Causal Machine Learning Analysis of Long-Duration Energy Storage for Power System Decarbonization Planning

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***Abstract*—As renewable penetration continues to increase, power system planning faces significant uncertainties from emerging technologies. Traditional correlation-based methods struggle to capture the structural impacts of these uncertainties on optimal decarbonization strategies. To address these limitations, this study develops a causal inference framework based on double machine learning (DML), providing a robust and interpretable approach to quantify structural causal effects of technological uncertainties on optimal planning decisions. By explicitly distinguishing true causal impacts from confounded correlations, the DML framework reveals previously obscured threshold effects and nonlinearities associated with long-duration energy storage (LDES). Specifically, this analysis identifies critical cost and efficiency thresholds beyond which LDES substantially reshapes the optimal resource mix, highlighting its structural role in enhancing system flexibility and substituting conventional short-duration storage. The proposed framework enables planners and policymakers to better understand complex system dynamics and design targeted, effective low-carbon incentive policies.**

***Index Terms*-- Double machine learning; heterogeneous causal effects; long-duration energy storage; planning interpretability.**

I. INTRODUCTION

A. Motivation

Guided by the dual-carbon goals, China's energy system is rapidly transitioning toward a clean, low-carbon, safe, and efficient structure, accompanied by fundamental changes in system configuration [1]. On one hand, adequacy requirements are expanding across multiple dimensions. With increasing renewable penetration, system security mechanisms are evolving profoundly, and the concept of adequacy has extended from power and energy balance to include flexibility and inertia support, exhibiting pronounced spatiotemporal heterogeneity. On the other hand, diverse energy resources and emerging technologies are driving low-carbon transformation. The introduction of hydrogen storage and coal-fired flexible retrofits brings heterogeneous cost structures, technological performance, and operational characteristics, further increasing planning complexity. As a complex large-scale system, planning must balance diverse stakeholder interests hand uncertainties, requiring rational decision among multiple feasible technological pathways [2].

Planning models serve as essential decision-support tools, yet conventional approaches based on fixed boundary conditions and least-cost optimization typically yield only a single deterministic solution [3]. Due to limited transparency and interpretability, these models often inadequately incorporate physical principles and domain-specific prior knowledge, resulting in uncertainties and coordination risks across temporal and spatial scales. Additionally, uncertainties associated with future technological costs, simplifications, and modeling assumptions imply that solutions identified purely through least-cost criteria rarely reflect genuinely optimal planning outcomes, necessitating more robust analytical approaches [4]. In medium- and long-term planning, the evolving and uncertain environment makes traditional single-factor analyses inadequate for accurately reflecting system adaptability and uncovering the structural causal relationships between critical factors and planning outcomes. Consequently, given multi-dimensional adequacy requirements and multi-technology coordination, planning decisions increasingly demand greater transparency and robustness. At the macro level, planning must effectively balance system security, stability, and low-carbon economy. At the micro level, models should explicitly capture the heterogeneous cost structures and operational characteristics of emerging technologies. Therefore, integrating causal interference into power system resource planning becomes essential to reveal the structural interactions among multiple factors, thus substantially enhancing the transparency, reliability, and interpretability of planning decisions.

B. Literature Review and Contributions

Given the multiple uncertainties associated with high renewable penetration, recent studies have increasingly emphasized improving the credibility and robustness of power system planning decisions. Existing approaches can be broadly classified into three categories. i) Comparative analysis of planning schemes, which designs multiple scenarios to compare techno-economic indicators and assess factor-level impacts [5], [6]. However, this method is qualitative and cannot quantify each factor's contribution to planning outcomes. ii) Single or multiple factor sensitivity analysis. By scanning boundary parameters, it examines how parameter variations affect planning outcomes and economic performance [7], [8]. Yet, it struggles to capture interactions among parameters, requires repeated computations for each variable, and performs poorly under large-scale or dynamic planning settings due to limited parameter ranges. iii) Analytical methods based on mathematical formulations. By employing mathematical techniques such as structural reconstruction, linear approximation, and dual analysis,

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979-8-3315-8138-1

the optimization results can be analytically approximated to derive interpretable decision rules or input–output mappings [9]-[11]. However, this approach is limited by numerical algorithms and model structures, leading to low efficiency in complex nonlinear planning models.

Overall, traditional planning analyses relying on sensitivity and scenario approaches remain fundamentally correlation-based, typically varying isolated parameters, such as LDES costs or efficiencies, while assuming all other conditions remain fixed. Such assumptions become unrealistic in complex, dynamic planning environments where multiple technological parameters, policy incentives, and market conditions evolve simultaneously and interact nonlinearly. Consequently, observed changes resulting from adjustments in individual parameters, like reductions in LDES cost, cannot accurately isolate their true causal impacts, as interactions among factors create confounded correlations rather than genuine causal relationships. In contrast, robust planning decisions demand explicitly distinguishing genuine causal effects from these confounded correlations. Unlike correlation-based approaches, causal analysis systematically quantifies the net causal impacts of simultaneous boundary shifts and constraint changes, which can provide reliable, interpretable guidance essential for understanding how emerging technologies like LDES structurally influence decarbonization planning outcomes. TABLE I summarizes the differences between correlation-based and causal approaches in power system planning.

TABLE I. CORRELATION AND CAUSAL ANALYSIS IN PLANNING

	Correlation	Causal Analysis
Planning Boundaries	Varying single parameters, others fixed.	Identifying causal effects under joint changes.
Constraints	Cannot quantify impact of constraint tightness.	Quantifying effects of constraint relaxation.
Interpretability	Easily biased by confounders.	Robust to confounders, explicitly causal.

Motivated by these limitations in traditional correlation-based planning methods, this study proposes an innovative causal inference framework leveraging Double Machine Learning (DML) to enhance interpretability, robustness, and transparency in decarbonization planning decisions. Specifically, the core contributions are as follows:

1) A structural causal inference method tailored for power system planning analysis. A causal inference framework based on (DML is developed, systematically addressing the inability of traditional sensitivity analysis to distinguish genuine causal effects from spurious correlations induced by confounding factors. It explicitly quantifies the structural, heterogeneous, and nonlinear impacts of long-duration energy storage (LDES) uncertainties on low-carbon power system transitions, offering transparent, credible, and traceable structural guidance for planning decisions.

2) A computationally efficient scenario generation method specifically designed for causal inference. Considering realistic constraints in power system planning, this study proposes a dimensionality-reduction and aggregation technique for planning scenarios. By clustering variables and systematically selecting representative scenarios, it rapidly generates comprehensive datasets required for causal inference, significantly improving computational efficiency and analytical reliability in large-scale, multi-dimensional decarbonization analyses.

3) Revealing structural causal mechanisms and generalized insights previously obscured by correlation analysis. Applying the proposed causal framework, this study uncovers nonlinear and threshold mechanisms linking LDES performance improvements and cost reductions to optimal planning decisions, demonstrating that traditional correlation-based approaches conceal more complex causal structures. Moreover, it quantifies how carbon policy frameworks systematically amplify these structural causal relationships, providing generalizable insights for coordinated technological innovation and policy design, thus deepening theoretical understanding of decarbonization planning mechanisms.

II. FRAMEWORK

In planning the transition of new power systems, it is crucial to account for uncertainties affecting outcomes. Traditional sensitivity and regression analyses fail to capture multi-factor interactions and often misestimate causal effects, limiting reliable decisions. To address this, the causal analysis framework based on DML is developed to remove high-dimensional confounding effects and provide unbiased estimates of true causal relationships between influencing factors and planning outcomes, as shown in the Figure 1.

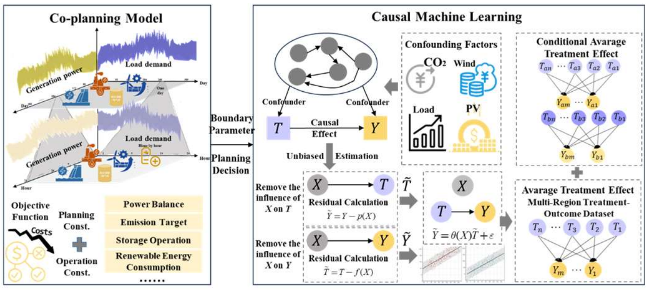

Figure 1. Causal analysis framework for planning decisions.

The framework includes two modules. The first is a coordinated planning model for multiple energy resources, integrating low-carbon policies, operational characteristics, and refined multi-timescale storage modeling. Using LDES as an example, various techno-economic scenarios are generated to produce planning solutions and form an input–output dataset for causal analysis. The second applies a DML-based causal analysis method to estimate the conditional average treatment effect (CATE), quantifying the heterogeneous and nonlinear impacts of LDES parameter variations on planning outcomes. This helps identify the true causal influence of LDES uncertainties and supports credible, region-specific planning and policy optimization.

III. MODEL FORMULATION

A. Coordinated Planning Model for Multiple Resources

In this section, a coordinated planning model for multiple energy resources is developed, including conventional, renewable, and storage units. The objective is to minimize the total system cost, which consists of fixed cost C_{sys}^{Inv}, operating cost

979-8-3315-8138-1

C_{sys}^{Ope}, and environmental cost C_{sys}^{Env}, while considering low-carbon policy constraints. The fixed cost includes the investment and maintenance costs of SDES and LDES $C_{SD}^{In\&M}$, $C_{LD}^{In\&M}$ and wind and photovoltaic units $C_{W}^{In\&M}$, $C_{PV}^{In\&M}$, as shown below.

$$\begin{aligned} &\min C_{sum} = C_{sys}^{In\&M} + C_{sys}^{Ope} + C_{sys}^{Env} \\ &C_{sys}^{In\&M} = C_{W}^{In\&M} + C_{PV}^{In\&M} + C_{LD}^{In\&M} + C_{SD}^{In\&M} \end{aligned} \tag{1}$$

The above coordinated planning model can be expressed in an abstract form as follows:

$$\begin{aligned} &\min_{\{x,y\}} \sum\nolimits_i \boldsymbol{c}_m^T \boldsymbol{x}_i + \boldsymbol{c}_n^T \boldsymbol{y}_i \\ &s.t.\ \boldsymbol{A}\boldsymbol{x}_i \le \boldsymbol{c}_l\ ,\ \boldsymbol{D}\boldsymbol{x}_i + \boldsymbol{E}\boldsymbol{y}_i \le \boldsymbol{f}, \boldsymbol{K}\boldsymbol{y}_i = 0 \end{aligned} \tag{2}$$

where, $\boldsymbol{c}_m$, $\boldsymbol{c}_n$, $\boldsymbol{c}_l$, $\boldsymbol{f}$, $\boldsymbol{A}$, $\boldsymbol{D}$, $\boldsymbol{E}$ and $\boldsymbol{K}$ represent vectors and matrices of appropriate dimensions. $\boldsymbol{x}_i$ denotes the investment decision variables for various energy resources, and $\boldsymbol{y}_i$ represents the operational state variables of the system and units. Detailed model constraints can be found in [1].

B. Causal Analysis Modeling of Planning Decisions

Using LDES as an example, we assess how its technological progress affects the deployment of other low- or zero-carbon resources and system costs, quantifying the causal link between inputs and planning outcomes. Since controlled experiments are infeasible and data are influenced by high-dimensional confounders, a DML-based causal inference method is applied to identify the nonlinear effects of LDES techno-economic variations, providing reliable insights for multi-resource co-planning in decarbonization.

The installed capacities of low-carbon resources (multi-timescale storage) and zero-carbon resources (wind and solar) are defined as outcome variables Y, while the techno-economic parameters of LDES serve as treatment variables T, with all other planning factors treated as confounders W. In practical planning, T and W are highly correlated because storage technologies, carbon policies, and regional generation structures often change together, causing the estimated coefficient β to mix true effects with confounding effects and lose causal meaning. We assume that the outcome Y is a function of both the treatment and the confounders, and that the treatment itself can be modeled as a function of W or its subsets, as follows.

$$Y = \theta(W)\cdot T + h(W) + \varepsilon,\ \mathbb{E}[\varepsilon \mid W] = 0\ \ Y \in \mathbb{R}^r, W \in \mathbb{R}^c \tag{3}$$

$$T = f(W) + \delta,\ \ \mathbb{E}[\delta \mid W] = 0,\ \ \mathbb{E}[\varepsilon\cdot\delta \mid W] = 0\ \ T \in \mathbb{R}^t, W \in \mathbb{R}^c \tag{4}$$

Taking the conditional expectations of both sides of equations (3)-(4) and subtracting them removes the bias in treatment effect estimation caused by high-dimensional covariates.

$$Y - \mathbb{E}[Y \mid W] = \theta(W)\cdot(T - \mathbb{E}[T \mid W]) + \varepsilon \tag{5}$$

where, $\mathbb{R}^r$ denotes the set of outcome variables, $\mathbb{R}^t$ the set of treatment variables, and $\mathbb{R}^c$ the set of covariates. $\theta(W)$ represents the heterogeneous causal effect between the treatment and outcome variables, $h(W)$ is a potential nonlinear function of the confounders W, and $f(W)$ captures the influence of W on T. ε and δ are centered error terms with finite variance.

The conditional expectation functions $p(W)$ and $f(W)$ are estimated using traditional machine learning regression methods, and the residuals are substituted into equation (5) to estimate the causal effect between the residuals $\tilde{Y}$ and $\tilde{T}$.

$$p(W) = \mathbb{E}[Y \mid W],\ f(W) = \mathbb{E}[T \mid W] \tag{6}$$

$$\tilde{Y} = Y - p(W),\ \tilde{T} = T - f(W) = \delta \tag{7}$$

$$\tilde{Y} = \theta(W)\cdot\tilde{T} + \varepsilon \tag{8}$$

Since $\tilde{Y}$ and $\tilde{T}$ have been orthogonalized, the common influence of confounders W has been removed. Thus, the optimal parameter θ is obtained by minimizing the residual sum of squares. By searching θwithin the parameter space Θ to minimize the sample mean squared error, we obtain an unbiased estimate of the causal effect of the treatment T on the outcome Y.

$$\hat{\theta} = \arg\min_{\theta\in\Theta} \mathbb{E}_n\left[\left(\tilde{Y} - \theta(W)\cdot\tilde{T}\right)^2\right] \tag{9}$$

After obtaining θ, the average treatment effect (ATE) of T on Y can be derived. Furthermore, we can estimate the CATE, which measures the expected change in Y when the treatment shifts from t_0 to t_1 under a given condition $W = w$.

$$\begin{aligned} &\vartheta_{ATE} = \frac{1}{n}\sum_{i=1}^{n} \hat{g}(W_i) \\ &\vartheta_{CATE}(t_0, t_1, w) = \mathbb{E}\left[Y(T = t_1) - Y(T = t_0) \mid\ W = w\right] \end{aligned} \tag{10}$$

When the planning context changes, perturbations in certain input boundaries treated as Treshape the feasible region $\Omega(T)$. The CATE captures how a structural shift from T to $T + \Delta T$ moves the boundary of $\Omega(T)$and induces corresponding adjustments in the optimal solution $Y(T)$, representing a strictly structural causal effect.

$$\Omega(T) = \{x : A(T)x \le b(T)\} \tag{11}$$

The CATE estimated by DML reflects the marginal impact of this deformation on the optimal solution Y, thereby carrying a structural causal meaning. In contrast, traditional regression captures only statistical covariation in the data and cannot reveal how parameter perturbations reshape the feasible region and alter the structure of the optimal solution.

$$\vartheta_{CATE}(t_0, t_1, w) \approx \partial\mathbb{E}[Y]/\partial T,\ \ W = w \tag{12}$$

Thus, CATE is not a simple statistical slope but a structural derivative of the optimal solution, capturing how perturbations to planning boundaries reshape the feasible region and induce systematic shifts in planning outcomes. It reflects the model's intrinsic decision logic rather than surface-level data correlations, thereby revealing how boundary changes propagate through constraints to affect the final optimal plan.

For solving the planning models, considering the data requirements of causal analysis for planning inputs and out-puts, a fast algorithm based on variable aggregation and temporal coupling is designed to meet the data requirements of causal analysis. The 8760h annual load is aggregated to a daily scale to reduce dimensionality, and typical days are selected for hourly simulation. Coupling between the daily and hourly timescales is then established to ensure coordinated operation of LDES and SDES.

IV. Case Study

This study uses historical wind, solar, and load data from the Northwest Power Grid, with 2030 as the target year and an annual load growth rate of 3.93% [12]. Investment and operating costs for wind and solar are taken from [1] and the carbon cost is set at 20 \$/t [13]. LDES techno-economic parameters for 2030, including cost reductions, efficiency gains, and duration changes, are based on studies of China's energy storage development [14]. Using these parameters, multiple LDES scenarios are generated, and correlation and causal analyses are compared to identify the true effects of LDES technological uncertainties on planning outcomes.

A. Correlation Analysis between Multiple Planning Boundary Factors and Planning Decisions

Future planning uncertainties are modeled through random combinations of planning boundaries. Based on the generated input–output dataset, the relationships between boundary conditions and multi-timescale storage planning outcomes are analyzed, as shown in Figure 2. The horizontal axis represents STES and LDES capacities and powers, while the vertical axis shows different planning factors. Bubble size indicates the absolute correlation strength, with blue and red denoting positive and negative correlations, respectively, and deeper colors indicating higher significance.

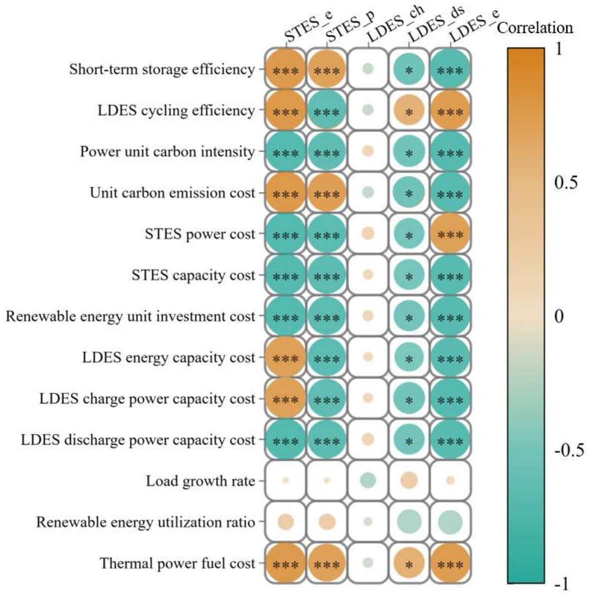

Figure 2. Correlation between boundaries and planning results.

In Figure 2, the correlation between inputs and outputs shows that SDES planning results are strongly related to its efficiency and economic parameters, while LDES is highly sensitive to carbon-related boundaries and economic parameters. Renewable energy utilization is strongly positively correlated with LDES but weakly with SDES, indicating that under high renewable integration, the system tends to increase LDES to balance inter-day and inter-week energy fluctuations. Notably, positive correlations appear between LDES efficiency and STES capacity, between conventional unit carbon intensity and storage planning results, and differing correlation directions between carbon costs and storage types. These seemingly counterintuitive patterns indicate that correlation analysis alone cannot reveal the true effects between inputs and planning outcomes, as economic parameter impacts may be obscured by confounding factors. This may lead to misleading conclusions such as higher carbon prices suppress LDES investment or lower SDES costs constrain LDES expansion, highlighting the need for causal analysis to accurately identify the true causal effects of boundary factors in planning.

B. Causal Effect Analysis Results

In this section, a causal analysis based on DML is employed to move beyond simple correlation and reveal the true effects of economic and technical boundaries on planning decisions. The DML framework isolates nonlinear influences from confounding factors on planning outcomes. Figure 3(a)-(d) illustrate the causal effects of storage capacity cost on LDES energy capacity, charging and discharging power capacity, and SDES capacity. The horizontal axis represents the influencing factors, while the vertical axis shows the CATE, indicating the change in planning outcomes caused by a unit variation in the influencing factor.

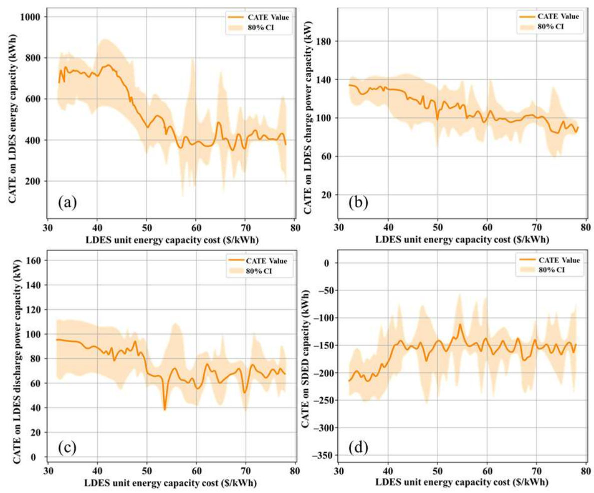

Figure 3. Causal effects of storage economic costs on planning results.

It shows that LDES economic costs and technical performance have varying impacts on planning outcomes. In Figure 3(a), the unit energy capacity cost displays an inverted U-shaped causal relationship with planned LDES energy capacity, with the strongest expansion effect at moderate cost levels (35-50 \$/kWh). This reflects the nonlinear interaction between investment feasibility and system constraints. Figure 3(b)-(c) show that as costs fall below 50 \$/kWh, expansion effects on LDES charging and discharging capacities intensify, with 1\$ reduction increasing capacities by up to 130 kW and 90 kW, respectively. Figure 3(d) indicates a substitution between LDES and SDES: at costs below 40 \$/kWh, each 1 \$ reduction can reduce SDES capacity by up to 220 kW. At higher LDES costs, declining marginal system value and energy-to-power ratio constraints weaken and stabilize this substitution effect.

Figure 4(a)-(d) illustrate the causal effects of LDES round-trip efficiency on the planned LDES energy capacity, charging and discharging power capacities, and SDES capacity. As shown in Figure 4(a)-(c), when the efficiency exceeds 50%, its expansion effect becomes markedly stronger, indicating greater investment attractiveness. The 1% increase in efficiency can expand the LDES capacity by up to 52kWh. (d)

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shows that when the efficiency exceeds 40%, the substitution effect of LDES on SDES intensifies, reaching up to 12 kWh.

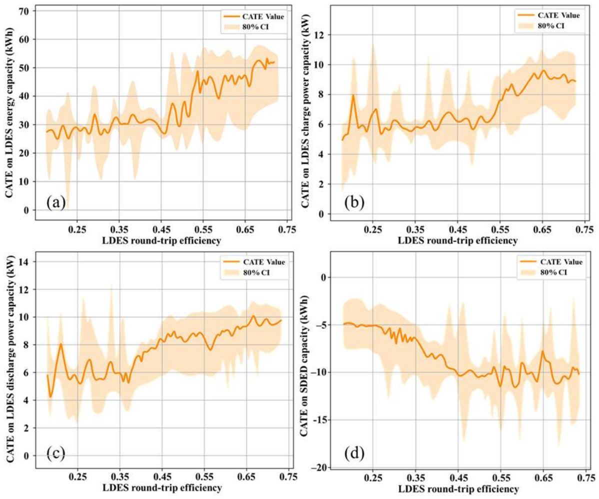
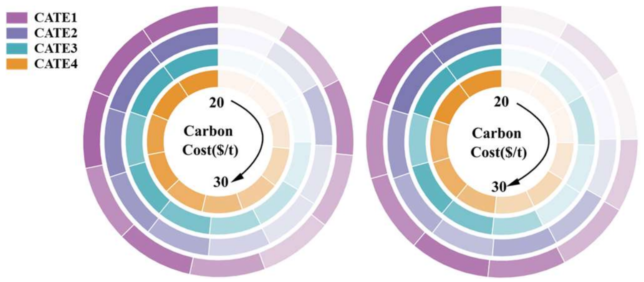


Figure 4. Causal effects of storage round-trip efficiency on results.

C. Heterogeneous Causal Effects under Carbon Prices

Given the uncertainty of future carbon costs, this section analyzes how the causal effects between LDES economic parameters, technical performance, and planning outcomes vary with carbon price. Figure 5(a) and (b) report the maximum effects of unit energy capacity cost and round-trip efficiency on storage planning results. The ring denotes carbon prices of 20–30 \$/t. CATE1-4 measure impacts on LDES energy capacity, charging and discharging power capacity, and SDES capacity. Results show that as carbon costs rise, the effects of LDES unit capacity cost and efficiency on planning outcomes strengthen. This indicates that under higher carbon prices the seasonal flexibility and low-carbon value of LDES become more salient, and the system tends to deploy LDES in place of high-carbon units. The findings underscore policy relevance: deploy storage incentives to lower upfront costs for investors and coordinate them with carbon pricing.



(a) Economic factor (b) Technical factor

Figure 5. Variation of causal effects under different carbon prices.

V. CONCLUSION

This study proposes a causal inference framework based on DML, significantly advancing traditional correlation-based planning analyses. By explicitly quantifying heterogeneous and nonlinear causal impacts of LDES uncertainties, this approach offers a robust and transparent decision-making tool for decarbonized power system planning. The structural causal analysis demonstrates critical threshold effects in LDES cost reductions, indicating substantial increases in optimal LDES deployment under moderate future cost scenarios. These insights underscore the necessity for integrated low-carbon policies, specifically suggesting that regionally coordinated carbon pricing combined with targeted storage incentives will effectively accelerate the adoption and integration of LDES technologies. Future research may extend the proposed causal framework to other emerging technologies and regional scenarios to further generalize insights for broader low-carbon power system transitions.

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