Stochastic Dominance of Renewables to Replace Hydropower under Policy Uncertainty

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ABSTRACT Regional energy managers and decision-makers face a world where climate change is introducing uncertainty over future power generation, as well as financial impacts from potential carbon taxation. A unique opportunity to explore is the rising interest in hydropower substitution with renewable resources, either to promote ecosystem services such as increasing the survivability of migratory fish or mitigating future loss of generation due to severe drought conditions. To address these concerns, a case study of the Columbia River Basin was conducted to evaluate the substitution of four Lower Snake River dams. A multistage methodology was chosen to evaluate grid adequacy, climate change performance, and the implications of tax uncertainty on the substitution portfolios. A specialized energy model was used to provide the adequacy and input for a Monte Carlo simulation to test the impact of an uncertain tax. The outcome is a carbon tax strategy region that suggests preferences under different taxes for risk-averse decision makers, alongside adequacy and climate metrics. We conclude that policymakers should consider a carbon tax between $86 and $132 to incentivize a portfolio that marginally reduces emissions compared to the pre-dam removal baseline or a tax greater than $135 to incentivize another portfolio that significantly reduces emissions. This study makes three important contributions: (1) it provides a methodology for evaluating electricity generating portfolios in the presence of a carbon tax, (2) it evaluates adequacy metrics for technology substitutions with intermittent alternatives and climate change impacts, and (3) it offers specific guidance for energy policy making.

INDEX TERMS Carbon tax, hydropower substitution, regional energy planning, renewable energy, stochastic dominance

I. INTRODUCTION

How should energy generation portfolios and resource strategies be evaluated in the face of carbon tax of uncertain magnitude? This question preoccupies the mind of electricity risk managers, as their primary role is not only to ensure an adequate power supply but also to do so at low costs, given operational constraints. The likelihood of an imminent tax becomes crucial given the increasing efforts to estimate the social cost of carbon (SCC), the cost associated with the damage of emitting additional units of CO₂ [1]–[4]. For a long time, electricity has been pegged at private costs to the detriment of externalities owing to conventional generation technologies. As society contemplates the social cost of carbon, it becomes imperative for the ecosystem to generate assets to be evaluated in bids to accommodate renewable sources, such as wind and solar.

The significance of planning ahead cannot be overstated, as carbon tax is a key factor in climate change policymaking. Emission tax skeptics should recognize that the winds are changing, not in their favor. The impacts of climate change are influencing beliefs and the efficacy of climate action and are creating supporting forces that increase the likelihood of passing carbon tax legislation to reduce emissions [5],[6]. While effective mitigation efforts are currently lacking [7], funding renewable energy and taxing fossil fuels are seen as the easiest government actions against climate change [8]. Therefore, high-time energy portfolio evaluations incorporate emission taxes to enhance financial evaluations in risk management alongside adequacy and climate considerations.

However, the challenge is the wide variations in value estimations, including the debate over using a global tax or smaller domestic values for each country [9]–[12]. Currently, there is no accepted standard, and internalizing SCC through a carbon tax remains to be bridged in meaningful and equitable ways [13],[14]. This uncertainty poses financial risks when evaluating portfolios with different energy technology combinations. This is paramount when a pre-tax generation portfolio could be financially preferable but increases CO₂ emissions over another costlier portfolio that reduces emissions and could be preferable under a tax policy.

This study intends to understand the thresholds of renewable technology portfolios that are informed by the
external cost of emissions, given the opportunity to substitute existing generation sources for environmental reasons. Aside from decommissioning fossil fuels as a clear decarbonization effort, the future role of some dams is also under scrutiny given their benefits and trade-offs in river basin dynamics [15]–[23]. Dam removal has had environmentalists, economists, energy planners and politicians at odds for several decades [19]–[21]. The question is whether to favor hydropower and development activities or remove a dam in favor of other ecosystem services, mainly increasing the survivability of migratory fish populations [22]–[24]. On the one hand, energy planners and economists emphasize the negative impacts of removal on the power supply and development. On the other hand, environmentalists cite dams as a threat to marine ecosystems. Making matters more complicated, many aging dams in the U.S. are becoming obsolete or uneconomical to maintain, which highlights the need for financial incentives for dam removal and trading schemes [25]–[28].

In addition to traditional concerns over environmental threats, there are rising challenges due to climate change. While climate change will have different impacts across regions, it is evident from the literature that hydropower is sensitive to changes in precipitation, heating degree days, and cooling degree days, leading to potential operational and cost performance implications [29]–[32]. In extreme cases, such as drought conditions impacting the Southwest United States, the hydropower system is faced with risks to generation ability and reservoir dam refill probabilities that could have cascading effects throughout the region [33]. This further raises the question of the future of dams under severe climate change conditions, and alongside questions of ecosystem services, leads to the evaluation of substitution portfolios as a mitigating step.

Consequently, the analysis in this study concerns the evaluation of hydropower substitution portfolios, given different tax ranges. This research was conducted in the Columbia River Basin (CRB), where recent years have seen renewed pressure to remove four Lower Snake River (LSR) dams (Ice Harbor, Lower Monumental, Little Goose, and Lower Granite) to increase the survivability of the migratory salmon population in the Pacific Northwest [34],[35]. Previous research has found that removing the four LSR dams amounts to an actual effective contribution of 1,088 MW, which is much lower than the 3,033 MW nameplate capacity rate [36]. This is promising for determining feasible substitution portfolios that account for adequacy, climate, and financial performance metrics to better understand risk management.

The methodology integrates a regional energy model with Monte Carlo simulation. The energy model is used to develop hydropower substitution portfolios, and the Monte Carlo simulation is used to analyze the amortized annual cost uncertainty of each portfolio under different carbon tax policies. This methodology focuses on three performance metrics: adequacy, climate, and financial uncertainty. For adequacy, the expected unserved energy (EUE), loss of load events (LOLEV), and loss of load hours (LOLH) are compared for the generated risk-comparable portfolios that all have a 5% loss of load probability (LOLP). Adequacy metrics are essential for long-term energy planning, especially for power systems that rely on the substantial integration of renewable resources and battery storage [37]–[41].

For climate, the approximated difference in CO₂ emissions of each portfolio from the baseline scenario, that is, pre-dam removal, was evaluated. This provides the emission contribution of each portfolio, as the range of renewable technology influences the overall performance of the power grid differently, either by increasing or decreasing the existing fossil fuel dispatch. Finally, for financial uncertainty, different carbon tax policies are analyzed from a stochastic dominance perspective, and a frontier for selecting portfolios is determined. As the financial impact of a carbon tax may favor one substitution portfolio over another, it is essential to include this dimension in power systems [42]–[44].

The outcome provides the strategy region for portfolio selection under different tax policies and stochastic dominance, a measure of preference for risk-averse decision-makers. The results focus on the integration of the performance metrics and indicate the favorability of the two substitution portfolios, given the associated carbon taxation. First, a wind-only portfolio that substantially reduces emissions is only financially preferred at a higher tax of $135/Ton CO₂. Second, a mixed technology scenario of 50% wind and 50% solar PV is also favorable with marginal emission reduction but is preferable with a carbon tax between $86 and $132. Although a third portfolio that uses only solar PV is financially dominant for any tax value below $86, it increases overall emissions and trades off financial preferability with climate performance. Lastly, in the regulatory dimension, policymakers are provided with tax level ranges that would favor emission-reducing portfolios without choosing an arbitrarily high tax value.

While this methodology does not provide the result of an optimization problem typical for multi-criteria decision-making formulations for sustainable energy [45]–[49], it maintains the significance of decision makers in evaluating the tradeoffs of each portfolio based on multiple performance metrics for evaluation by stakeholders.

These contributions are threefold: First, the study provides a methodology for evaluating electricity generating portfolios in the presence of the social cost of externalities; second, it evaluates adequacy metrics for technology substitutions with intermittent alternatives and climate change impacts; and third, it offers specific guidance for energy policymaking.

II. BACKGROUND

This literature review draws on three strands of research: regional energy planning, carbon tax policies, and stochastic dominance. Recognizing the building blocks of energy planning, that is, reliability and adequacy metrics, paves the way for generating hydropower substitution portfolios and
evaluating their impact. Understanding the status of carbon tax estimations provides the rationale for setting a broad external emission tax in the financial analysis and why identifying the strategy region is beneficial. Finally, the definitions of stochastic dominance are integral to the probabilistic assessment of portfolio preferences that ensure the lowest risk for the lowest amortized annual costs.

A. REGIONAL ENERGY PORTFOLIOS

Regional energy planning is guided by probabilistic reliability and adequacy metrics. These approaches to reliability and adequacy evaluation include analytical methods and simulation tools. Energy models consider all relevant generation sources and their operations, incorporating constraints and return probabilistic risk metrics [50]–[52]. Reliability captures whether the system is operational and adequacy measures the quality of the operation [52],[53]. By evaluating the current and future system energy configurations, energy planners can compare the probabilistic risk associated with alternative energy and climate change policies to produce optimal resource expansion plans.

Adequacy metrics may be assigned thresholds that represent acceptable tolerance for the risk of shortfalls for consumers. The most commonly used metrics in regional energy planning are loss of load probability (LOLP), loss of load hours (LOLH), loss of load events (LOLEV), and expected served energy (EUE). The LOLP is defined as the probability that the load will surpass the available generation over a specified period. Using Monte Carlo analysis, it is equal to the number of simulations with one or more shortfalls during the specified period divided by the total number of simulations. The annual LOLP is used in the Pacific Northwest to ensure that resource expansion portfolios provide adequate power supply. The currently accepted LOLP risk level for the Pacific Northwest is 5%, that is, the likelihood of observing a curtailment in a future year has no more than a 5% chance.

The other metrics are generally not used in the Pacific Northwest, and therefore do not currently have standard acceptance values. LOLH is the expected number of hours per year when the demand is expected to surpass generation. Similar to LOLP, it can be calculated using Monte Carlo simulations, and is the total number of shortfall hours divided by the total number of simulations, assuming that the simulations are over an entire year. The LOLEV, also referred to as the loss of load frequency, is defined as the expected number of shortfall events per year, where a shortfall event is defined as a contiguous set of shortfall hours. The EUE is the expected amount of load not served per year, calculated as the sum of curtailments across simulations in megawatt hours divided by the number of simulations. These are the three adequacy metrics for the hydropower substitution portfolio considered in this study.

Within the realm of energy planning, variable renewable resources such as hydropower, wind, and solar present modeling challenges because they have greater uncertainty and dependence on river flows, wind velocity, and sun availability respectively [54]–[56]. As such, much effort has been directed toward exploring renewable energy capacity and efficiency contributions to the power grid [57]–[60]. Such studies are especially important when the regulatory realm is uncertain and renewable energy policies heavily influence energy decisions [61]–[63]. However, energy utilities and power providers are not the only ones affected by renewable energy and climate change policies. Organizations are increasingly attempting to integrate environmental performance measurements that rely on renewable energy and emission reductions [64]–[66] and strive to better understand energy investments in research and development on the other [67]–[69].

To calculate the actual effective capacity of adding new resources, the associated system capacity contribution (ASCC) is utilized as the percentage of the nameplate capacity that can be reliably counted for adequacy [70]. Each resource has a unique ASCC value that varies based on the geographical location, period of use, amount of resource added, and overall resource mix. Using the ASCC, energy models simulate technology portfolios until reaching 5% LOLP, with renewable technologies often requiring a higher installed nameplate capacity expansion than fossil fuel technologies. When all portfolios reach 5% LOLP, they are considered risk-comparable for reliability. However, the remaining adequacy metrics of LOLH, LOLEV, and EUE for each portfolio may vary.

B. UNCERTAINTY IN CARBON TAXATION

However, the debate on taxing emissions is not new. One leading idea is to equate an emission tax, that is, a carbon tax, to the present value of the economic damage attributed to carbon emissions, known as the social cost of carbon. In the early 2000s, disparities between existing estimation methodologies and parameter uncertainties influenced SCC calculations [71]–[73]. The sensitivity of estimating SCC lies in the development and input data for climate and socio-economic models, known as integrated assessment models (IAMs), which are heavily dependent on probabilities and discount rates [9],[74],[75].

The significance of estimating an accurate SCC is the determination of an optimal carbon taxation policy. The leading idea is that the carbon tax should be equal to the marginal damage value from emissions, known as the Pigovian solution. However, from the start, estimations ranged from $35, $70, and $140 per ton CO2, depending on the likelihood, discount rate, and cost parameters [71], while others claimed that the SCC estimations were too high [72],[73]. The study in [73] further speculated that if the carbon tax is set to the SCC value, it would bankrupt businesses and imply collectivization of the economy. In the United States, the SCC value recognized by the federal government is approximately $40–$50 per ton CO2, a value much smaller than the estimates found in most peer-reviewed publications [1],[4],[74],[76]. For example, [4], who used a survey-based approach for expert judgement, found the
average SCC to be around $200. Even after removing outliers and focusing on experts reporting the highest confidence, SCC was estimated to be between $80 and $100. Further, [9] found a larger variation for SCC between $177 and $805, with a median of $417. On the contrary, [1] suggested that the SCC value, at least in 2015, was approximately $31, which is more aligned with government estimations around $77–$76, depending on discount rates and preferences of using global or domestic considerations [3],[10].

This variation is why this study focuses on understanding the potential tax strategy region. Because estimations of SCCs are debated and diverse, it is more important to evaluate the impact of a broad range of taxes on portfolio selection in this study. Thus, the methods for estimating SCC are outside the scope, and the financial model uses the carbon tax values found in the literature associated with low, medium, and high costs.

C. DETERMINING PORTFOLIO PREFERENCES

Originating from decision theory and analysis, stochastic dominance offers probabilistic rankings based on preferences according to shared assumptions of utility and the known distribution of portfolios under investigation [77]. The concept was developed to answer the following question: Given several risky options, which should decision makers prefer? The answer lies in distinguishing between “any decision maker” and “any risk-averse decision maker”. This concept has become beneficial in financial investment and risk decisions under uncertainty [78]–[81], as well as in energy management decisions [83]–[86]. The advantage of stochastic dominance is that one does not need to know the actual utility function of the portfolio under investigation; rather, decision makers need only agree that utility is consistent across portfolios.

By relying on the shared utility assumption and graphical positioning of CDFs, decision makers can determine preferences by type of dominance, including first-, second-, or nth-order [77],[78]. The significance of stochastic dominance is that decision-makers can consider the probability of outcomes, that is, a lower risk for choosing the least costly portfolio. A portfolio that is first-order stochastic dominant (FSD) is preferred by any decision maker, whereas a portfolio that is second-order dominant (SSD) is always preferred by any risk-averse decision maker [80],[81],[85],[86].

When the uncertain outcome is desired to be smaller, such as the annual cost, an FSD portfolio will always be preferred because the probability of resulting in lower costs will always be higher than that of other portfolios. A portfolio that is SSD is expected to outperform other portfolios most of the time, with a higher likelihood. In this study, stochastic dominance is used alongside financial uncertainty analysis and evaluation of the strategy region for portfolios according to different carbon tax options.

III. METHODOLOGY

The methodology uses four phases, which are visualized in the methodology flowchart in Figure 1. The first phase used a regional energy model to generate seven hydropower substation portfolios that relied on different combinations of renewable energy. The second phase utilized the output of the energy model as the input for the financial analysis of the amortized annual costs for each portfolio. The third phase extracts the climate impact (i.e., change in CO$_2$ emissions) of each portfolio and identifies the carbon tax impacts on the strategy region and stochastic dominance. The final phase integrates performance metrics to provide decision-makers with substitution recommendations.

The black arrows represent the flow of data between phases. The output of the regional energy model takes the unique resource capacity and overall fossil fuel dispatch of each portfolio as the input for the financial model’s portfolio parameters. The output of the initial uncertainty model, the amortized annual cost, is then revised in the third phase to evaluate CO$_2$ emissions and the impact of carbon tax uncertainty on the portfolio strategy region and stochastic dominance. The last phase provides a multi-criterion ranking based on performance metrics.

A. REGIONAL ENERGY MODEL

Putting risk planning in a real-world river basin context, this research relies on GENESYS, the regional energy model for the CRB (NPCC). GENESYS is a Monte-Carlo hourly...
chronological simulation that incorporates fossil fuel, nuclear, and renewable resources, along with conservation and fixed out-of-region energy supply, tailored to the CRB. The model simulates individual hydroelectric project operations monthly and uses approximation methods to simulate hourly hydro generation in aggregates. Hydropower generation is guided by reservoir control levels, known as rule curves, which are determined by the Bonneville Power Administration and other federal agencies that provide a maximum monthly elevation for flood control, a minimum monthly elevation for power generation, and a target monthly elevation to maximize the end-of-year refill probability. The model drafts or fills reservoirs based on power needs and forecasted river flows but is constrained by these rule curves and other operating constraints.

The output of each GENESYS simulation is provided in several reports and obtained through external R-code analysis, including the dispatch, adequacy metrics, and estimations for the capacity needed to satisfy the LOLP. By modifying the configuration of the generation resources in the model, such as increasing wind, solar, or battery storage, or decreasing fossil fuel plants, GENESYS was used to evaluate the impact of these changes. This research utilized GENESYS to evaluate seven substitution portfolios for the removal of the four LSR dams. First, a baseline scenario was generated for the 2025 operating year, which satisfied the 5% LOLP threshold after the planned decommissioning of additional coal plants in the CRB. Keeping all energy sources constant, the baseline scenario used natural gas to offset the loss of generation and reach the 5% LOLP adequacy standards. The choice to use natural gas is warranted as the regional plan is still being developed and natural gas is a convenient placeholder.

Second, the four LSR dams were removed from the operation of the model to test the impact of adequacy. Finally, seven substitution portfolios are simulated, iterating each one until the LOLP of 5% is reached again to compensate for the loss of the dams.

When LOLP is higher than 5%, GENESYS provides anticipated capacity needed to reduce the LOLP by 5%. When the LOLP is below 5%, the ASCC can be used to anticipate how much of the resources will decrease. When all substitution portfolios reach 5% LOLP, they are deemed risk comparable, and the adequacy metrics of EUE, LOLEV, and LOLH can be compared.

The seven hydropower substitution portfolios relied on different resource generation configurations, including (A) wind only, (B) solar only, (C) 50% wind and 50% solar, (D) 250 MW battery storage with equal remaining wind, solar, and natural gas; (E) 500 MW battery storage, with remaining wind, solar, and natural gas; (F) 750 MW battery storage, with remaining wind, solar, and natural gas; and (G) 1000 MW battery storage with remaining wind and solar. The actual nameplate capacity of each technology, including the “remaining with,” refers to the outcome of the energy model and iterations of adding resources according to each portfolio’s percentages until it reaches 5% LOLP. The only hard parameter is the nameplate capacity of the battery storage level and natural gas, as these represent potential expansion levels, which is a growing point of interest in the field. Portfolios D and E are referred to as low storage portfolios, and F and G as high storage. The natural gas of portfolios D, E, and F was set to 74 MW. These substitution portfolios were formed following expert judgement for potential resource expansion scenarios.

B. PORTFOLIO FINANCIAL UNCERTAINTY

Portfolio cost uncertainty relies on Monte Carlo simulation to evaluate the amortized annual cost of risk-comparable portfolios. Monte Carlo simulation in energy models is a common approach for estimating cost uncertainty, including when a carbon tax is added [87], [88].

Table 1 provides all financial model variables. The deterministic parameters include the estimate of the effective capacity (MW) for each portfolio, as assessed by GENESYS.

| Variable | Definition | Unit | Type  | Source          |
|----------|------------|------|-------|-----------------|
| ACE      | Amortized CAPEX | $/year | Random | Calculated      |
| AOC      | Annual operating cost | $/year | Random | Calculated      |
| TAC      | Total Annual Cost | $/year | Random | Calculated      |
| RC       | Recurring cost | $/year | Random | Calculated      |
| RES      | Resource expansion | MW | Constant | Energy Model |
| CAPEX    | Capital Expenditure | $/MW | Random | NREL ATB       |
| FXC      | Fixed O&M cost | $/MW | Random | NREL ATB       |
| FP       | Fuel price | $/MWh | Random | NREL ATB       |
| FFD      | Fossil Fuel dispatch | MWh | Constant | Energy + Math Model |
| VAC      | Variable O&M cost | $/MWh | Random | NREL ATB       |
| E        | Emissions | Ton CO2 | Constant | Energy + Math Model |
| EF       | Emission factor | Ton CO2/MWh | Constant | DOE |
| AEC      | Annual emission cost | $/year | Random | Calculated      |
| ET       | Emission tax | $/Ton CO2 | Random | Calculated      |
| TACT     | Total Annual Cost with Tax | $/year | Random | Calculated      |
| i        | Portfolio | A−G | Index  |                  |
| j        | Resource | Wind, solar, battery, coal, gas | Index  |                  |
| t        | Carbon tax value | $10−$200 ±$10 | Index  |                  |
along with the expected fossil fuel dispatch of coal and natural gas (MWh). The uncertain parameters include cost data from the NREL Annual Technology Baseline (ATB), including capital expenditure (CAPEX), fixed operation and maintenance (FOM), variable operation and maintenance (VOM), and fuel cost. Financial uncertainty is achieved by randomly selecting projected costs between 2021 and 2025 for different resource types made available by NREL.

To account for both capital expenditure and annual operation and maintenance costs, the objective function calculates the total annual cost as a summation of the amortized CAPEX and annual operating costs seen in equations (1)–(3), with subscript $i$ representing the portfolios and subscript $j$ representing the resource. $ACE_i$ amortization spans 30 years at a 2.375% interest rate.

$$AC_i = \sum_j RES_{ij} \cdot CAPEXi$$

$$AOC_i = \sum_j RES_{ij} \cdot FXCj + \sum_j FFD_{ij} \cdot VAC_j + \sum_j FFD_{ij} \cdot FP_j$$

$$TAC_i = ACE_i + AOC_i$$

The components of equation (2) capture the fixed O&M ($\sum RES_{ij} \cdot FXCj$), variable O&M ($\sum FFD_{ij} \cdot VAC_j$), and fuel costs ($\sum FFD_{ij} \cdot FC_j$). Fixed O&M is determined by the capacity expansion of each resource per portfolio multiplied by the projected resource fixed cost (FXC). However, the variable O&M and fuel costs are derived from the fossil fuel dispatch of each portfolio, including natural gas and coal. The VOM was calculated using the variable costs (VAC) and fuel through the projected fuel price (FP).

A key part of equation (2) requires the isolation of the fossil dispatch impact of each portfolio from the overall dispatch of the existing power grid, as shown in equation (4). As GENESYS evaluates the entire power grid, it is possible to isolate fossil dispatch by subtracting the baseline dispatch, that is, before each portfolio is introduced, from the dispatch post-portfolio introduction. This approach for isolating coal and natural gas dispatch is approximately 95% of the average coal and natural gas dispatch. The remaining 5% is accounted for in the energy market dynamics and does not influence the overall trends observed.

$$FFD_{ij} = FFD_{ij} - FFD_{baseline,j}$$

Uncertainty evaluation was achieved by generating 2,000 simulations for each portfolio. The result provides decision makers with a financial performance metric, amortized annual cost that includes uncertainty, for optimal financial alternatives prior to incorporating a carbon tax.

**C. FRONTIERS FOR ENERGY PORTFOLIOS UNDER INCREASING CARBON TAX – THE STRATEGY REGION**

By evaluating financial performance under different tax policies, the tax frontier at which one portfolio is favorable to another, known as the strategy region, can be determined. The tax evaluation process requires four steps: (i) extracting the CO$_2$ emissions associated with each portfolio; (ii) evaluating low, medium, and high tax ranges; (iii) simulating the entire tax range for the complete strategy region; and (iv) determining the strategy region sensitivity through regression.

The first step converts the fossil fuel dispatch calculated in equation (4) to emissions through an emission factor from the US Department of Energy for natural gas and coal to calculate portfolio emissions, as shown in equation (5). Aside from feeding into additional equations, the results of equations (4) and (5) lead to the climate performance metric of the seven portfolios, offering insight into the level of change to dispatch and GHG emissions achieved by the portfolios.

The second step integrates the carbon tax into the model to calculate the annual emission cost, as shown in equation (6). Subscript $t$ represents the chosen emission tax value per ton of CO$_2$. The new objective function was then modified in equation (7) to include the emission cost.

$$E_t = \sum_j FFD_{ij} \cdot EF_j$$

$$AEC_{it} = \sum_t E_t \cdot ET_t$$

$$TACT_{it} = ACE_i + AOC_i + AEC_{it}$$

The three carbon tax ranges of low, medium, and high rates correspond to $50, 100,$ and $150 per ton of CO$_2$, respectively. A uniform distribution of $10 +/- around each rate was introduced to include the uncertainty of the exact rate. This approach combines two methods to evaluate carbon tax impacts: (1) using different taxation levels, such as those utilized in [87], and (2) using a uniform distribution, such as that utilized in [88]. By implementing both tax levels (low, medium, and high) and a probability distribution within the tax levels, a greater level of sensitivity is captured. A uniform distribution was chosen because there is no accepted standard for carbon tax probabilities. This step provides an initial observation of the influence of carbon tax on financial portfolios to suggest changes in decision favorability under different tax scenarios.

The third step for the expected strategy region is to simulate a range of carbon tax values from $10 to $200 in $10 increments, again utilizing the $10 +/- uniform distribution around each increment. The purpose of this step is to generate the expected cost and complete the influence of a carbon tax to isolate the strategy region. The average annual cost based on each tax value was calculated using equation (8).

$$Average TACT_{it} = \frac{\sum TACT_{it}}{\# of simulations (2000)}$$

The outcome of equation (8) provides the expected annual cost of each portfolio given different tax values and leads the way for observing the strategy region, that is, which portfolios are expected to be cheaper under each tax value. However, using the expected annual costs overlooks the sensitivity around the regional intersection points.
The final step overcomes this lack of sensitivity by generating 2000 regression lines for each portfolio, with each line representing one instance for a portfolio’s annual cost associated with 19 tax values ($10,$20...$200) and their uniform $10+/−$ distribution. The intersection points of the two portfolios can then be calculated using Excel INTERCEPT and SLOPE functions across each portfolio. This process generates 2000 intersection points for tax values and annual costs between two portfolios that indicate, with statistical confidence, the sensitivity around tax values. The outcome develops the strategy regions and optimal portfolio preferences according to tax ranges, and determines the portfolio climate tax performance metric.

D. STOCHASTIC DOMINANCE

A key outcome of the tax analysis is to provide decision-makers with the confidence to determine a probabilistic preference for the portfolios under each tax scenario based on the shared utility and behavior of distribution. For example, when considering stock investments where the utility is return on investment (ROI), decision-makers assume that all investors prefer portfolios with higher utility, that is, a higher ROI. In the case of energy portfolios, however, the utility for decision makers has lower costs, such as annual costs.

For distribution, decision-makers compare the cumulative distribution functions (CDFs) for the annual costs of all portfolios. For example, consider two portfolios F and G with CDFs $F(x)$ and $G(x)$, respectively. When utility favors higher values, if $F(X) \leq G(x)$, that is, the CDF of F is entirely under G, for all $x$ with at least one strong inequality for $x_0$, then F is first-order stochastic dominant (FSD) over G. However, if utility favors smaller values, such as amortized annual cost, then F FSD G only if $F(X) \geq G(x)$ with the CDF of F entirely above G [80]. In this study, the utility assumption prefers smaller values, given costs.

The two stochastic dominance rules considered in this study are first-and second-order. When utility favors smaller x’s, such as annual cost, FSD occurs if one portfolio’s CDF is entirely to the left of and above all other CDFs without any intersections, as seen in the example provided in Figure 2a. However, if CDFs intersect, one can no longer claim FSD; then, SSD is considered, as shown in Figure 2b, and the enclosed areas S must be evaluated.

Here, the dominance of one portfolio over another is determined by the area enclosed between CDF intersection points [78],[80]. The general rule for any number of intersection points is that the sum of the positive enclosed areas, $S^+_i$, when the portfolio in question is above the compared option (F over G), is larger than the sum of the negative areas, that is, $S^-_i$ where the compared portfolio is above (G over F), as seen in questions (9)−(11), where subscript $a$ is the minimum value, $b$ is the point of intersection, and $c$ is the maximum value. When neither first-order nor second-order dominance is determined, F and G are considered non-dominating unless other approaches are used in tandem, and preferability is evaluated by other considerations, such as expected values and variance.

$$S^+_i = \int_{b}^{c} (F(x) - G(x))dx$$  \hspace{1cm} (9)
$$S^-_i = \int_{a}^{b} (G(x) - F(x))dx$$  \hspace{1cm} (10)
$$SSD = \sum S^+_i - \sum S^-_i \geq 0$$  \hspace{1cm} (11)

The first step in evaluating stochastic dominance is to determine whether FSD exists using a graphical CDF analysis. Under each tax scenario, the CDFs of the portfolios are graphically evaluated to isolate if one portfolio FSD the rest. If yes, that portfolio is the dominant option and is considered preferable by any decision maker. If no portfolio is ruled by the FSD because of intersections, then the intersecting portfolios are considered.

The second step, if required, evaluates the set to test for the SSD. Relying again on $F(x)$ and $G(x)$ for an example, when the enclosed area under the curve $\sum S^+_i \over G \geq \sum S^-_i \over F$ then the conclusion is that portfolio F dominates portfolio G by SSD. In addition to numerical integration to find the area under the curve, trapezoidal estimation is another tool [80],[83]. To minimize the estimation error of the area under the curve, instead of using a fitted distribution, the actual simulated CDF is used to calculate the areas under the curve via trapezoidal estimation, as shown in equation (12).

$$S_i = \sum_{i=0}^{n} \frac{F(x_i) + F(x_{i+1})}{2} \cdot (x_{i+1} - x_i)$$  \hspace{1cm} (12)

In addition, the point of intersection $F(x_{intersection})$ suggests the overall proportion of simulations and the likelihood that F is expected to be cheaper than G. For example, if that point of intersection occurs at probability $F(x) = 0.75$, and SSD is determined, then the dominant portfolio is expected to be cheaper than the dominated portfolio 75% of the time. In this study, the CDFs of the seven substitution portfolios A-G are identified as $A(x), B(x), ..., G(x)$, respectively. If no portfolio is ruled as an SSD, then the expected mean and variance are used as uncertainty considerations.

Having explained stochastic dominance, readers may recognize that it is a natural extension of measures of risk preferences, although it is yet to be widely utilized. Leading approaches to risk minimization focus on downside risk.

Figure 2: Illustration of FSD (A) and SSD (B) when utility favors lower annual cost.
relating to the negative deviation from the expected value, or costs when considering energy systems, such as the conditional value at risk (CVaR) for worst-case scenarios [89],[91]. However, stochastic dominance and CVaR conditions are related. More precisely, SSD conditions are consistent with CVaR conditions [90],[92],[86],[93] The significance is that if portfolio F is SSD over G, then the CVaR of F is also preferable to G.CVaR and stochastic dominance can both be used as modeling constraints and post-result evaluation. When designing optimization problems, it is more beneficial to use these as constraints, where efforts are made to reduce the efficiency frontier. However, in the post-result evaluation, while CVaR represents a risk measure, stochastic dominance represents a preference. Thus, this study’s research methodology utilizes stochastic dominance to evaluate the investment preferences associated with each portfolio under different tax values. The research team is confident in this approach given the increasing applications of stochastic dominance in energy decisions and a strong relation to CVaR.

D. INTEGRATING PERFORMANCE METRICS

The integrated analysis ranks each portfolio using performance metrics and highlights the tradeoffs. The adequacy evaluation assumes equal weights for EUE, LOLH, and LOLEV; therefore, the overall ranking of the metric is calculated by summing the relative ranking 1-7 of each metric, with 1 being the best and 7 the worst. For example, a portfolio with the best (lowest) value for all metrics will be scored as 3 (1+1+1), while a portfolio with the worst (highest) values will score 21 (7+7+7). After evaluating the overall adequacy score, each portfolio received an overall ranking of 1-7 based on the lowest adequacy score.

The climate performance metric follows a similar logic, with portfolios receiving a score of 1-7 based on the emission impact, with one having the best performance and seven the worst. An emission reduction is considered the best, with a higher reduction favorable to a lower reduction. If all portfolios increase emissions, the portfolio with the smallest increase ranks 1. Finally, the financial metric is based on the lowest expected annual cost coupled with stochastic dominance for each carbon tax scenario. Because the analysis also considers climate and adequacy, stochastically dominated portfolios cannot be ruled out, as there could be a situation in which a portfolio is stochastically dominant but exhibits the worst or adequate climate performance. As decision-makers need to understand all metrics, the analysis ranks the financial uncertainty of the expected amortized cost while noting the stochastic dominant options. These metrics lead the recommendation to be based on tradeoffs and tax conditions that favor one portfolio over another.

IV. RESULTS

The results are organized according to the methodology structure. The first is the energy model outcome formulation of substitution portfolios, and adequacy performance. Second, we evaluate the initial phase of the financial uncertainty model, representing the no-carbon tax scenario. Third, climate performance is discussed, leading to the final component of the results, the stochastic dominance of the portfolios under different carbon tax policies, and the strategy region.

A. FORMULATION OF SUBSTITUTION PORTFOLIOS AND ADEQUACY PERFORMANCE

As the first phase of the integrated methodology is to generate substitution portfolios for the four LSR dams, the ASCC values are used to iterate the GENESYS runs for each portfolio until 5% LOLP is achieved. This process resulted in portfolio A requiring substantially higher additional nameplate capacity than the remaining portfolios: 2.5 times the required expansion for portfolio C and 4.5 times the expansion for portfolio F [31]. A difference in capacities, as seen in Table 2, can suggest potential cost variation.

| Portfolio | Wind | Solar | Battery | Gas | Total |
|-----------|------|-------|---------|-----|-------|
| A         | 7209 | 0     | 0       | 0   | 7209  |
| B         | 0    | 2043.5| 0       | 0   | 2043.5|
| C         | 1395 | 1435.5| 0       | 0   | 2830.5|
| D         | 994  | 1055.5| 250     | 74  | 2373.5|
| E         | 868  | 899.5 | 500     | 74  | 2341.5|
| F         | 348  | 379.5 | 750     | 74  | 1551.5|
| G         | 335  | 354.5 | 1000    | 0   | 1689.5|

Table 3 presents the adequacy performance of each portfolio, including EUE, LOLH, and LOLEV. Portfolio B demonstrated the best performance with the lowest values across the three metrics.

| Adequacy Metric | Curtailment Event Statistics |
|-----------------|-----------------------------|
| Portfolio | EUE | LOLH | LOLEV | Magnitude (MWh) | Duration (Hours) | Frequency (Years) |
| A         | 672  | 0.56 | 0.170 | 3951          | 3.32            | 5.88            |
| B         | 451  | 0.40 | 0.123 | 3653          | 3.28            | 8.11            |
| C         | 535  | 0.48 | 0.147 | 3646          | 3.25            | 6.82            |
| D         | 579  | 0.50 | 0.147 | 3945          | 3.41            | 6.82            |
| E         | 600  | 0.50 | 0.150 | 4002          | 3.36            | 6.67            |
| F         | 822  | 0.64 | 0.170 | 4838          | 3.75            | 5.88            |
| G         | 913  | 0.67 | 0.167 | 5478          | 4.03            | 6.00            |

An interesting finding is that the high storage portfolios F and G result in the worst performance for EUE and LOLH. Wind-only portfolio A shows only mild increases in EUE and LOLH from portfolios C, D, and E. The conventional interpretation of the metrics is also provided in the table, where adequacy is calculated to measure the expected event duration, magnitude, and frequency of occurrence. The LOLEV was converted to the expected frequency of curtailment events using the LOLEV inverse. The expected event duration, in hours, is LOLH multiplied by the expected number of years between events, that is, LOLH*(1/LOLEV).

Finally, the expected curtailment magnitude in MWh is the EUE multiplied by the years between events.
The conventional interpretation leads decision makers to see that from an adequacy perspective, portfolio B is the optimal substitution portfolio by having the longest expected frequency of 8.1 years, around 1.3 years longer than the runner up. Decision makers should also note minimal variation in the expected duration of curtailment between portfolios. The greatest variability was observed for the expected magnitude. While portfolio B has a marginally higher loss than portfolio C, the frequency favors portfolio B with solar only.

B. FINANCIAL UNCERTAINTY

Following the adequacy phase, the next phase of investigation is the financial uncertainty of the portfolios prior to introducing a carbon tax. As expected with portfolio A, given the high resource expansion, the high resource expansion needed for wind-only generation results in a substantially higher expected annual cost than the other portfolios, as seen in Figure 3, alongside the histogram and CDFs. Portfolio B is the cheapest, followed by portfolios F and G. Portfolio C is the second costliest, followed by D and E.

A closer examination of the CDF shows that portfolio B is FSD, as B(x) is above and to the left of the rest, indicating that B is preferred by any decision maker, given the highest probability to achieve the lowest cost. Furthermore, the histogram illustrates the narrow distribution of portfolios, except for A. The spread of A is due to its larger resource capacity and higher variability in costs.

C. CLIMATE METRIC

Climate performance, the next component, is dependent on the fossil fuel dispatch of coal and natural gas in the overall power grid caused by each portfolio. In other words, even if a portfolio comprises only renewable sources, such as portfolios A, B, C, and G, their operational characteristics impact the grid and influence the dispatch from existing resources, including fossil fuels. CO2 emissions were then calculated after isolating the impact of each portfolio [94]. Figure 4 shows the fossil fuel dispatch difference (MWh) and the associated changes in emissions from the baseline.

The surprising finding is that portfolio A significantly reduces fossil fuel dispatch, resulting in an annual emission reduction of almost 20%. In other words, portfolio A has better climate performance than the contribution of the four LSR dams to the power grid. The only other portfolio to demonstrate improved performance is C, offering a 0.3% annual reduction. The rest of the portfolios demonstrated an increase in emissions from the baseline, with the high storage portfolio increasing emissions by approximately 10% each, due to the largest increase in fossil fuel dispatch. Portfolio B, which showed favorability in terms of adequacy and pre-tax amortized costs, now receives a different outlook, ranking 5th in terms of climate performance due to a 5% increase in annual emissions. The significant reduction in emissions of portfolio A paves the way for understanding the importance of accounting for carbon tax. Depending on the carbon tax, an annual emissions reduction of 20% or an increase of 5%–10% could swing the favorability of one portfolio to the other.

D. CARBON TAX ANALYSIS

Following climate performance, the introduction of a low tax ranging from $40–$60 leads to two main observations derived from Figure 5. First, portfolios with increased emissions also increased their amortized annual costs, with all portfolios showing a higher spread of costs seen in the histogram. However, the tax is not high enough to make portfolio A financially attractive, although the costs are reduced. Second, under the low tax option, portfolio B remains FSD and preferable for any decision maker.
Evaluating a medium tax policy paints a different picture, as shown in Figure 6. First, there is no longer first-order dominance of any portfolio. The medium tax spreads the annual cost of portfolio A to a point where a small percentage of simulations were found to be the cheapest. Likewise, portfolio C is expected to be cheaper than portfolio B until intersecting, and the impact of the spread is noticeable on the remaining portfolios as well, with F and G now the costliest.

Considering the CDFs, portfolios A, B, and C are the feasible options. Portfolios B and C are entirely above and to the left of the rest except portfolio A, which is included because of the intersection with B and C. The areas enclosed by the CDFs $A(x)$, $B(x)$, and $C(x)$ are presented in Table 4. As the remaining portfolios are dominated given graphical positioning of their CDFs in relation to A and B, they do not need to be evaluated alongside their intersections with C.

The resulting dominance analysis shows that Portfolio C is SSD under a medium tax. This is determined by the fact that both C and B are SSDs over portfolio A, but C is SSD over B. Thus, portfolio C is preferred by any risk-averse decision maker. Further, portfolio C is expected to be cheaper than B, almost 80% of the time, given the point of intersection.

The high tax policy continues the trend seen in the medium tax range in terms of the cost spread, as presented in Figure 7. Portfolio A is now expected to be the least costly portfolio, with a small percentage (1%) of simulations resulting in negative costs, meaning that carbon tax savings outweigh overall costs.

Under high tax, no portfolio is FSD given the intersection of C and A, while Portfolio C dominates the rest. The enclosed areas are listed in Table 5. As $S7 > S8$, portfolio A is SSD over portfolio C and preferable by any risk-averse decision maker. Even though portfolio A intersects the rest of the portfolios because they are dominated by C, there is no need to compare them.

The impact of the low, medium, and high tax policy demonstrates the changing financial favorability of the portfolios, with the overall trend presented in Figure 8. Although some of the differences in expected annual costs are not large, the application of stochastic dominance decision makers can clearly indicate preferences.

Under a low tax policy, portfolio B is preferred by all decision makers. With the medium policy, portfolio C is SSD and preferable by any risk-averse decision maker with the likelihood of being the cheapest 80% of the time. Lastly, under a high tax policy, portfolio A is preferable for the risk-averse decision maker and provides a 70% likelihood of being cheapest. These findings aid decision makers in understanding the considerations of financial uncertainty around carbon tax values. However, this analysis only
enables a broad recommendation based on expected tax brackets. The next phase is to identify the actual tax ranges for the portfolio strategy regions.

**E. FRONTIER OF CARBON TAX STRATEGY REGIONS**

To find the strategy region, instead of simulating tax brackets, the financial model simulated $10 tax increments, with an additional uniform distribution of +/-$10 around each value between $10 and $190. Figure 9 shows the expected annual cost for each tax value. Corresponding to the findings of the tax bracket analysis, the dominance of portfolios B, C, and A becomes pronounced. Portfolio B is preferred with a carbon tax below some value between $80 and $90, portfolio A after $130–$140, and portfolio C between the tipping points for B and A. In fact, a tax greater than $200 would result in portfolio A having an expected negative cost; that is, savings from avoided emissions outweigh costs.

![Figure 9: Average annual costs under each carbon tax increment](image)

The confidence of the strategy region is calculated by analyzing the 2000 intersection point between portfolios B and C for the lower bound and C and A for the upper bound. The mean intersection between portfolios B and C is $85.052, with 95% confidence intervals of ($83.856–$86.249). The upper tipping point of portfolios A and C has a mean value of $133.672 with confidence intervals of ($131.963–135.291). If the carbon tax falls within either of the two tipping point intervals, the relevant portfolios are expected to have a comparable annual cost, suggesting that climate and adequacy take the lead. The additional significance of these tipping points is that decision-makers can now understand the ranges for which the portfolio is expected to be financially preferable. B is preferable when the tax is less than $83.856. If the tax is between $86.25 $ and $131.96, C is preferred. Finally, if the tax is greater than $135.29, then A is preferred, as shown in Figure 10, with the strategy region and intersection uncertainty.

![Figure 10: Frontier of strategy region for each tax range](image)

It should also be noted that the regression fit, demonstrated by the R² values, was very high for the generated regression lines. R² values were determined using Excel’s RSQ function for each simulation. Across the portfolios, the average R² is 0.99, with very narrow confidence intervals, as shown in Table 6. This suggests that the results provide meaningful outcomes for analysis and recommendations.

| Portfolio | N  | R² Mean | StDev | SE Mean | 95% CI for μ          |
|-----------|----|---------|-------|---------|-----------------------|
| A         | 2000 | 0.990085 | 0.002267 | 0.000051 | (0.989986, 0.990184) |
| B         | 2000 | 0.990195 | 0.002258 | 0.000050 | (0.990096, 0.990294) |
| C         | 2000 | 0.990224 | 0.002174 | 0.000049 | (0.990129, 0.990320) |

With the newly identified strategy region, decision-makers might wonder if dominance preferences change. While the pre-determined low, medium, and high tax range policies fall completely within the lower, middle, and upper bounds, respectively, as the distribution expands, the dominance could have also been influenced. The financial model was simulated again for each strategy region using a uniform distribution across the ranges. For the lower bound favoring portfolio B ($1–$85), stochastic dominance remains unchanged at FSD, meaning that any decision maker would prefer B for the highest probability of the lowest annual cost. The middle range favoring C sees a shift in portfolios A and B CDFs, but maintains C’s SSD, as presented in Figure 11a. Under $85–$133, Portfolio A shifted the left-hand tail of the distribution (cheapest costs) from 5% to 20%, while portfolio B shifted to the right, reducing the proportion of cheaper simulations than C from 20% to 3%. Calculating the areas under the curves formed by the intersections of A, B, and C shows that portfolio C is preferred by all risk-averse decision makers as it is SSD over portfolios A and B.

Lastly, as seen in Figure 11b, the upper region analysis ($133–$200) confirms that portfolio A is SSD over C. Under this tax region, portfolio A results in almost 20% of simulations with a negative annual cost, that is, overall savings. As seen before, when the carbon tax tips are over $200, the expected annual cost of A is negative. However, the main significance for decision makers is that portfolio A is SSD, even under this broad tax range, making it preferable for all risk-averse decision makers.
Interestingly, despite the large difference in carbon tax values that influence the strategy region, the actual difference in the expected annual cost between the two comparisons is marginal. Figure 12 depicts the minor variation in the cost distribution of the intersection points, a point strengthened with the almost overlapping 95% confidence intervals of ($259,902,801, $262,347,774) for portfolios B-C and ($263,237,368, $265,486,061) for portfolios A-C.

This finding is aligned with the climate performance of portfolio C, which exhibits a minimal reduction in emissions of only 0.3% annually. As such, an expected reduction of 66,616 tons of CO₂ does not lead to substantial financial gains, and the expected annual cost does not seem to be sensitive to taxes. However, portfolio A is expected to reduce 3,750,154 tons of CO₂ and is therefore more sensitive to tax changes. In contrast, portfolio B is expected to increase emissions by 1,016,387 ton CO₂, also making it tax sensitive. Because portfolios A and B intersect the more financially stable portfolio C, the two intersection points are similar.

IV. SYNTHESIS

Decision makers can now determine an optimal portfolio or understand the trade-offs of each alternative by reviewing the relative ranking of each performance metric. The performance metrics are translated to the unified rankings presented in Figure 14 for the no-tax policy scenario, with 1 being the best and 7 the worst. Under the no-tax scenario, Portfolio B stands out as the best in terms of adequacy impact and financial performance. However, Portfolio B ranks 5th in climate. High battery storage portfolios are the 2nd and 3rd cheapest options, but the worst in terms of adequacy and climate. Portfolio A is a clear climate winner but tradeoffs adequacy and cost. Lastly, portfolio C is 2nd best for climate and adequacy, but 6th in cost.

The inclusion of carbon tax policies illustrates the meaningful impact of this study. First, the inferiority of portfolios F and G stands out for having the worst financial performance, making them worst across the board in any metric, second only to portfolio A’s low tax financial performance. Second, portfolio C stands out for consistently ranking 2nd across adequacy, climate, and low- and high-tax, while ranking 1st (preferred by a risk-averse decision maker) under the medium tax policy as SSD with 80% likelihood of lower costs. Portfolio B now exhibits the impact of increased emissions as a loss of rankings under medium and high taxes.

The worst portfolios are F and G, which represent the high-storage portfolios. Both have the worst performance of adequacy metrics, increasing emissions by 10% annually.
over the baseline (1,964,132- and 2,003,866-Ton CO$_2$ respectively) and quickly becoming the most expensive under medium and high carbon tax policies (see Figure 8).

To decide on an optimal portfolio, decision makers must determine what external influences place additional weight on their considerations. Although the strategy region shows portfolio B as financially preferred for a wide tax range of $1–$83, the elephant in the room is that portfolios A and C are the only options that do not increase CO$_2$ emissions from the energy supply; portfolios A and C reduce 3,750,154- and 66,616-Ton CO$_2$ annually, respectively. As nations race to reduce GHG emissions, stakeholders can place more weight on portfolios that reduce emissions.

The challenge with portfolio A is that it is only financially attractive with a high carbon tax of greater than $135 per ton of CO$_2$. Although this value is within the realm of the social cost of carbon available in the academic literature, it is far from the current estimations of the US government. Decision makers that prioritize climate change mitigation and side with the feasibility of a high carbon tax would find portfolio A the preferable choice for any risk-averse decision maker. However, decision makers who are more conservative in their estimation of a high carbon tax would find that portfolio C suggests minimal financial risk. With a broad range of $86–$132 per ton CO$_2$, decision makers can be confident portfolio C will result in the financially preferred option, with a low impact of carbon tax variability. The fact that portfolio C also reduces emissions only strengthens the preference of the portfolio for the risk-averse stakeholders while satisfying minimal climate considerations. Finally, the results also pave the way for policymakers to determine a carbon tax level that favors the development of emission-reducing portfolios, such as A, and to some extent C, without choosing an arbitrary tax value.

IV. CONCLUSION

Decision makers must prepare for a future in which emissions will be taxed as the main tool for climate change mitigation. The looming question around carbon tax policy is the value of tax emissions. Therefore, energy and risk managers must be equipped with the knowledge to determine preferable decisions based on uncertain carbon tax policies.

The substitution portfolios presented in this study vary in terms of their climate change performance, financial uncertainty, and adequacy impact on the power grid in the CRB. While wind-only portfolio A far outperforms the rest regarding climate performance by reducing 3,750,154 ton CO$_2$ annually, it requires a high carbon tax of over $135,292 per ton CO$_2$ to be financially preferable by risk-averse decision makers. The only other portfolio to reduce emissions is wind-and-solar portfolio C, with a minor reduction of 66,616 tons of CO$_2$. In terms of financial uncertainty, portfolio C has minor sensitivity to a carbon tax, and the expected amortized annual cost does not vary substantially for any tax, including in its favorable strategy region of $86.25–$131,962. Finally, leading portfolios in terms of adequacy performance are solar-only, wind, and solar. However, the performance variation showed minor differences, with the largest variation found in the expected event frequency of the LOLEV.

The integrated methodology suggests that the leading alternatives are the wind-and-solar portfolio C and wind-only portfolio A. Portfolio C is recommended given its annual cost resistance to fluctuations of carbon tax, 2nd best adequacy impact, and marginally reducing emissions. Portfolio A is recommended to substantially reduce emissions and is economical with higher carbon tax values. Deciding between the two depends on the decision makers’ consideration of the probable carbon tax and mitigation efforts.

However, one additional use of the tax strategy outcome could be by policymakers to determine the carbon tax level that results in truly reducing emissions in the CRB. In other words, the results of illuminate the carbon tax that incentivizes the development of emission-reducing portfolios without setting the tax arbitrarily too high. The study’s contribution is to advance a methodology for evaluating electricity generating portfolios in the presence of the social cost of externalities in the form of a carbon tax; in addition, the methodology allows the evaluation of adequacy metrics for technology substitutions with intermittent alternatives and climate change impacts; lastly, the study offers specific guidance for energy policy making.

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