tag{5}$$

$$\underline{\mathbf{p}}^{\mathrm{g}}_{i,y,r,t} \leq \mathbf{p}^{\mathrm{g}}_{i,y,r,t} \leq \bar{\mathbf{p}}^{\mathrm{g}}_{i,y,r,t} \tag{6}$$

$$\mathrm{soc}_{i,y,r,t} = \mathrm{soc}_{i,y,r,t-1} + \mathrm{ch}_{i,y,r,t}\eta - \mathrm{dis}_{i,y,r,t}/\eta \tag{7}$$

$$\mathrm{soc}_{i,y,r,1} = \mathrm{ch}_{i,y,r,1}\eta - \mathrm{dis}_{i,y,r,1}/\eta \tag{8}$$

$$\mathrm{soc}_{i,y,r,T} = 0 \tag{9}$$

$$0 \leq \mathrm{soc}_{i,y,r,t} \leq \sigma_{i,y} \tag{10}$$

$$0 \leq \mathrm{ch}_{i,y,r,t} \leq \sigma_{i,y}/4 \tag{11}$$

$$0 \leq \mathrm{dis}_{i,y,r,t} \leq \sigma_{i,y}/4 \tag{12}$$

Constraint (3) determines power flows from nodal injections, while (4) enforces system-wide power balance. Thermal limits on line flows are imposed by (5). Generator dispatch is constrained by (6), where renewable units are modeled with zero minimum output and scenario-dependent upper bounds to allow curtailment, while conventional generators are dispatchable within their operating limits. Storage operation is captured by (7)–(12), which describe SoC dynamics with efficiency losses, zero SoC conditions at the beginning and end of each representative day, and charging and discharging limits. Consequently, storage operation is constrained within individual representative days, preserving inter-day independence but limiting the model's ability to capture inter-day energy shifting. Finally, to reflect the irreversibility of transmission and storage investments, monotonicity constraints are enforced:

$$x_{y-1} \preceq x_{y} \tag{13}$$

Remark: Reconductoring increases thermal limits while leaving line electrical parameters largely unchanged [14], permitting the use of the PTDF-based power flow model which assumes fixed network topology and electrical parameters.

The size of Model 1 grows linearly with the number of planning periods and representative days ($Y \times R$), necessitating scalable solution strategies for large instances.

III. Methodology

To solve the multiperiod formulation presented in Model 1, a multicut Benders decomposition (BD) framework is employed. In a baseline multicut BD, Model 1 is decomposed into a master problem (MP) that determines first-stage investment decisions and a collection of subproblems (SPs) that evaluate operational decisions under fixed investments. At each iteration, dual information from each SP is used to generate a corresponding cut, which is added to the MP until convergence. However, baseline implementations struggle to converge, with significant oscillations in MP iterates and dual degeneracy across investment configurations.

To address these computational challenges, this work develops a trust-region (TR) stabilization and relaxation-based warm-start strategy for BD applied to grid planning problems. While these techniques were previously applied in either single-period expansion models [8] or simplified multiperiod settings [4], the present work extends them to a multiperiod all-years formulation by introducing **per-period trust-region constraints** on investment decisions. The multiperiod all-years (AY) TR-Benders procedure is described next, and presented in detail in Appendix A (Algorithm 1).

A. AY TR-Benders Master Problem (MP)

The MP determines transmission reconductoring and storage investment decisions for each planning period. Its objective includes auxiliary variables $\theta_{y,r}$ that provide lower bounds on the operational cost $c^{\mathrm{op}}_{y,r}(\cdot)$ for each representative day and period. In addition, a proxy variable ρ underestimates system-wide load shedding across all periods and is constrained to zero via (15). At each iteration, θ and ρ are refined through Benders cuts and accumulated via (16). The MP at iteration k is given in Model 2.

Remark: Both Models 1 and 2 include load-shed slack variables ξ to ensure recourse feasibility. The two-stage formulation relies on a penalty term to discourage load shedding, whereas the Benders formulation instead uses the master proxy variable ρ to enforce zero load shedding in the final solution, avoiding the need to tune the penalty parameter as the number of representative days increases.

B. Benders Subproblem (SP)

After the kth iteration of an MP solve, the investment configuration solution x^{k} is broadcast to all the SPs. Constraints (17)-(18) enforce the investments to match the MP solution at period y. Their dual variables, $\pi^{y,r,k}_{\gamma}$ and $\pi^{y,r,k}_{\sigma}$, respectively, are used to construct the Benders cuts.

Model 2 Benders Master Problem (MP)

$$
\begin{aligned}
z_k^{\mathrm{MP}} = \min \quad & (1) + \textstyle\sum_{y\in\mathcal{Y},r\in\mathcal{R}} d_y \Omega_{\mathcal{R}}(r)\theta_{y,r} + \rho \\
\text{s.t.} \quad & (13), \quad y \in \mathcal{Y} && (14)\\
& \rho = 0 && (15)\\
& \textstyle\bigcup_{y\in\mathcal{Y},r\in\mathcal{R}} \mathcal{C}_{y,r}^k && (16)
\end{aligned}
$$

Model 3 Benders Subproblem (SP)

$$
\begin{aligned}
\min \quad & c_{y,r}^{\mathrm{op}}(\gamma_y^k, \sigma_y^k) \\
\text{s.t.} \quad & (3)-(4), \quad \forall t \in \mathcal{T} \\
& (5), \quad \forall ij \in \mathcal{E}, t \in \mathcal{T} \\
& (6), \quad \forall i \in \mathcal{N}, t \in \mathcal{T} \\
& (7), \quad \forall i \in \mathcal{N}, t \in \{2, ..., T\} \\
& (8)-(9), \quad \forall i \in \mathcal{N} \\
& (10)-(12), \quad \forall i \in \mathcal{N}, t \in \mathcal{T} \\
& \gamma_{ij} = \gamma_{ij}^k \quad (\pi_\gamma^{y,r,k}), \quad \forall ij \in \mathcal{E} && (17)\\
& \sigma_i = \sigma_i^k \quad (\pi_\sigma^{y,r,k}), \quad \forall i \in \mathcal{N} && (18)
\end{aligned}
$$

Each SP is solved using a two-phase procedure. In Phase I, load feasibility is enforced by minimizing total load shedding, $\sum_{i\in\mathcal{N},t\in\mathcal{T}} \xi_{i,y,r,t}$. If nonzero load shedding is detected, the SP terminates and generates a *feasibility cut* for the load-shed underestimator ρ. Otherwise, Phase II minimizes the operational dispatch cost (Model 3), yielding an *optimality cut* for the operational cost underestimator $\theta_{y,r}$. The feasibility and optimality cuts are, respectively:

$$\rho \geq \textstyle\sum_{i\in\mathcal{N},t\in\mathcal{T}} \xi_{i,y,r,t} + (\pi^{y,r,k})^\top (x_{y,r} - x_{y,r}^k) \quad (19)$$

$$\theta_{y,r} \geq c_{y,r}^{\mathrm{op}}(x_{y,r}^k) + (\pi^{y,r,k})^\top (x_{y,r} - x_{y,r}^k) \quad (20)$$

To further accelerate SP solves, constraints (3) and (5) are imposed via lazy constraint generation under the PTDF formulation, yielding an equivalent but more tractable SP. Details of implementation are shown in Appendix B.

C. Per-period Stabilization

Baseline Benders implementations are susceptible to oscillatory MP iterates and dual degeneracy when multiple transmission–storage configurations yield similar operating costs. To mitigate these challenges in the multiperiod setting, the MP is stabilized using l_1 trust region constraints **applied in a per-period basis**. The investments are stabilized about an anchor point $(\breve{\gamma}, \breve{\sigma})$ that corresponds to the incumbent investment trajectory achieving the best known upper bound. The trust region constraints are:

$$\textstyle\sum_{ij\in\mathcal{E}} \left|\gamma_{ij,y} - \breve{\gamma}_{ij,y}\right| \leq \mathrm{rad}_\gamma, \quad \forall y \in \mathcal{Y} \quad (21)$$

$$\textstyle\sum_{i\in\mathcal{N}} \left|\sigma_{i,y} - \breve{\sigma}_{i,y}\right| \leq \mathrm{rad}_\sigma, \quad \forall y \in \mathcal{Y}, \quad (22)$$

where rad_γ and rad_σ denote the transmission and storage TR radii, respectively. The specific parameter values are discussed in Section IV-D.

In addition to improving convergence, the TR stabilization accelerates SP solves by restricting the search to nearby investment configurations, leading to more consistent congestion patterns across iterations. This, in turn, enhances the effectiveness of the lazy constraint generation by reducing the number of newly violated flow constraints.

The MP is further strengthened using provably valid inequalities that impose per-period minimum required storage capacity to ensure load feasibility, thereby improving convergence performance; their derivation and proofs are provided in Appendix C.

D. Benders Warm-start (WS)

To initialize the MP away from trivial zero-investment solutions with extreme load shedding, a relaxation-based warm-start (WS) procedure is employed. The WS is constructed by solving continuous relaxations of Model 1 sequentially across planning periods, enforcing monotonic investment decisions between periods. For each period $y \in \mathcal{Y}$, the continuous relaxation is solved independently for all representative days $r \in \mathcal{R}$, yielding relaxed investments $(\gamma^{y,r}, \sigma^{y,r})$. These are aggregated by taking the component-wise maximum across representative days and rounding up to the admissible investment granularity:

$$\bar{\gamma}_y := \left\lceil \max_{r\in\mathcal{R}} \gamma^{y,r} \right\rceil, \quad \bar{\sigma}_y := \left\lceil \max_{r\in\mathcal{R}} \sigma^{y,r} \right\rceil.$$

The aggregated investments are enforced in subsequent periods via monotonicity constraints,

$$\gamma^{y,r} \geq \bar{\gamma}_{y-1}, \qquad \sigma^{y,r} \geq \bar{\sigma}_{y-1}, \quad \forall r \in \mathcal{R}.$$

This procedure yields a warm-started investment trajectory consistent with intertemporal monotonicity (13) and worst-case operational requirements across representative days. The BD is initialized at $(\bar{\gamma}, \bar{\sigma})$.

To further reduce degeneracy, investment decisions are restricted to candidate sets inferred from the relaxed solutions in the final planning period:

$$\mathcal{E}_c := \{\, ij \in \mathcal{E} \mid \exists r \in \mathcal{R} : \ \gamma_{ij,Y}^{Y,r} > 0\},$$

$$\mathcal{N}_c := \{\, i \in \mathcal{N} \mid \exists r \in \mathcal{R} : \ \sigma_{i,Y}^{Y,r} > 0\}.$$

E. Convergence of TR-Benders

In baseline BD, the MP optimum z_k^{MP} provides a valid global lower bound (LB), representing a theoretical minimum system cost over all feasible investment configurations. With the introduction of TR constraints, the MP is restricted to a local neighborhood, rendering z_k^{MP} only a *local* LB. A valid global lower bound LB* is therefore constructed separately; its construction is presented in Appendix D.

Whenever all SPs are solved and no load shedding is observed (i.e. $\sum_{i\in\mathcal{N},t\in\mathcal{T}} \xi_{i,y,r,t} = 0 \ \forall y \in \mathcal{Y}, r \in \mathcal{R}$), the resulting solution is feasible and yields objective $\hat{z}^k := c^{\mathrm{cap}}(x^k) + c^{\mathrm{op}}(x^k)$. The upper bound (UB) is then updated as UB $:= \min\{\mathrm{UB}, \hat{z}_k\}$.

During TR-Benders, the current UB is also used to enforce a strict level-set constraint that ensures the MP explores strictly better investment configurations.

$$z_k^{\mathrm{MP}} < \mathrm{UB} \quad (23)$$

In practice, the level-set constraint is relaxed to $z_k^{\mathrm{MP}} \leq \mathrm{UB}-\delta$, where $\delta > 0$ is a small numerical tolerance.

The algorithm terminates once the relative optimality gap satisfies $(\mathrm{UB}-\mathrm{LB}^*)/\mathrm{UB} \leq \epsilon$ for a specified tolerance $\epsilon > 0$.

IV. Case Study

The proposed methodology is evaluated on the ACTIVSg2000 test system, a large-scale 2000-bus representation of the Texas grid developed using publicly available data and statistical representations of real-world power systems [15]. Investment planning periods are considered every 5 years, $\mathcal{Y} = \{2030, 2035, 2040, 2045\}$, with an annual interest rate of $\alpha = 0.05$. For each planning period, system operations are evaluated at the end of the period after investment decisions have been implemented; for example, operations for period $y = 1$ (2030–2034) are evaluated in year 2030.

A. Network Data

The ACTIVSg2000 test system has 2000 buses, 3206 transmission lines, 423 conventional generators, and 175 renewable generators. A PTDF cutoff of 0.005 is applied to sparsify the network matrix, a common technique used to remove negligible sensitivities and improve computational tractability [16]. Generation capacity projections are based on the EIA Annual Energy Outlook [17], with all resources scaled uniformly to account for expected capacity additions and retirements. A 1.5% annual load growth is applied uniformly across all buses. Detailed generation, load, and discounting projections for the case study are provided in Appendix E.

A set of 18 representative days ($R = 18$), each spanning 24 hours, is selected from a full year of load, wind, and solar data. The representative days (listed in Appendix F) are chosen using a max–min diversity criterion applied to normalized daily profiles, to identify a diverse set of operating conditions, and are assigned equal probabilities.

B. Investment Parameters

Line upgrades via reconductoring are assumed to double thermal limits [12], giving $\Delta_{ij}^{c} = \bar{\mathbf{p}}_{ij}^{\mathrm{f}}$. Storage investments are restricted to discrete units with an energy rating of 250 MWh each, with up to 12 units permitted per node (3 GWh total). A charge and discharge efficiency of $\eta = 95\%$ is assumed, yielding a round-trip efficiency of 90.25%. Investment cost assumptions for the case study are summarized in Appendix E. Reconductoring costs are adapted from [12], and storage costs are adapted from [13]. Annualized capital expenditures are computed by applying a capital recovery factor (CRF) to the overnight investment cost, based on the interest rate α and asset lifetime l, as $\mathrm{CRF} := \frac{\alpha(1+\alpha)^l}{(1+\alpha)^l-1}$. Battery storage is assumed to have a 15-year lifetime, consistent with the median value reported in published battery storage cost projections [13]. Although reconductored transmission lines typically exhibit lifetimes of 40–60 years [18], the case study is restricted to the 2030–2050 planning horizon; therefore, an effective lifetime of 20 years is assumed for line upgrades.

C. Comparison with Rolling Horizon (RH)

One common approach to multiperiod planning is the use of a rolling horizon (RH) framework, in which single-period models are solved sequentially. To compare against the AY formulation, the case study is also solved using RH. Under RH, investment decisions are determined period by period and are myopic, as future-period projections are not anticipated. For each planning period, a separate instance of the TR-Benders algorithm is solved. The WS procedure in Sec. III-D is modified such that the investments enforced in period y are taken from the optimal single-period TR-Benders solution in period $y-1$, causing RH to alternate between WS and TR-Benders across periods. In contrast, the AY methodology performs a single WS phase to initialize a joint multiperiod investment trajectory, followed by a single execution of TR-Benders that jointly optimizes investments across all periods.

D. Computational Setup and Hyperparameters

All computational experiments are conducted using a Julia implementation based on JuMP v1.23.2 [19], with optimization performed using Gurobi v1.3.1 [20] on the Georgia Tech PACE Phoenix cluster [21] (24-core Intel Xeon nodes, Linux). Each worker is allocated 12GB of RAM, consistent with the 288GB memory available per node.

The TR hyperparameters were selected based on preliminary computational experiments. The storage TR radius was fixed at $\mathrm{rad}_\sigma = 1$ due to the greater degeneracy observed in storage investment decisions, while the transmission TR radius was initialized at $\mathrm{rad}_\gamma = 1$ and updated dynamically (Appendix A) to balance stabilization and exploration of promising transmission expansion plans. For all WS procedures, the load-shed penalty was set to $\lambda = 50{,}000\$/\mathrm{MWh}$, which yielded zero load-shed solutions across all tested instances.

The RH experiments are run with sequential time limits of 24/24/24/72 hours, while the AY formulation is solved with a time limit of 144 hours.

V. Results

A. All-Years Multiperiod (AY) Computational Performance

The AY warm-start procedure, denoted "AY-WS" required 4.2 hours of runtime and produced an objective value of \$29.14B with an optimality gap of 3.63%. The AY TR-Benders algorithm was then executed with a 144-hour time limit, resulting in a total runtime of 148.2 hours. The resulting investment plan, denoted "AY-Final" achieved a total cost of \$28.25B with a final optimality gap of 0.59%. Figure 1 plots the optimality gap across total runtime of the AY method, which includes WS runtime. AY attains a solution quality of under 1% optimality gap within 64 hours, illustrating the method's ability to solve high-resolution planning instances.

Figure 2 compares the MP and SP solve times over the 338 AY TR-Benders iterations for the representative day of August 11, 2045. The reported SP solve times include both the Phase I (load-shed minimization) and, when applicable, the subsequent Phase II (operational cost minimization) solves. This day corresponds to the highest system load in the year

TABLE I
COMPUTATIONAL PERFORMANCE AND OPTIMALITY GAPS

Method	Runtime (h)	Best UB ($B)	Gap (%)
RH-Final	147.4	28.31	0.81
AY-WS	4.2	29.14	3.63
AY-Final	148.2	**28.25**	**0.59**

and occurs in the final planning period (2045), which also has the highest penetration of renewable generation. These operating conditions induce severe congestion across the network and require substantial storage utilization to satisfy demand, making this day the most computationally challenging among all representative days and planning periods. Consequently, it produces the longest SP solve times and determines the duration of each TR-Benders iteration, since progress cannot occur until all SPs are evaluated.

On average, the MP solves in 0.43 minutes, whereas the SPs require an average of 25.1 minutes. The MP solves account for only 1.7% of the TR-Benders runtime. This highlights the relatively low computational complexity of the MP, typical to grid planning problems [4], [8], and is further mitigated by trust-region stabilization. Although extending single-period BD to the multiperiod setting scales the MP size by Y, the TR constraints restrict the search to a localized region of the solution space. The resulting MP remains computationally lightweight even under a multicut implementation, where each iteration introduces up to $Y \times R$ cuts. These results demonstrate that the proposed AY methodology scales well with respect to the MP: increasing the number of representative days R is largely inconsequential due to parallelizable SP solves, while scaling the number of planning periods Y remains tractable given the consistently fast MP solve times. Moreover, this efficiency enables the MP to accommodate additional modeling features, such as budget constraints, decarbonization targets, and emissions policies.

B. Comparison with Rolling Horizon (RH) Formulation

Table I compares the computational performance and achieved optimality gaps of the AY methodology with the RH approach. “RH-Final” refers to the final investment plan produced by RH after all periods have been executed sequentially. Reported runtimes represent total wall-clock time expended, including warmstart. Final solves were terminated upon reaching prescribed time limits; thus, reported runtimes reflect imposed limits rather than time to proven optimality.

RH-Final attains a high-quality solution with an optimality gap of 0.81% in 147.4 hours. In comparison, AY achieves comparable solution quality in less than half the runtime, reaching an optimality gap below 0.81% within 72 hours (Fig. 1). This reduction in solution time reflects the increased parallelism of the AY formulation compared to RH.

The optimality gap obtained by RH-Final and AY-Final are, however, comparable. This outcome is likely influenced by the structure of the case study: although generation types and load are geographically heterogeneous, future-year load and generation projections are applied uniformly across the network.

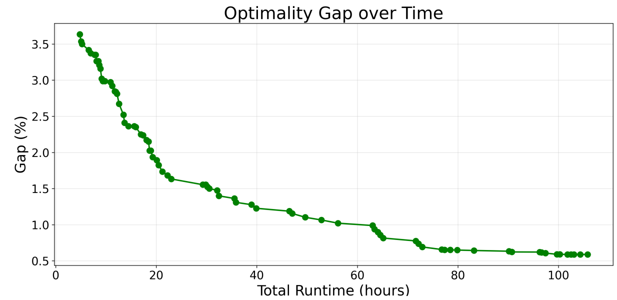

Fig. 1. AY TR-Benders optimality gap over total runtime (including WS)

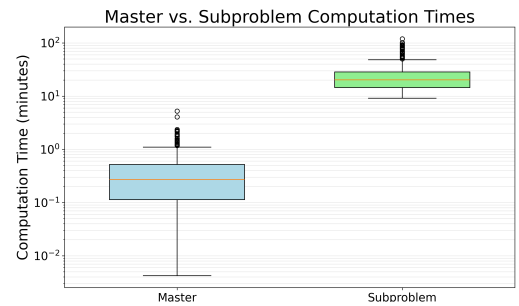

Fig. 2. AY TR-Benders MP and SP computation times

Consequently, the case study does not capture spatially and temporally heterogeneous shifts (e.g. a large computing load emerging at one node in 2030 followed by the introduction of a new generator at another node in 2035) which may mitigate the otherwise myopic limitations of the RH approach by reinforcing consistent intertemporal trends.

C. Investment Result Comparison

Table II compares cumulative first-stage investment decisions under RH-Final and AY-Final, while Table III reports the corresponding solution costs. Incremental first-stage investments are reported in undiscounted terms to reflect physical build decisions, whereas total period costs are discounted and include operational costs.

Relative to the RH, the AY invests more cumulatively in transmission reconductoring and less in storage capacity. This shift results in a lower final objective value and optimality gap, reflecting the higher unit cost of storage relative to reconductoring (Appendix E). Moreover, incremental investment patterns show that AY front-loads reconductoring investments more aggressively than RH, reducing the need for storage investments in later periods. This behavior is consistent with the multiperiod perspective of the AY, under which earlier transmission upgrades can be economically justified in anticipation of increasing future system requirements.

Notably, both RH-Final and AY-Final incur almost identical total period costs in 2030 despite differing line configurations, highlighting the degeneracy of investment configurations with similar costs. Overall, these results indicate that the multiperiod formulation better internalizes future system needs and consequently favors earlier transmission investments.

TABLE II
CUMULATIVE FIRST-STAGE INVESTMENTS

Method	Quantity	2030	2035	2040	2045
RH-Final	# Lines	214	333	453	527
	# Storage Units	0	26	83	148
	Storage Capacity (GWh)	0	28.00	96.75	167.50
AY-Final	# Lines	299	398	502	568
	# Storage Units	0	32	77	138
	Storage Capacity (GWh)	0	27.75	96.50	165.75

TABLE III
INCREMENTAL FIRST-STAGE INVESTMENT AND TOTAL PERIOD COST ($)

Method	Costs	2030	2035	2040	2045
RH-Final	Incr. Line	67.3M	59.8M	27.4M	31.5M
	Incr. Storage	0	2.70B	6.62B	6.81B
	Total Period (discounted)	5.83B	6.97B	8.36B	7.15B
AY-Final	Incr. Line	91.9M	71.4M	65.3M	25.1M
	Incr. Storage	0	2.67B	6.62B	6.67B
	Total Period (discounted)	5.84B	6.96B	8.37B	7.07B

VI. CONCLUSION

This work proposes an all-years (AY) multiperiod formulation for the TEP+Storage problem. The formulation is solved using a trust-region–stabilized Benders decomposition. New per-period trust-region constraints are introduced, complemented by a relaxation-based warm-start procedure. The proposed method is evaluated on a 2,000-bus synthetic Texas system and achieves a final optimality gap of 0.09%. Compared with a rolling-horizon (RH) approach, the AY approach attains comparable or improved solution quality with substantially reduced computational effort, benefiting from joint optimization across periods and increased parallelism. The consistently low computational burden of the master problem further indicates favorable scalability to larger planning horizons and model extensions.

The AY formulation also favors earlier transmission reconductoring, leading to lower cumulative investment in costly storage relative to RH and illustrating the advantages of joint multiperiod optimization. Future work will investigate enhanced stabilization strategies, such as one-sided trust-region constraints informed by conservative warm-starts, as well as more heterogeneous future projection scenarios, temporal linking of storage state-of-charge across representative days, and additional parallel procedures for generating valid inequalities.

VII. AI USAGE DISCLOSURE

AI tools were used to assist with code implementation and debugging, as well as for editorial support to improve clarity and writing style. AI tools were not used to generate research results, derive models, produce figures, or create original scientific content.

Algorithm 1 AY TR-Benders

Require: $\mathcal{Y},\mathcal{R}$; ϵ; $\mathrm{TL}_{\max}$; LB^*; $(\bar{\gamma},\bar{\sigma})$; $(\mathcal{E}_c,\mathcal{N}_c)$

Initialize MP with $(\mathcal{E}_c,\mathcal{N}_c)$
$k \leftarrow 0$; $\mathrm{UB} \leftarrow +\infty$; $(\breve{\gamma},\breve{\sigma}) \leftarrow (\bar{\gamma},\bar{\sigma})$
$\mathrm{rad}_\sigma \leftarrow 1$; $\mathrm{rad}_\gamma \leftarrow 1$
while elapsed time $< \mathrm{TL}_{\max}$ **do**
  $k \leftarrow k+1$
Master Problem (MP)
  while MP is infeasible **do**
    $\mathrm{rad}_\gamma \leftarrow \mathrm{rad}_\gamma + 1$
    Re-solve MP
  end while
  $\rightarrow (\gamma^k,\sigma^k)$
Subproblems (SPs) and Cut Generation
  NoShed $\leftarrow$ TRUE
  for all $(y,r)\in\mathcal{Y}\times\mathcal{R}$ **(in parallel) do**
    Fix $(\gamma_y,\sigma_y)\leftarrow(\gamma_y^k,\sigma_y^k)$
    Solve Phase-I SP $\rightarrow \pi^{y,r,k}$, $\sum_{i,t}\xi_{i,y,r,t}$
    if $\sum_{i,t}\xi_{i,y,r,t} > 0$ **then**
      NoShed $\leftarrow$ FALSE; add feasibility cut (19)
    else
      Solve Phase-II SP $\rightarrow \pi^{y,r,k}$, $c^{\mathrm{op}}_{y,r}(\gamma_y^k,\sigma_y^k)$
      Add optimality cut (20)
    end if
  end for
Bounds / TR / Level Set Update
  if NoShed **then**
    $\hat{z}^k \leftarrow c^{\mathrm{cap}}(\gamma^k,\sigma^k) + c^{\mathrm{op}}(\gamma^k,\sigma^k)$
    if $\hat{z}^k < \mathrm{UB}$ **then**
      $\mathrm{UB}\leftarrow\hat{z}^k$; $(\breve{\gamma},\breve{\sigma})\leftarrow(\gamma^k,\sigma^k)$
      $\mathrm{rad}_\gamma \leftarrow 1$
      Update level set (23)
    end if
  end if
  if $(\mathrm{UB}-\mathrm{LB}^*)/\mathrm{UB}\le\epsilon$ **then**
    break
  end if
end while
return $(\breve{\gamma},\breve{\sigma})$ with objective UB

APPENDIX

A. Multiperiod All-Years TR-Benders Algorithm

Algorithm 1 describes the implementation of the proposed AY TR-Benders algorithm.

B. PTDF Lazy Constraint Generation

Algorithm 2 outlines the PTDF lazy constraint generation used in SP solves for both Phase I and Phase II. Generated constraints are stored and persist across TR-Benders iterations.

C. Valid Inequalities for Minimum Required Storage Capacity

For each planning period $y \in \mathcal{Y}$ and representative day $r \in \mathcal{R}$, let $s^{\mathrm{feas}}_{y,r}$ denote the minimum total storage capacity obtained by solving a feasibility-only relaxation that enforces zero load shedding, neglects operating costs, and fixes all

Algorithm 2 PTDF Lazy Constraint Generation

Require: y, r; batch size k_b; fixed investments (γ_y, σ_y)

Initialize SP model with (γ_y, σ_y) fixed
repeat
  Solve SP model
  Compute PTDF-implied flows:
  $$[\mathbf{p}^{\mathrm{f}}_{ij,y,r,t}]_{ij=1}^{E} \leftarrow \Phi \times \mathrm{inj}^{y,r,t}$$
  Compute violation magnitudes:
  $$v_{ij,t} \leftarrow |\mathbf{p}^{\mathrm{f}}_{ij,y,r,t}| - |\bar{\mathbf{p}}^{\mathrm{f}}_{ij} + \gamma_{ij,y}\Delta^{c}_{ij}|$$
  $\mathcal{V} \leftarrow \{(ij,t) : v_{ij,t} > 0\}$
  if $|\mathcal{V}| > 0$ **then**
    Sort $\mathcal{V}$ by $v_{ij,t}$ (descending)
    $\mathcal{B} \leftarrow$ the k_b largest elements of $\mathcal{V}$
    for all $(ij,t) \in \mathcal{B}$ **do**
      Add PTDF flow constraint (3) for (ij,t):
      $$\mathbf{p}^{\mathrm{f}}_{ij,y,r,t} = \sum_{k\in\mathcal{N}} \Phi_{ij,k}\, \mathrm{inj}^{y,r,t}_{k}$$
      Add thermal limit constraint (5) for (ij,t):
      $$-\bar{\mathbf{p}}^{\mathrm{f}}_{ij} - \gamma_{ij,y}\Delta^{c}_{ij} \le \mathbf{p}^{\mathrm{f}}_{ij,y,r,t} \le \bar{\mathbf{p}}^{\mathrm{f}}_{ij} + \gamma_{ij,y}\Delta^{c}_{ij}$$
    end for
  end if
until $|\mathcal{V}| = 0$
return Final SP solution (and objective value)

transmission upgrades at their maximum values (i.e., $\gamma_y = \gamma_y^{\max}$).

Theorem 1. *For any period $y \in \mathcal{Y}$, any investment plan that achieves zero load shedding for all $r \in \mathcal{R}$ must satisfy $\sum_i \sigma_{i,y} \ge \max_{r\in\mathcal{R}} s^{\mathrm{feas}}_{y,r}$*

Proof. Fix $y \in \mathcal{Y}$. Consider any first-stage decision (γ_y, σ_y) that yields zero load shedding for all $r \in \mathcal{R}$. Fix an arbitrary $r \in \mathcal{R}$. The quantity $s^{\mathrm{feas}}_{y,r}$ is obtained from a relaxation with (i) storage decisions relaxed to be continuous and (ii) transmission upgrades fixed at their maximum values, which weakly enlarges the feasible set relative to Model 1 for day r. Hence, any zero-load-shed feasible plan must satisfy $\sum_i \sigma_{i,y} \ge s^{\mathrm{feas}}_{y,r}$. Since this holds for every $r \in \mathcal{R}$, it follows that

$$\sum_i \sigma_{i,y} \ge \max_{r\in\mathcal{R}} s^{\mathrm{feas}}_{y,r}. \tag{24}$$

□

Constraint (24) is imposed in the MP for each planning period $y \in \mathcal{Y}$ to further improve the performance of TR-Benders. The quantities $s^{\mathrm{feas}}_{y,r}$ are computed in parallel with the WS phase and then rounded to the nearest admissible discrete investment level to ensure feasibility with the discrete formulation. This yields values of $\{0.0, 27.75, 96.00, 165.00\}$ GWh for planning periods $\{2030, 2035, 2040, 2045\}$, respectively.

D. Global Lower Bound for Optimality Assessment

To compute a valid global LB for the multiperiod expansion problem, costs are decomposed into per-period first-stage (investment) and second-stage (operational) components.

For each planning period y, a *first-stage LB* is obtained by solving an investment minimization problem with continuous relaxations of the investment decisions that enforces zero load-shed, but does not consider operating costs. This problem is solved in parallel for each day $r \in \mathcal{R}$, yielding day-specific minimum investment costs. To ensure feasibility across all days, the maximum of these minimum investment costs across all $\mathcal{R}$ is taken, resulting in the minimum cumulative investment necessary to guarantee zero load-shed across all representative days in period y. The *incremental first-stage LB* for each period is computed as the increase in the cumulative investment cost relative to the previous period.

A *second-stage LB* is computed by minimizing operational costs assuming maximal feasible first-stage investments, yielding an optimistic but valid bound on operational expenditures.

Each period's total LB is formed by summing the incremental first-stage LB and the second-stage LB and applying the period discount factor. The discounted period-wise costs are summed to obtain a valid global LB for the multiperiod problem. The per-period decomposition of the LB is shown in Table IV. The multiperiod problem then has $\mathbf{LB}^* = \$\mathbf{28.08\,B}$.

TABLE IV
PER-PERIOD DECOMPOSITION OF VALID LOWER BOUND ($)

Quantity	2030	2035	2040	2045
Cumulative 1st-Stage LB	0.19M	2.74B	9.39B	16.03B
Incremental 1st-Stage LB	0.19M	2.74B	6.65B	6.65B
2nd-Stage LB	5.74B	6.13B	6.95B	7.99B
Discounted Period LB	5.74B	6.95B	8.35B	7.04B

E. Case Study Parameters

Table V summarizes the projections of generation and load relative to the base year 2022, and the discount factors referenced to 2030. Table VI shows the investment cost configuration for transmission reconductoring and storage installation.

TABLE V
GENERATION AND LOAD PROJECTIONS

Type	Base Capacity (GW), 2022	2030	2035	2040	2045
Coal	14.5	0.82	0.82	0.82	0.82
Natural Gas	75.1	0.79	0.73	0.71	0.72
Nuclear	7.1	0.98	0.90	0.80	0.80
Solar	2.5	4.51	6.00	6.87	8.04
Wind	15.5	2.02	2.23	2.26	2.32
Load	–	1.13	1.21	1.31	1.41
Discount Factor	–	1.00	0.78	0.61	0.48

TABLE VI
INVESTMENT COST CONFIGURATION

Type	Overnight Cost	CRF	Annualized Cost
Reconductoring	$813/MW-km	0.0802	$65/MW-km
Storage	$1,000,000/MWh	0.0963	$96,300/MWh

F. Representative days

The following 18 representative days are used in the case study, each with equal weight ($\frac{1}{18}$):

$$\mathcal{R} = \{\text{Jan } 27, \text{Feb } 23, \text{Mar } 6, \text{Mar } 11, \text{Mar } 22, \text{Mar } 27, \text{Apr } 3, \text{Apr } 22, \text{May } 10, \text{May } 19, \text{Jun } 21, \text{Jul } 11, \text{Aug } 11, \text{Sep } 2, \text{Sep } 10, \text{Nov } 16, \text{Dec } 3, \text{Dec } 8\}.$$

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I. Review #56A

A. Paper summary

The authors propose a multi-investment-period Benders decomposition for a TEP/GEP investment+operational problem, to help with computational performance and present a 2000 bus case study of the Texas power system.

B. Comments for authors

I think the paper is interesting both from the methodological point of view, but also ambitious with respect to the case study that you are tackling. The paper is easy to follow and you are solving a real-life problem, which I think is a big plus.

The introduction should be improved. The literture review is a bit lacking for me. There are numerous works in the literature that do GEP+TEP (where the GEP includes storage). The use of the word "multiperiod" is misleading because it is ambiguous. You are referring to having multiple investment periods, but a "period" could also refer to the period in the operational setting, so that was unclear to me until much later in the paper. Another point to consider (probably the most important one here) is that you do not know the actual truth to compare your results to. In particular, the full-scale model - the one that is not a simplification- where you have full spatial and temporal resolution. How far away are you from that one? I don't think that the gold standard (full model) is numerically tractable, but you could calculate a regret (fixing investment decisions of your AY and RH models and then running the operational model with full hourly resolution to see what the actual cost of operation would be). In this way you could more easily compare the quality of the different solutions that you are getting from AY and RH, which right now are difficult to compare. The fact that you are solving AY until 0.1% of the optimality gap is great, but how close is this model to the gold standard. We don't know. Moreover, you only account for very short-term storage (that lives within the representative day), but you cannot capture (with the current model) long-term storage. That is fine, however, that should be stated very clearly as a shortcoming of the method.

Some more detailed comments/questions that arose when I read the paper:

I would include a discussion on the tractability of large-scale models. In the end, something's gotta give (either spatial representation or temporal representation). You maintain spatial resolution, however, you do aggregate temporal resolution. From 365 days per year, to only 18 (and if I got it correctly then it is only 18 out of 4 investment years). How does this simplification in temporal aggregation affect your solution quality with respect to the full-scale model? I guess this also depends on whether you are focusing on GEP or TEP, but I would not omit the discussion.

Why is only storage investmetn considered? Why not other generating technologies (thermal power plants, renewables)?

Again, if you had long-term storage (such as a hydro reservoir), then you could not apply your methodology because that exceeds the representative day.

You mentioned a PTDF formulation of the DC optimal power flow. However, to my knowledge, the PTDFs are affected by line investments. So, how can you keep them fixed when your TEP investment is not known before solving the model?

When comparing AY and RH, the results look very similar. Is it all worth the effort?

C. Summarize your recommendation in one to two sentences

The paper shoud definitely be accepted because the proposed metehodology (Trust region Benders) is interesting, as is the case study.

— Sonja Wogrin

II. Review #56B

A. Paper summary

The paper develops an all-years transmission expansion planning (TEP) model that jointly decides when and where to reconductor lines and add storage, while evaluating hourly operations on representative days with a PTDF/DC network model. To solve the resulting large MIP, it uses a trust-region multicut Benders approach with per-period trust regions, a relaxation-based warm-start, and parallel subproblems. The main insight is that optimizing all years together can justify earlier transmission upgrades and slightly less later storage than a rolling-horizon approach, while keeping the master problem tractable and achieving small reported final gap on the 2,000-bus case.

B. Comments for authors

Strengths:

- The problem is very relevant and the scale is meaningful. A multiperiod PTDF-based TEP model with reconductoring plus storage on 2k bus system is a worthwhile testbed.
- The computational work and engineering of the entire pipeline is strong, especially per-period trust regions, parallel multicut subproblems and lazy PTDF enforcement.

Issues:

- This is an interesting work that extends the prior Wu-Haider-Van Hentenryck framework from a rolling-horizon application to a joint all-years model with per-period trust-region constraints, which is meaningful for capturing intertemporal coordination. Since this is an ”incremental” work rather than new algorithms, authors should clearly position the work as an all-years extension and comparative study of the aforementioned paper, not as a major new decomposition algoirthm.
- The objective appears inconsistent as written: Eq. (1) uses CRF-based annualized investment costs but charges each increment only once, while Eq. (2) uses representative-day operating costs without an explicit annual/block scaling factor. Please clarify the cost units and whether the model is using annualized costs or one-time present-value investment costs.
- Because load-shedding slack makes the recourse always feasible, the main concern is not subproblem infeasibility but whether the restricted master stalls when the trust region is too small. The paper expands rad(gamma) until the MP is feasible, but gives no sensitivity analysis or rationale for keeping rad(sigma) fixed, nor does it discuss the interaction with the level-set and candidate-set restrictions. A clarification on these points would strengthen section III.

Minor:

- Include the solver and package versions in the computational setup.
- Fig. 2 would be easier to interpret if the authors reported the number of AY TR-Benders iterations used in the plot, and clarified whether the MP/SP times include all iterations or only iterations with full Phase-II solves for the Aug 11, 2045 subproblem.

C. *Summarize your recommendation in one to two sentences*

Interesting and relevant paper; I would support acceptance if the issues are fixed and the contribution is framed more clearly compared to the TR-Benders work in [7] (Wu-Haider-Van Hentenryck).

— *Anonymous reviewer*

III. Review #56C

A. *Paper summary*

The paper studies the multiperiod transmission expansion planning with storage problem using a high-resolution DC/PTDF network model. The proposed all-years formulation jointly optimizes transmission reconductoring and battery investments across multiple planning periods, with monotonic investment variables and hourly operations represented through representative days. The resulting large-scale MIP is solved with a multicut Benders decomposition enhanced by per-period trust-region stabilization and a relaxation-based warm start. Subproblems are solved in parallel, with lazy PTDF constraint generation and simple valid inequalities on storage capacity to improve performance. The numerical performance of the proposed method is validated on the ACTIVSg2000 system.

B. *Comments for authors*

Strengths:

- The paper presents a clear multiperiod all-years (AY) formulation for TEP+Storage that jointly optimizes transmission reconductoring and storage investments while preserving PTDF-based DC network physics. The formulation adopts several practical modeling choices commonly used in the literature, including PTDF sparsification, the assumption of invariant line parameters under reconductoring, and the omission of complementarity constraints for battery charge/discharge, justified by their limited empirical impact on investment decisions.
- The proposed solution approach combines multicut Benders decomposition with per-period trust-region stabilization, a warm-start strategy, and feasibility and optimality cuts. The implementation also incorporates practical enhancements such as lazy PTDF constraint generation and a separate global lower-bound construction, aimed at improving stability and computational performance.

Weaknesses:

- The modeling and algorithmic contributions are largely incremental. The formulation relies on standard components commonly used in TEP+Storage models, and the trust-region Benders stabilization adapts existing techniques rather than introducing a fundamentally new method. In addition, the paper does not provide a sensitivity analysis of key algorithmic parameters.
- The baseline comparison is relatively narrow, focusing primarily on a rolling-horizon approach implemented with a similar decomposition framework. Alternative stabilization strategies or decomposition methods are not evaluated.
- Some implementation choices, such as the load-shedding penalty escalation and the selection of the trust-region radius, are not clearly specified or systematically analyzed.

Additional comments:

- In (20), the operational cost underestimator ($\theta_{y,r}$) appears to consider only the sum of slack variables rather than the operational cost defined in (2) at the corresponding iteration. This may be a typographical error.
- Typo in (15): the constraint should include ($\rho \geq 0$); otherwise, the subproblem becomes unbounded.

C. Summarize your recommendation in one to two sentences

The paper is technically sound and presents a detailed large-scale implementation of an AY TEP+Storage model, but the contributions are largely incremental and the evaluation and baseline comparisons are limited.

— *Anonymous reviewer*

IV. Brief response to reviewers (optional)

We thank the reviewers for their constructive comments and suggestions. Their feedback helped improve the clarity, positioning, and presentation of the manuscript.

We also identified and corrected an implementation error affecting the transmission investment costs, recomputed all computational experiments, and updated the reported numerical results accordingly. Although several optimality gaps changed slightly, all final optimality gaps remain below 1.0%, and the conclusions of the paper are unchanged.

- Reviewer A. We clarified the scope of the literature review by identifying the subset of TEP+Storage studies most relevant to the present work and added two additional references. We also explicitly define "multiperiod" as referring to multiple investment planning periods and clarify that storage operation is restricted to individual representative days, together with a note of this limitation in the future work section. We appreciate the reviewer's suggestions regarding benchmarking against a full-resolution model and assessing the impact of different resolutions (temporal, spatial, etc.). While we agree that these are important questions, we believe they are best addressed in studies focused on model-resolution fidelity rather than in the present work, whose primary focus is the proposed decomposition methodology.
- Reviewer B. We revised the manuscript to more clearly position the proposed methodology as an extension of the previously published single-period framework. We corrected the description of the objective function to consistently reflect annualized costs, expanded the discussion of trust-region hyperparameter selection, and clarified the computational setup by reporting software versions and additional details for Figure 2.
- Reviewer C. We refined the framing of the manuscript to more clearly position the proposed methodology as an extension of the previous single-period framework rather than as a fundamentally new decomposition algorithm. We also expanded the discussion of the trust-region hyperparameter selection by providing the rationale behind the chosen values based on preliminary computational experiments and specified the load-shedding penalty used in the two-stage formulation. We appreciate the reviewer's suggestions regarding a comprehensive sensitivity analysis and comparisons with alternative stabilization strategies. While these were not included in the present revision, we believe they represent valuable directions for future investigation. We also corrected the typographical issues identified in the mathematical formulation.

Overall, we appreciate the reviewers' feedback and hope the resulting revisions have improved the clarity and presentation of the work.

V. Brief summary of changes made to the final paper

During preparation of the revised manuscript, an error affecting the reported transmission investment costs (which had been incorrectly treated as independent of the existing thermal limits) was identified and corrected in the model. All computational results presented in the revised manuscript have been recomputed and verified accordingly. Following this correction, several numerical results and reported optimality gaps changed slightly. However, all reported final optimality gaps remain below 1.0%, and the overall findings and conclusions of the paper are unchanged. Several clarifications and modifications have also been incorporated throughout the manuscript:

- The description of the objective function has been corrected to consistently reflect annualized costs (typographical correction).
- The relationship between the proposed approach and the previously published single-period framework in [8] has been clarified, emphasizing that the present work extends that framework to a multiperiod setting.
- The treatment of load-shedding slack variables in both the two-stage and Benders formulations has been clarified through an explanatory remark.
- Additional discussion has been added regarding the selection of the trust-region hyperparameters.
- A discussion has been added further clarifying that storage operation is constrained within individual representative days, together with a note in the future work section regarding inter-day storage dynamics.
- The description of Figure 2 has been clarified to specify the total number of Benders iterations and that the reported SP solve times include Phase II solves when applicable.
- The literature review now more clearly identifies the subset of TEP+Storage studies most relevant to the present work, and two additional references have been added.
- The term multiperiod is explicitly defined as referring to multiple investment planning periods and the associated timing of investment decisions.

Finally, several typographical inconsistencies identified by the reviewers have been corrected.