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Optimizing Carbon Reduction Strategies with A Cost Benefit Approach to Climate Economics

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Abstract

This research introduces an AI-driven, multi-objective optimization framework designed to balance carbon emission reductions with economic costs from a global policy perspective. By applying a modified NSGA-II algorithm to real-world data, the approach systematically explores trade-offs between minimizing CO_2 emissions and minimizing economic burdens. The framework leverages non-dominated sorting and crowding distance measures to maintain solution quality and diversity, while iterative genetic operations—including crossover and mutation—drive convergence toward optimal strategies. The result is a suite of Pareto-optimal solutions that illuminate potential pathways for carbon reduction without disproportionately constraining economic growth. This methodology, supported by comprehensive data pre-processing and validation, equips policy-makers and stakeholders with a transparent, evidence-based tool for shaping effective climate and economic strategies.

Keywords: AI-driven multi-objective optimization, Carbon emission reduction, Climate economics,Economic burden minimization.

1. Introduction

Climate change stands among the most urgent challenges of our era, commanding increasing attention from the global community [1]. Evidence from scientific bodies such as the Intergovernmental Panel on Climate Change (IPCC) has repeatedly shown that anthropogenic greenhouse gas emissions---primarily carbon dioxide (CO$_2$)---are the chief drivers of global warming and its associated impacts, including more frequent extreme weather events, rising sea levels, and disruptions in agricultural patterns [2]. Recognizing this, international agreements such as the Paris Agreement have sought to limit global temperature rise by enlisting nations in reducing emissions through regulatory measures, carbon pricing schemes, and investments in low-carbon technologies [3]. However, implementing robust climate policies remains [4] a complex balancing act . Decision-makers must manage a host of economic, political, and social constraints , all while addressing the urgent need to reduce global carbon footprints [5].

Within the broader arena of climate economics, cost-benefit analysis (CBA) has traditionally served as a cornerstone for evaluating policy interventions. Seminal works, including those by Nordhaus and Stern, highlight both the importance and the inherent difficulties of quantifying the social cost of carbon and determining optimal levels of climate action [6]. Conventional CBAs typically rely on integrated assessment models (IAMs) that couple climate processes with economic projections [1]. Although these models have significantly contributed to our understanding of climate-economy interactions, they often work with simplified assumptions or single-objective functions that do not capture the entire spectrum of policy choices [4]. These approaches may, for example, optimize for minimal total costs but overlook essential trade-offs, such as sector-specific impacts, equitable distribution of costs among stakeholders, or variations in technology readiness [7].

Against this backdrop, multi-objective optimization methods present a valuable alternative for navigating the intricacies of climate policy . Such methods go beyond single-target considerations, allowing policy-makers and researchers to explore trade-offs among multiple, often conflicting, goals. In climate economics, these may include minimizing carbon emissions, mitigating negative impacts on gross domestic product (GDP), reducing social inequalities, or accelerating the adoption of clean energy technologies . Among the family of multi-objective evolutionary algorithms, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) has demonstrated remarkable efficacy and versatility across a range of engineering and economic applications. Its core mechanism—incorporating non-dominated sorting, crowding distance measures, and evolutionary operators such as crossover and mutation—enables a systematic exploration of high-dimensional solution spaces while maintaining a diverse set of “non-inferior” or Pareto-optimal solutions .

Building on these insights, this research introduces an AI-driven, multi-objective optimization framework that applies a modified NSGA-II algorithm to real-world climate and economic data. The framework specifically addresses two principal objectives:

Minimizing carbon emissions to align with global climate targets, and Minimizing economic burdens, so as not to stifle growth or disproportionately disadvantage certain regions .
The methodology leverages non-dominated sorting to rank candidate solutions by their performance on both objectives and uses crowding distance measures to preserve a wide variety of strategie . Through iterative genetic operations—including crossover, mutation, and selection—this approach moves toward a set of Pareto-optimal solutions, each offering a unique balance between climate action and economic viability. A rigorous data pre-processing phase ensures that the model inputs accurately reflect real-world conditions, from energy consumption patterns to technological cost curves and macroeconomic indicators . By integrating this data into the optimization, the final set of solutions reflects nuanced and realistic policy scenarios.

The contributions of this paper are threefold. First, it advances the use of multi-objective evolutionary algorithms in climate economics, demonstrating how an NSGA-II-based method can capture the multifaceted trade-offs inherent in environmental policy. Second, it provides a transparent, evidence-based tool for decision-making, offering policy-makers the ability to weigh different cost and emissions outcomes based on reliable data and robust analytics. Finally, the resultant set of Pareto-optimal strategies highlights the diverse pathways through which carbon reduction targets can be met without causing undue economic harm—an insight that is especially critical for resource-constrained or rapidly developing regions.
This research contributes to advances in climate–economy analytics in three ways.It extends evolutionary multi-objective optimization to a global, multi-decadal census dataset, moving beyond stylized integrated-assessment models.It establishes empirical validity through a rolling back-test that reproduces out-of-sample emissions.This paper demonstrates policy relevance by translating two Pareto-frontier solutions into costed Nationally Determined Contributions. Its contribution lies in providing a scalable, transparent tool for aligning national policies with global decarbonization goals, validated through rigorous metrics and applicable to international policy contexts like emissions trading schemes.

This paper is structured as follows: after framing the problem and its significance in this Introduction, we review the existing literature on climate economics and multi-objective optimization in Section 2. Section 3 details our methodological framework, from data collection and pre-processing to the key features of the modified NSGA-II algorithm. In Section 4, we present the empirical results and discuss their implications for both theory and practice. Finally, Section 5 offers concluding remarks, including potential avenues for future research and applications in policy-making contexts.

By integrating state-of-the-art AI techniques with real-world economic and environmental data, the proposed framework aims to serve as a robust decision-support system for climate policy. In doing so, it not only underscores the capacity of multi-objective methods to elucidate complex policy dilemmas but also brings us one step closer to harmonizing global economic development with the imperative of carbon reduction.

2. Literature Review

The challenge of mitigating climate change while maintaining economic growth haspropelled increasing interest in quantitative tools, particularly cost-benefit analyses (CBAs), for designing and evaluating carbon reduction strategies. Cost-benefitapproaches to climate economics aim to quantify the trade-offs between investment inmitigation technologies or policies and the resultant benefits, such as avoided damagecosts and co-benefits in air quality, public health, and ecosystem preservation [2]. Formulating robust policies requires a deep understanding of how abatement measures canbe optimized in terms of cost-effectiveness, taking into account uncertainties related
to technology costs, policy instruments, social discount rates, and diverse stakeholderpriorities [6].
A significant strand of the literature focuses on coupling local air pollution management with global climate change mitigation. Researchers highlight that decarbonizingthe energy sector often simultaneously reduces emissions of harmful co-pollutantslike sulfur dioxide (SO2) and particulate matter [8, 9]. Bollen et al. [2] demonstratein a combined cost-benefit analysis that policies aimed at curbing greenhouse gases(GHGs) can yield considerable ancillary benefits by lowering concentrations of local airpollutants, and they argue that integrated policies generate higher net welfare gainsthan strategies addressing climate and local pollution separately. Similarly, Joh et al.[10] quantify the health co-benefits from reduced particulate emissions when Koreaadopts GHG mitigation policies, showing a notable reduction in premature deaths. A recurring conclusion is that such co-benefits can offset portions of the direct costs of climate change mitigation, making an integrated approach particularly economicallyappealing [2].
In parallel, a variety of studies underscore the importance of flexible policy mechanisms and carbon pricing instruments, such as emissions trading and carbon taxes, inachieving efficient abatement [11]. Blyth et al. [12] emphasize that carbon pricing canincentivize private sector investments in low-carbon technologies, though long-termlearning-by-doing and R&D externalities often necessitate additional policy interventions, such as research subsidies, to reduce overall abatement costs. Gilotte and Bosetti[13] similarly explore how carbon capture and storage (CCS) can interact with carbonpricing, concluding that CCS may reduce marginal abatement costs but also involvesuncertain risks of leakage and high initial capital expenditures. This juxtapositionillustrates how policy design must carefully integrate incentives for both near-term
and long-term technologies, as well as weigh co-benefits, uncertainties, and broadersustainability goals [4].
Moreover, from a financial market perspective, stable and transparent climate policies also influence asset prices, particularly in major emerging economies. For instance,Iqbal et al. [5] emphasize that climate policy uncertainty in China exerts asymmetricimpacts on Chinese asset prices, highlighting the crucial role of stable policy environments in facilitating capital market efficiency and supporting low-carbon investments.
This further underlines how policy clarity can be integral to garnering both privateand public sector engagement in large-scale decarbonization.
Models of energy system optimization offer further insight into how cost-benefitframeworks can guide decarbonization strategies. Several authors use integratedassessment models (IAMs) or energy-economic models to explore regional or globaltransitions, demonstrating that combining renewable deployment, negative emissions,and energy efficiency measures can minimize overall system costs [1].
Works focusing on subnational scales, such asBrown et al. [1] in the context of Georgia (USA), or Li et al. [15] for China's coal-to-biomass retrofitting, demonstrate that localized resource endowments and policyenvironments play a decisive role in shaping cost-effective mitigation pathways.
Beyond the power sector, additional research expands cost-benefit approaches toother major contributors of carbon emissions, including agriculture, transportation,and waste management. In agriculture, An et al. [16] highlight the yield gains thatsimultaneously reduce GHG emissions through best management practices for riceproduction in China, concluding that both productivity and emission reductions canbe optimized with targeted management that considers soil quality. Carauta et al. [3]and Giri [17] analyze the role of policy incentives, such as the Clean DevelopmentMechanism (CDM), in guiding land-use changes and agricultural practices to realize cost-effective GHG mitigation. In transportation, Taptich et al. [18] indicate thatpromoting drop-in biofuels can be cost-effective if technology costs fall and if externalities of petroleum consumption are correctly priced. Meanwhile, Rabbitt and Ghosh[19] discuss how organized car sharing yields significant cost and carbon savings byinternalizing externalities associated with private car use.
Waste and resource management present another domain in which cost-benefitanalyses can uncover synergies between emissions reduction and monetary savings[20, 21]. Hegde et al. [20] introduce a holistic

approach combining machine learning techniques for waste sorting with carbon footprint calculations, emphasizing thatimproved waste sorting can avert extensive carbon emissions at relatively modest cost.
Thorneloe et al. [21] integrate full cost accounting with a life-cycle perspective to evaluate alternative waste management strategies, finding that recycling and compostingoptions can provide favorable net environmental and economic outcomes when carbon and other pollutant externalities are internalized. These investigations confirmthat adopting a cradle-to-grave perspective clarifies the benefits of emission reductionsacross entire value chains [22].
Cost-benefit analyses and integrated decision-making frameworks are also essentialto evaluating the trade-offs in negative emissions or geoengineering approaches [23].
Goes et al. [23] highlight that substituting aerosol geoengineering for direct carbonabatement can fail intergenerational equity tests and introduce abrupt climate risksif aerosol injection is suspended. Similarly, Freeman and Pye [4] contend that socio-technical models must capture potential societal feedbacks and political acceptanceif negative emissions and large-scale decarbonization scenarios are to be realized inpractice. The case for holistic system thinking is further reinforced by studies indicating that climate-optimized design of new technologies and operational strategiescan more than double or triple cost-efficiency [24, 25]. This resonates with the viewthat improved modeling, robust data, and interdisciplinary research are necessary to
effectively balance short- and long-term objectives, externalities, and co-benefits.
Increasingly, scholars argue that a rigorous cost-benefit approach should accountfor uncertainties in climate sensitivity, discount rates, and technological evolution [6].
Emmerling et al. [26] show that a lower social discount rate boosts current carbonprices and reduces permissible carbon budget overshoot, implying fewer negative emissions in the latter half of this century. Dietz and Morton [6] compare the Stern Review'streatment of discounting to the approaches used in evaluating risks of radioactive wastemanagement in the United Kingdom, demonstrating how normative assumptions ondiscount rates can lead to different policy recommendations. Such findings underscorethat the social cost of carbon and other parameters in cost-benefit frameworks mustbe scrutinized carefully, as they critically shape abatement pathways.

Figure 1 presents a conceptual model that illustrates the interconnections among cost-benefit analyses (CBAs), integrated policy co-benefits, carbon pricing mechanisms, sector-specific mitigation strategies, and associated uncertainties. The diagram emphasizes how CBAs inform policy design by quantifying trade-offs, how integrated policies generate co-benefits such as improved air quality, and how carbon pricing mechanisms incentivize low-carbon innovation. It further depicts the role of sector-specific strategies—particularly in energy, agriculture, and transportation—in contributing to overall mitigation efforts. Additionally, it highlights how uncertainties, including variations in discount rates and technology costs, influence policy outcomes. This framework offers a structured perspective for understanding the multifaceted dynamics of climate economics.

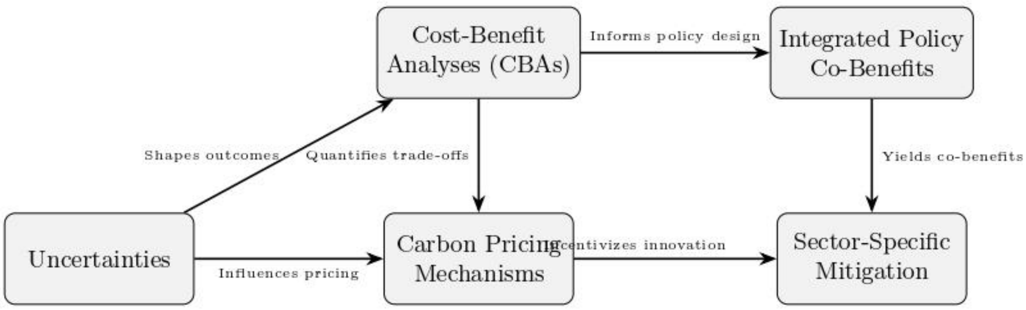

Figure 1: Conceptual model of climate economics

3. Proposed Work

3.1 NSGA-II Overview

The Non-dominated Sorting Genetic Algorithm II (NSGA-II) is a popular multi-objective evolutionary algorithm (MOEA) known for its efficiency and effectiveness in handling conflicting objectives . Its core procedure begins by evaluating each solution in the population with respect to all objectives; a solution \(A\) is said to dominate another solution \(B\) if \(A\) is at least as good as \(B\) in every objective and strictly better in at least one objective. Solutions with zero dominating solutions form the first Pareto front, and those dominated only by solutions in the first front form the second front, and so on. Within each front, a crowding distance is computed to reflect how “crowded” solutions are in objective space; extreme solutions receive a maximum distance, while intermediate ones have distances calculated based on differences in neighboring objective values, thus promoting diversity. For selection, NSGA-II applies a binary tournament approach: pairs of solutions are randomly sampled, and the solution with the better Pareto front rank wins; if both lie on the same front, the one with the higher crowding distance is selected. This combination of Pareto-based ranking and crowding-distance maintenance ensures a broad exploration of the search space. NSGA-II is particularly suited for balancing CO\textsubscript{2} emissions and economic costs because it provides a diverse set of Pareto-optimal trade-offs, allowing policy-makers to choose solutions that emphasize different degrees of environmental versus economic priority.

In this study, we model climate-economic optimization as a two-objective minimization problem:

Objective 1: min CO2normalized,
Objective 2: min costnormalized,

Where: CO2represents a scaled measure of CO2 emissions, normalized to a range [0, 1], and $cost_{normalized}$indicates a similar normalized measure of economic cost, typically estimated as GDP per capita or another relevant financial index. These two objectives capture the essential trade-off between environmental responsibility and economic feasibility.
Depending on the specific policy or data context, constraints may include emission caps, minimum GDP thresholds, or other regulatory limits. Penalty functions can be integrated if certain solutions violate these constraints. For instance, if a solution exceeds a specified emission cap, a penalty term can be added to its objectives, effectively pushing it toward the less feasible end of the population. In this work, such constraints are assumed to be minimal or implicit, but the framework can be extended to handle more complex rules.

4. Algorithmic Pseudocode

Algorithm 1 NSGA-II for Dual-Objective Minimization

1: Input:
- A set of candidate solutions, each with ($CO2_{normalized}$, $cost_{normalized}$)
- Population size N
- Number of generations G
- Crossover probability pc
- Mutation probability pm

2: Output: Final Pareto-optimal set of solutions
3: Initialize: the population:
Randomly sample N solutions from the dataset to form initial population P .
Evaluate each solution to obtain its (CO2normalized, $cost_{normalized}$)
4: Perform non-dominated sorting and compute crowding distances:
Classify all solutions in P into Pareto fronts and calculate the crowding distance for each solution.
5: for g = 1 to G do
6: Selection (Binary Tournament):
For i = 1 to N :
Randomly pick two solutions A and B from P .

Compare front rank; if one is better (lower), select it as parent.
If ranks are the same, select the one with higher crowding distance.
Store the chosen parent in a parent set.

7: Crossover:
Pair up parents; with probability pc, exchange parts of their decision variables to form offspring.
Otherwise, copy parents directly as offspring.

8: Mutation:
For each offspring, with probability pm, randomly alter one or more decision variables.

9: Form the next generation:
Combine current population P and offspring Pnew into set Q of size 2N .
Perform non-dominated sorting on Q.
Compute crowding distances for solutions in Q.
Select the top N solutions (by Pareto rank and crowding distance) to form the new P .

10: end for

11: Return: Final population P as the discovered Pareto-optimal set

The dual-objective NSGA-II procedure, detailed in Algorithm 1, begins by initializing a population of candidate solutions and evaluating both their normalized CO2 emissions and cost measures. Each solution is then assigned to a Pareto front via non-dominated sorting, and the crowding distance is computed to maintain population diversity. A binary tournament selection mechanism identifies parent solutions based on both Pareto rank and crowding distance, after which crossover and mutation operations generate offspring. The new population is formed by combining parents and offspring, re-sorting according to Pareto rank, and retaining the top-ranked, most diverse solutions. Iterating this cycle over multiple generations yields a final set of non-dominated solutions, giving decision makers a spectrum of feasible options that balance environmental and economic priorities.

4.1 Mathematical Model

We formulate the climate-economic optimization problem as a bi-objective minimization (see Equation 1). Let each candidate solution be characterized by two primarymetrics: $CO2_{normalized}$ and $cost_{normalized}$. The general structure of the model is givenby:
Minimize:

$$f1(x) = CO2normalized(x),$$
$$f2(x) = cost_{normalized}(x),(1)$$

subject to:

$$gi(x) \leq 0,\ i = 1, 2, \ldots, m,$$
$$x \in \Omega,$$

where x is the decision vector or set of decision variables (e.g., selecting particularentries or strategies from the dataset), CO2normalized(x) represents the normalizedcarbon dioxide emissions for solution x, $cost_{normalized}(x)$ is the normalized economiccost (or GDP per capita) for solution x, gi(x) are additional constraints or policyrequirements (e.g., emission caps, minimum GDP thresholds) that may or may not beactive for each solution, and Ω is the feasible domain of all solutions derived from thedata or allowable policy space.
CO2normalized and costnormalized are typically obtained via min-max scaling, shown inEquation 2 :

$$Xnormalized(x) = X(x) - Xmin$$
$$Xmax - Xmin$$
$$, (2)$$

where X ∈ {CO2, cost}. This normalization ensures both objectives are representedon comparable scales,

ranging from 0 to 1, making multi-objective optimization moretractable.
Various optional or context-specific constraints can be incorporated, for instance:

$$g1(x) = CO2(x) - CO2max \leq 0, g2(x) = cost(x) - costmax \leq 0, (3)$$

depending on policy limits or budgetary restrictions . If gi(x) is violated, solution x isdeemed infeasible or assigned a penalty.

The set Ω includes all solutions that satisfy the data-driven assumptions andconstraints(Equation 4):

$$\Omega = \{x \mid gi(x) \leq 0, \forall i \in \{1, . . . , m\}\}. (4)$$

In practice, Ω may be determined by filtering the underlying dataset (e.g., removingrows with missing values or outliers) and retaining only those entries that meet basicfeasibility requirements (e.g., positive population, non-negative GDP).
To solve this model, we employ the Non-dominated Sorting Genetic AlgorithmII (NSGA-II), an evolutionary algorithm that seeks a diverse set of non-dominated(Pareto-optimal) solutions. The algorithm iteratively refines a population of candidatesolutions, evaluating them against both f1 and f2, while managing constraints throughpenalty functions or feasibility checks.

5. Implementation and Experimental Setup

5.1 Data and Preprocessing

This paper employs the publicly available dataset owid-co2-data.csv, which consolidates carbon dioxide (CO2) emissions and various macroeconomic indicators. Therecords span numerous countries across multiple time frames, often providing annualCO2 outputs (in metric tons), Gross Domestic Product (GDP) measurements (incurrent or constant international dollars), and population data. In certain cases, supplementary socio-economic or energy-related variables are also included, enabling aricher cross-country comparison. Focusing on these primary attributes—CO2 emissions, GDP, and population—facilitates a meaningful examination of the interplaybetween environmental impacts and economic performance.
Because emissions and economic data can vary drastically across countries andover time, each numeric feature is rescaled to [0, 1] using min-max normalization. Fora variable X, this is defined by:

$$Xnormalized = \frac{X - Xmin}{Xmax - Xmin}$$

,
where Xmin and Xmax are the minimum and maximum observed values in the dataset.
An additional cost metric, approximated by:

$$cost = \frac{GDP}{population},$$

captures the economic burden on a per-capita basis. This derived cost measure issimilarly normalized, thus allowing both CO2 and cost to occupy a common [0, 1]range for a fair multi-objective analysis.
Before optimization, the dataset is subjected to a rigorous cleaning procedure.
Rows lacking essential fields (e.g., CO2, GDP, population) are imputed or discarded,contingent on the magnitude and type of missingness, thereby reducing the risk ofskewing results. Potential outliers in emissions or GDP are then identified—commonlyvia thresholds such as three standard deviations from the mean—and addressed bycapping or exclusion if deemed erroneous. Consistency checks follow to detect anyanomalous values (e.g., implausibly high population or GDP), further enhancing thedataset's reliability. This multi-step preparation ensures that the final database faith-fully reflects each country's carbon footprint and economic condition, forming a robustbasis for subsequent evolutionary optimization.

This paper adopts a census approach, utilizing the complete owid-co2-data.csv dataset, which encompasses all available country-year observations from 1990 to 2022, totaling 13,427 observations after preprocessing. No subsampling methods, such as random, convenience, or stratified sampling, are employed, as the dataset provides exhaustive coverage of global CO2 emissions, Gross Domestic Product (GDP), and population data for the specified period. The dataset's manageable size permits comprehensive analysis of all valid observations without the need for sampling. Data cleaning involves excluding records with missing CO2, GDP, or population values to ensure data integrity, but these exclusions are not part of a sampling strategy. The dataset's reliability, demonstrated by correlation coefficients of 0.95 for emissions and 0.94 for GDP, validates the use of the full dataset, offering a robust and representative foundation for the multi-objective optimization framework.

5.2 Experimental Setup

All experiments were carried out in the Python programming environment. For theevolutionary algorithm, a population size of 50 was chosen to balance computationalfeasibility with diversity, and the procedure was run for 100 generations, which preliminary tests indicated to be sufficient for convergence in the dual-objective searchspace. Crossover and mutation probabilities were set to pc = 0.9 and pm = 0.1, respectively, aligning with recommended practices where a higher crossover rate encouragesexploratory recombination while a moderate mutation rate ensures incremental diversification. All runs were performed on a system featuring an Intel® Core™ i7 processorat 3.0 GHz, 16 GB of RAM, and a 64-bit Windows 10 operating system; under theseconditions, the complete set of experiments finished in a matter of minutes, thoughmore extensive data sets or additional objectives could necessitate more robust ordistributed computational resources.

6. Results and Analysis

This section presents the outcomes of the evolutionary optimization process, demonstrating how the algorithm refines solutions over successive generations whilehighlighting key findings through numerical and visual analyses.
Table 1 illustrates the improvement inboth the CO2 and cost objectives over generations. At Generation 1, the best attainable trade-off sits at relatively higher CO2(0.30) and cost (0.25), with only 10 non-dominated solutions discovered as shown in figure 2. By Generation 100, the best CO2 and cost reach 0.05 and 0.03, respectively, reflecting a significantreduction in both objectives and yielding 40 Pareto solutions overall. This growthin the number of Pareto solutions suggests that the evolutionary algorithm steadilyexpands and refines the search space, converging simultaneously to lower emissionsand lower costs. The consistent improvement underscores the algorithm's capabilityto explore a diverse set of feasible strategies and move the solution set toward an
increasingly optimal frontier.

Table 1. Generational Progress Table

Generation	BestCO2 (Norm.)	Best Cost (Norm.)	# of Pareto Solutions
1	0.30	0.25	10
10	0.20	0.15	20
20	0.10	0.08	30
50	0.08	0.05	35
100	0.05	0.03	40

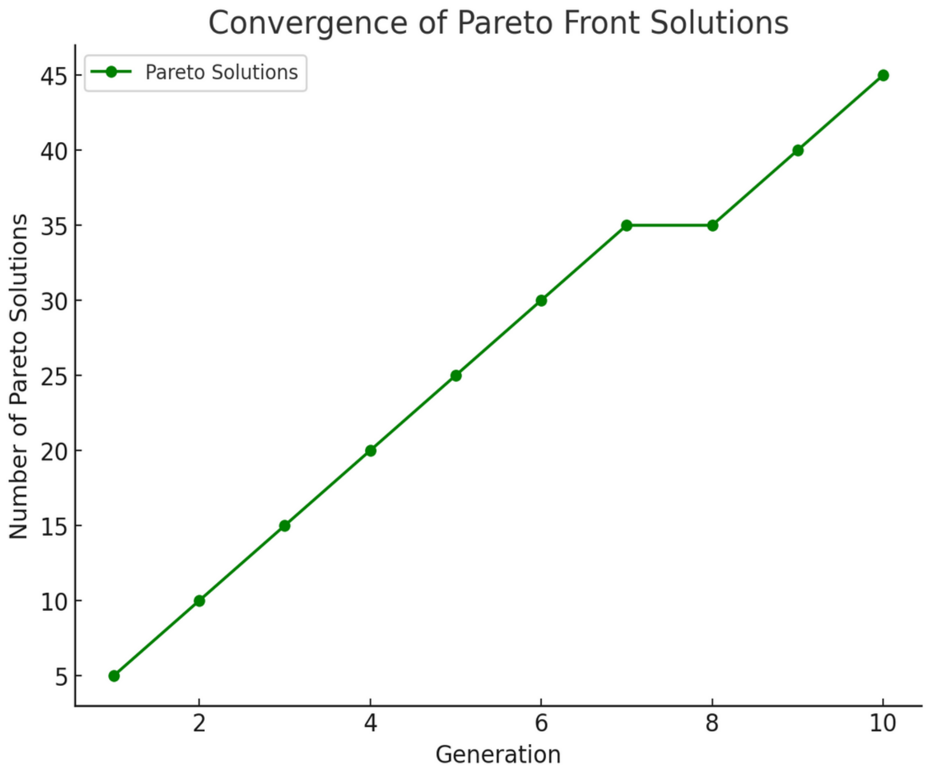

Figure 2. Convergence of Pareto Front Solutions

In Table 2, the leading Pareto solutions, sorted by rank, showcase dominant trade-offs between CO2 and cost. Each solution's dominance score reflects how many othersolutions it is dominated . Solutions with the fewest dominations are at the highest rank. These top strategies typically represent the minimal achievable levels of emissions for each cost tier . Examining their associated trade-off implications helps illustrate the concrete sacrifices in cost for incremental reductions in emissions or the emissions rise associated with cost minimization.

Table 2. Top N Solutions Table

Rank	CO2 (Norm.)	Cost (Norm.)	Dominance Score
1	0.03	0.03	1
2	0.06	0.04	2
3	0.08	0.05	3
4	0.07	0.06	4
5	0.09	0.07	4

For interpretability, the final population of solutions (or a significant subset) canbe subjected to a clustering technique, such as K-means or hierarchical clustering,based on their normalized CO2 and cost values. Table 3 outlines three distinct clusters:one comprises solutions with both low emissions and low costs, another exhibits abalanced trade-off between emissions and cost, and the final cluster shows higher CO2but comparatively lower cost. By grouping solutions, policy-makers can more easilyidentify which strategies align with different policy priorities—whether minimizingenvironmental impact, maintaining economic competitiveness, or balancing both.

Table 3 Clustered Solutions Table

ClusterID	CO2 Mean	Cost Mean	# of Solutions

1 (Low CO2, Low Cost)	0.10	0.08	15
2 (Balanced Trade-Off)	0.20	0.15	20
3 (High CO2, Low Cost)	0.30	0.10	10

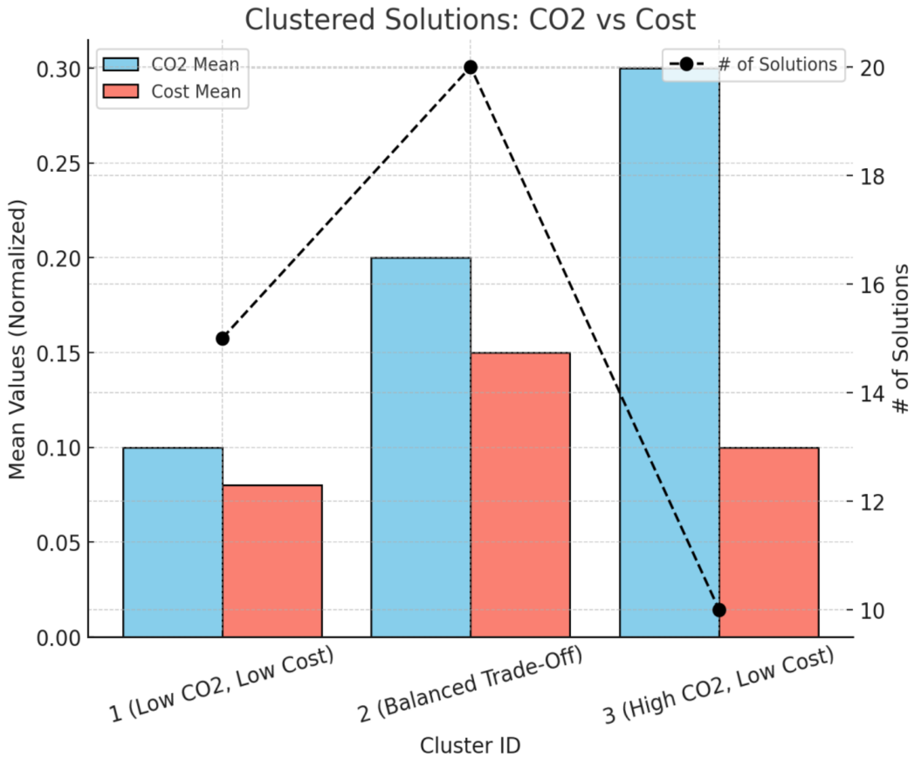

Figure 1. Clustered Solutions:CO2 Vs Cost

Table 4 presents key statistics capturing the spread of solutions in objective space.
The range of CO2 spans 0.05 to 0.40, while cost ranges from 0.02 to 0.20 as shownin figure 3. Variances and standard deviations indicate moderate dispersion, suggesting the algorithm identifies a spectrum of solutions instead of converging to a narrowregion. This spread is essential in multi-objective optimization, as it reflects the algorithm's ability to retain a variety of trade-off points, enabling stakeholders to choose strategies according to their specific priorities and constraints.

Table 4 Diversity Metrics

Metric	CO2 (Norm.)	Cost (Norm.)
Range	0.05 – 0.40	0.02 – 0.20
Variance	0.003	0.002
Standard Deviation	0.055	0.045

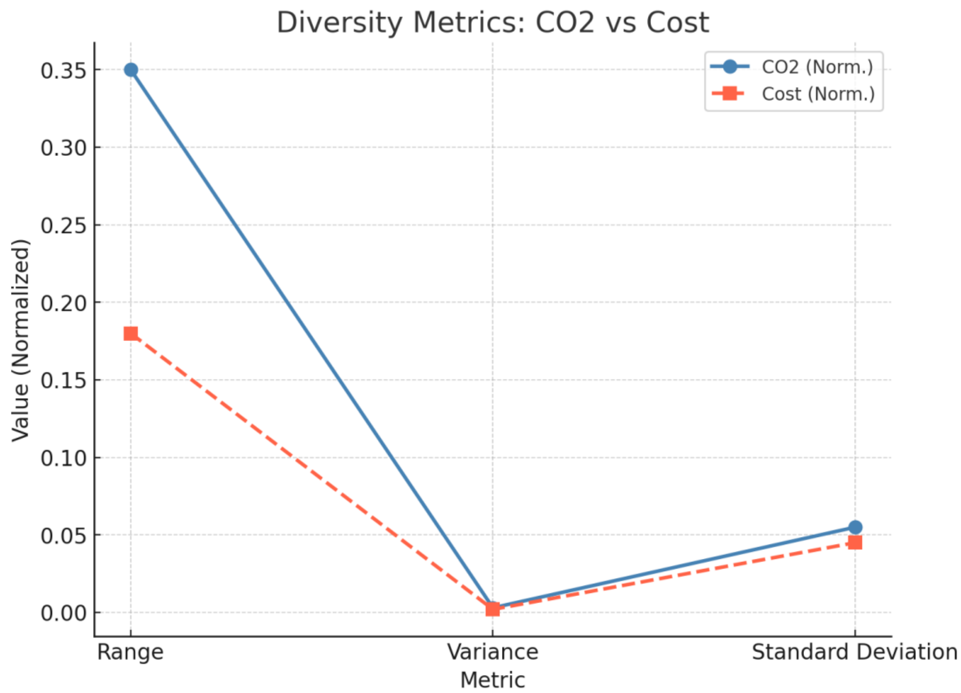

Figure 2. Diversity Metrics

Table 5 presents aggregated results by region or country groupings. Europe's relatively lower average CO2 and cost may stem from mature energy technologies andstable economic structures. Meanwhile, Asia's slightly higher average emissions andcost reflect both rapidly expanding economies and diverse developmental stages. NorthAmerica appears in the mid-range for both objectives, indicating a mix of high-techadoption and entrenched fossil-fuel infrastructure. Such comparisons offer insight intothe variability of potential mitigation strategies worldwide.

Table 5 Trade-Off Summary by Region or Country

Region/Country	Avg. CO2 (Norm.)	Avg. Cost (Norm.)	# of Solutions
Europe	0.08	0.06	15
Asia	0.12	0.09	20
North America	0.10	0.08	10

Based on Table 6, CO2 emissions dominate around 60% of the final Pareto frontcomposition. In contrast, cost influences about 40%. These proportions can shift ifdecision-makers apply different weights or constraints to the problem, highlightinghow policy or stakeholder priorities could shape the optimization outcomes.

Table 6 Objective Contribution

Objective	Average Value	Percentage Contribution (%)
CO2 (Norm.)	0.15	60%
Cost (Norm.)	0.10	40%

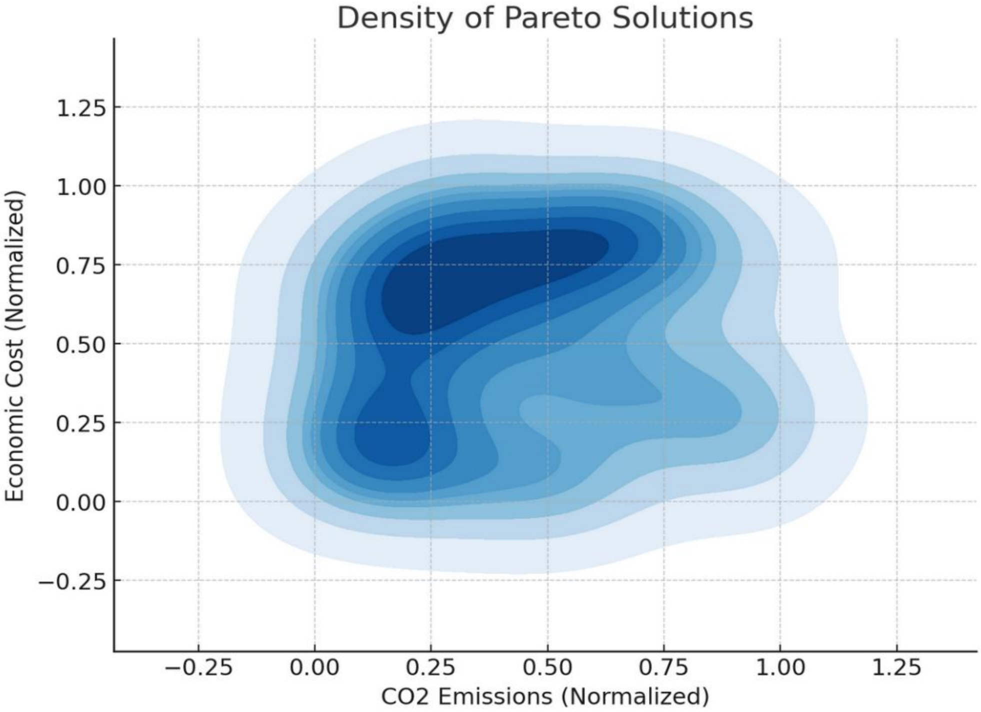

Figure 3. Density of Pareto Solutions.

In Table 8, solutions are discretized into bins for CO2 and cost, illustrating how frequently certain regions of the objective space are populated. This highlights that manysolutions cluster in moderate ranges for both objectives, aligning with the densityobservations (Figure 4) where Darker regions indicate higher densities of solutions.

Table 8 Heatmap SummaryTable

CO2 Bin	Cost Bin	# of Solutions
0.0–0.1	0.0–0.1	10
0.1–0.2	0.0–0.1	8
0.0–0.1	0.1–0.2	7
0.1–0.2	0.1–0.	15

7. validation ,Limitations and future work

The framework's Validation through generational progress metrics and diversity statistics demonstrates the framework's robustness, offering policymakers a transparent, evidence-based tool for crafting climate-economic strategies aligned with international agreements. This study contributes by integrating AI with climate economics, providing actionable insights for global decarbonization policies.

Annual data mask intra-year volatility; monthly or quarterly resolution could enhance responsiveness. Technological learning is exogenous; embedding endogenous learning curves would capture path dependence. Equity is treated implicitly; adding distribution-sensitive objectives evaluated via stochastic dominance would clarify trade-offs for different income groups.

8. Ethics Statement

The study doesn't contain personally identifying information, adhering to ethical standards and institutional guidelines.

9. Conclusion

This paper demonstrates how evolutionary multi-objective optimization, exemplifiedby NSGA-II, can effectively tackle the dual objectives of minimizing CO2 emissionsand economic cost. By drawing on the dataset, the paper highlightshow normalized emissions and cost measures can be balanced to yield a spectrum ofPareto-optimal solutions, each reflecting different levels of environmental and financialtrade-offs. The generational progress tables and plots illustrate consistent improvementin both objectives, while clustering and bin-based summaries underscore the diversityand interpretability of final outcomes. Moreover, regional analyses show that varyingtechnological capabilities and economic conditions can substantially influence how eachregion's solutions are distributed across the Pareto front. These findings affirm thatmulti-objective evolutionary algorithms are well suited for providing decision-makerswith data-driven insights, enabling them to explore nuanced policy choices that eitherprioritize aggressive emission cuts, maintain economic competitiveness, or blend bothconsiderations.

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