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Aligning Artificial Intelligence with Economic Policy for Decarbonisation: A Multi-Level Simulation Framework

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Abstract

Climate change is accelerating, yet policy responses remain fragmented, slow, and often outdated. This study presents the AI-Enhanced Decarbonisation Model (AEDM), a multi-level framework that integrates artificial intelligence with behavioural and welfare economics to support adaptive climate policymaking. AEDM evaluates decarbonisation strategies across micro (household and firm behaviour), meso (urban infrastructure), and macro (governance) levels. Using comparative simulations of Massachusetts (USA) and Seoul (South Korea), the model tests three scenarios: Business-as-Usual, Carbon Tax, and AI-Adaptive Policy. Results show that AI-driven policy feedback improves emissions reductions, lowers abatement costs, and enhances equity outcomes. The model consistently outperforms static interventions by aligning policy actions with dynamic system behaviour and social realities. This research contributes a scalable, policy-oriented tool that supports evidence-based, equitable climate transitions. Ethical and governance challenges of algorithmic policymaking are also discussed, with recommendations for future interdisciplinary research.

Keywords: Artificial Intelligence, energy transition, climate policy, behavioural economics, decarbonisation.

1. Introduction

The world has reached a definitive turning point in the urgency of decarbonisation, driven by the escalating impacts of climate change. Traditional policy and planning approaches often fall short of addressing the complexity and dynamism of today's climate-related socioeconomic systems. Mitigation and adaptation strategies are not only imperative but must also be precise and rapid to respond effectively to evolving conditions. Yet, pathways toward net-zero

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emissions remain fragmented, slow to adapt, and frequently obsolete by the time they are implemented at the local level.

At the same time, artificial intelligence (AI) has emerged as a powerful tool capable of processing complex, multidimensional data in real time and modelling the behaviour of dynamic systems under uncertainty. While much of the current literature focuses on AI's engineering and optimisation capabilities, its integration into economic policy design for sustainability remains limited. There is a growing need to reconceptualise AI not merely as a technical enabler but as a core component within policy-driven economic frameworks—designed to support socially equitable, context- sensitive, and adaptive energy transitions.

This paper introduces the AI-Enhanced Decarbonisation Model (AEDM), an innovative, multi-level framework developed to support energy transition decision making by aligning AI with key principles of behavioural and welfare economics.

AEDM operates across three levels of intervention—micro (household and firm behaviour), meso (infrastructure and urban systems), and macro (governance and regulatory environments)—and evaluates decarbonisation pathways based on their effectiveness, economic efficiency, and distributive equity. The model is applied in a comparative case study of two innovation-driven, high-emission regions—Massachusetts (USA) and Seoul (South Korea)—to explore how AI-enabled policy modelling can enhance the precision, adaptability, and resilience of climate action across diverse governance contexts.

2. Literature Review

The intersection of artificial intelligence (AI), climate policy, and economic modelling is a rapidly evolving research domain. AI systems have been proven extremely efficient in regulating energy demand, forecasting renewable energy availability, and enhancing system resilience in response to climate fluctuations (Liu et al., 2022; Chen et al., 2024). While AI has advanced significantly in energy systems optimisation, demand-side management, and environmental monitoring (Rolnick et al., 2022), its integration into policy development—particularly when combined with behavioural and economic modelling—remains underexplored.

Recent studies emphasise AI's capacity to address complex policy challenges in the energy transition. Kyriakarakos (2025) presents a broad analysis of how AI may accelerate decarbonisation across sectors, highlighting the importance of real- time energy data and infrastructure forecasting. Adewoyin and Adediwin (2025) argue that AI tools have improved energy access modelling and decentralised energy system management, particularly in developing economies.

From a modelling standpoint, reinforcement learning (RL) and agent-based modelling (ABM) are increasingly applied to simulate dynamic policy systems. Zhou and Dan (2025) use RL to show that adaptive policy feedback can outperform static interventions in emissions reduction and systemic resilience. Dave and Serasiya (2025) explore AI-powered smart grids and their capacity to optimise performance and adapt to consumer behaviour. Ukoba et al. (2024) highlight how integrating AI into smart energy systems can support carbon neutrality by improving system coordination and predictive planning across sectors. Wu et al. (2020) propose a hybrid agent-based modelling approach informed by AI to simulate low-carbon transition policies, demonstrating its value in capturing emergent behaviour under dynamic governance conditions. Pimenow et al. (2024) offer a comparative evaluation of neural network- based forecasting in grid decarbonisation, emphasising the role of learning-based control systems.

Köhler et al. (2009) emphasise that successful sustainability transitions depend on aligning technological innovation with institutional change and multi-level governance. Their work underscores the importance of integrated, cross-scalar approaches—an orientation mirrored in the AEDM framework, which explicitly models micro (behavioural), meso (infrastructure), and macro (governance) interactions. Prior models have laid important groundwork for simulating energy transitions, particularly through hybrid economic-environmental models that combine macroeconomic forecasting with technology diffusion (Mercure et al., 2016), or through agent-based systems focused on household or firm behaviour (Wu et al., 2020). However, these approaches typically isolate one policy level—micro, meso, or macro—and rarely incorporate AI for real-time adaptability. AEDM distinguishes itself by unifying all three levels in a single, feedback-responsive system. Its originality lies in aligning artificial intelligence with behavioural and welfare economics, and in simulating dynamic governance strategies across structurally distinct policy environments. The novelty lies in AEDM's ability to evaluate cross- scalar interactions and simulate adaptive climate governance under diverse institutional contexts.

Despite these advancements, few studies explicitly incorporate behavioural economics into AI-driven policy models. Traditional approaches often assume rational decision making, overlooking the role of social norms, cognitive biases, and institutional trust in shaping energy behaviour (Shogren, 2012). In parallel, Croson and Treich (2014) emphasise the need for incorporating empirically grounded behavioural assumptions—such as bounded rationality, fairness preferences, and reference dependence—into environmental economic models, reinforcing the case for integrating behavioural dynamics into AI-informed policy design. Velardi (2023) demonstrates how norm messaging and social comparison can influence consumption behaviour in both residential and commercial settings. Fan et al. (2023) contend that deep learning applications for sustainability must integrate behavioural dimensions to ensure ethical and adaptive system responses.

Institutional design and political economy also play a critical role in shaping the application of AI in policymaking. Cortez (2023) highlights the risks of assigning climate-sensitive decisions to AI systems without sufficient democratic oversight. Sokołowski (2021) contrasts AI regulatory frameworks in the EU and Japan, revealing divergent institutional pathways that influence adoption and policy scalability.

The growing attention to AI ethics and energy justice further reinforces these considerations. Qudrat-Ullah (2025) advocates for embedding ethical design principles in AI systems to avoid replicating structural inequalities in climate transitions. Miller et al. (2024) underline the need for governance policy that align AI technologies with sustainability and equity goals. Gill and Germann (2022) stress the importance of transparency and accountability in algorithmic decision making, while Sovacool et al. (2020) underline the necessity of participatory, inclusive AI systems to prevent the amplification of existing social disparities.

Together, these contributions support the development of integrated frameworks like the AI-Enhanced Decarbonisation Model (AEDM). Unlike purely technical optimisation tools, AEDM incorporates equity, behavioural responsiveness, and policy feedback—making it more suitable for adaptive, just, and context-aware climate governance.

3. Methodology

This chapter presents the methodological framework used in the development and application of the AI-Enhanced Decarbonisation Model (AEDM). The model integrates artificial intelligence techniques with principles of behavioural and welfare economics to evaluate decarbonisation pathways at multiple levels of the energy transition system. It is designed to simulate adaptive policy responses and socioeconomic dynamics under varying governance structures and climate policy scenarios.

AEDM is structured across three interdependent levels:

- Micro-level: models household and firm behavioural responses to energy pricing, regulation, and incentive schemes;
- Meso-level: simulates transformations in infrastructure systems, including energy grids, transportation networks, and industrial assets;
- Macro-level: evaluates the impact of governance mechanisms, carbon pricing regimes, and public investment strategies.

The model is grounded in behavioural economics, recognising that individuals and companies often make decisions based on limited information, varying motivations, and limited capabilities for prediction. It incorporates diverse human profiles and simulates non-linear responses to policy changes under real-world uncertainty and change. At the macro scale, the framework incorporates welfare optimisation principles, assessing trade-offs between economic efficiency (how much is the cost per ton CO_2), environmental effectiveness (whether it builds long-term resilience), and social equity (what is the energy burden on vulnerable populations).

AEDM comprises five interconnected modules:

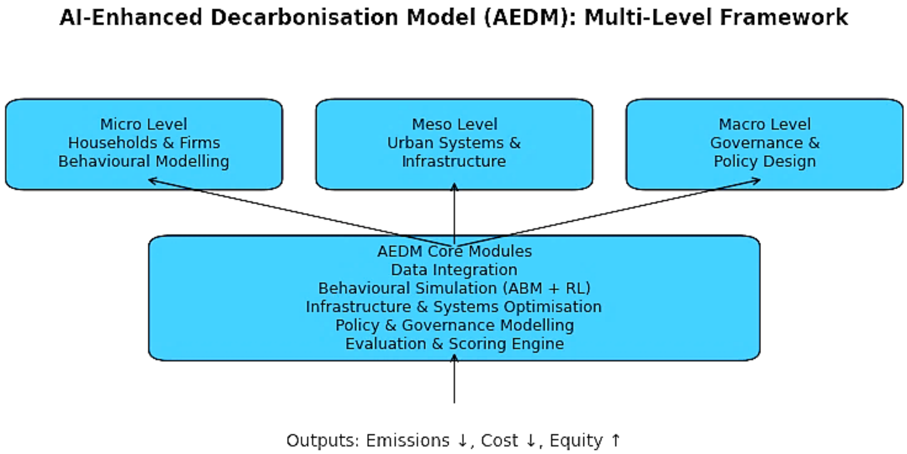
- Data Integration Module: consolidates real-time and historical data related to energy consumption, carbon emissions, economic indicators, and regulatory thresholds. The raw data underwent transformation and feature development to improve model interpretability supported by AI algorithms.
- Behavioural Simulation Engine: utilises agent-based modelling (ABM) enhanced by reinforcement learning to capture micro-level responses. Agents differ by income class, sector, and energy consumption profile, enabling a realistic simulation of behavioural diversity.
- Systems Optimisation Layer: simulates meso-level infrastructure transitions using system dynamics and AI-based optimisers. It includes investment cycles, grid evolution, and adaptive deployment of technologies (e.g., electric vehicles, heat pumps).
- Policy and Governance Module: models macro-level instruments such as carbon taxes, subsidies, mandates, and public-private investment structures. It supports scenario testing under different regulatory paradigms (centralised, decentralised, or hybrid).
- Evaluation Engine: scores each scenario on emissions reduction, system cost, resilience, and distributive equity. Monte Carlo simulations are used to test policy robustness under sociotechnical uncertainty.

3.1 Software Implementation and Simulation Environment

The AI-Enhanced Decarbonisation Model (AEDM) was implemented using Python 3.11. Agent-based components were developed using the Mesa modelling framework, while reinforcement learning logic was built using stable-baselines3 integrated with OpenAI Gym for simulation environments. Data processing, normalisation, and feature extraction were carried out using NumPy, pandas, and scikit-learn. Simulation dynamics and infrastructure modelling were coded as modular scripts to support policy scenario switching. Visualisation and diagnostics were created using matplotlib and seaborn.

Each simulation scenario was run over a 15-year time horizon (2025-2040), with policy levers (e.g., tax rates, subsidies, investment thresholds) dynamically adjusted at each time step in the AI-adaptive condition. Outputs—including emissions levels, marginal abatement cost, and equity scores—were stored and evaluated using custom metrics to compare scenarios. All code was modularised to allow replication and future model extension.

Figure 1. AEDM multi-level framework integrating micro (behavioural), meso (infrastructure), and macro (governance) systems with AI-based decision modules and decision outputs



Source: generated by the authors.

To assess the applicability and comparative performance of AEDM, a case study analysis was conducted using data from Massachusetts (USA) and Seoul (South Korea). These regions were selected due to their similarities, like carbon high emissions and strong focus on innovation but differing governance models—Massachusetts representing a decentralised energy governance system, and Seoul exemplifying a centralised, state-led policy environment.

Simulation parameters include:

- Time horizon: 2025-2040 (annual intervals); Each year, the simulation ingests regional data (energy use, carbon emissions, pricing signals), updates behavioural responses (elasticity-weighted), applies policy rules (carbon tax, subsidies, AI-adaptive levers), and evaluates system-level outcomes.
- Discount rate 3%, consistent with commonly used values and long-term climate policy and cost-benefit analysis (U.S. Office of Management and Budget, 2003).
- Carbon pricing baseline: \$50/ton CO_2-equivalent, increasing linearly over time; Energy price elasticity varies by income group (based on literature). Infrastructure turnover is modelled as 10-20 years.
- Behavioural elasticity: estimated using empirical findings from energy
- Economics literature (Croson & Treich, 2014).
- Infrastructure turnover cycles: assumed to range between 10-20 years, depending on sector.

3.2 Simulation Parameters Justification

A 3% real discount rate was applied to evaluate the present value of future costs and emissions reductions. This rate is widely used in climate policy modelling and aligns with recommendations from the IPCC and the U.S. Office of Management and Budget for long-term public investment assessments (IPCC, 2021; U.S. Office of Management and Budget, 2003). Lower discount rates (1-3%) are considered appropriate when evaluating intergenerational climate policies.

Behavioural elasticity refers to the degree to which agents (households, firms) adjust their energy use in response to changes in pricing, regulation, or incentives. In AEDM, elasticity values were calibrated based on empirical findings from Croson and Treich (2014), who report ranges of responsiveness to carbon taxes, rebates, and norm- based nudges. We implemented differentiated elasticities across income groups to reflect behavioural heterogeneity, in line with literature on bounded rationality and energy decision making.

Three policy scenarios were simulated: (i) Business-as-Usual (BAU), (ii) Price-based interventions (carbon tax and subsidy mechanisms), and (iii) AI-enhanced adaptive scenario, where feedback loops influence near-real-time adjustments in policy levers.

AEDM outputs are analysed in terms of emissions reductions, policy precision, economic efficiency, and social equity, offering insights into the adaptive capacity of each region’s policy environment. This methodology enables a multi-dimensional evaluation of the energy transition, moving beyond static forecasting toward a more responsive, AI-enabled economic modelling paradigm.

4. Analysis/Results Interpretation

This chapter presents the results of the comparative simulations run using the AI- Enhanced Decarbonisation Model (AEDM). The model was applied to two regions—Massachusetts (USA) and Seoul (South Korea)—to evaluate how different governance structures and policy tools affect decarbonisation outcomes under various scenarios. Each simulation spans a 15-year period (2025-2040), modelling system responses to three policy configurations: (i) Business-as-Usual (BAU), (ii) Price-Based Intervention, and (iii) AI-Enhanced Adaptive Policy.

4.1 Emissions Reductions

Both regions showed significant improvements in emissions outcomes under the AI- enhanced adaptive scenario. In Massachusetts, total CO_2-equivalent emissions declined by 36%, compared to 21% under BAU and 29% under carbon tax-only interventions. South Korea, operating under a more centralised governance structure, achieved a 42% reduction with adaptive AI feedback, versus 27% and 33% under the other two scenarios.

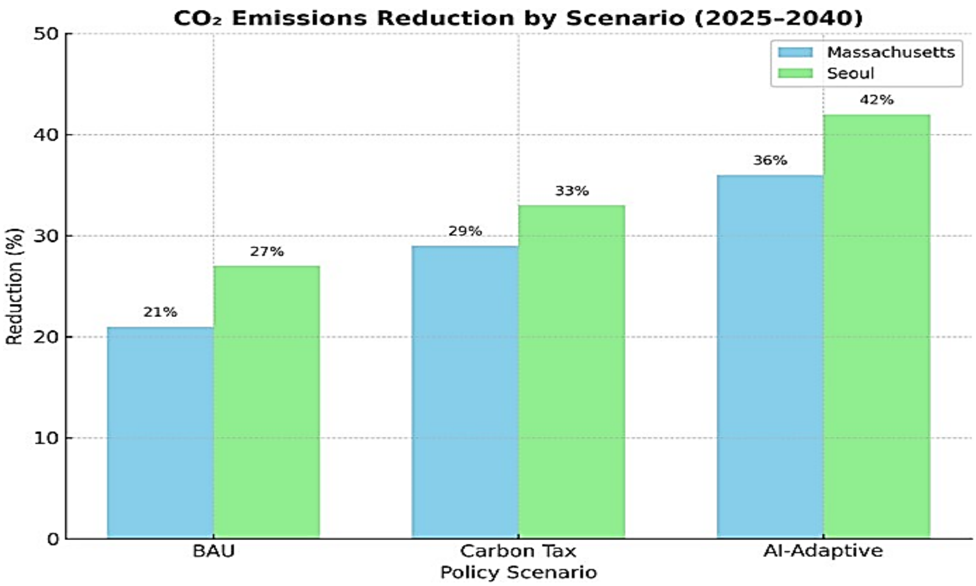
These findings suggest that adaptive, feedback-driven policies respond more effectively to systemic change and better align with real-world behavioural and energy use dynamics.

Table 1. Input assumptions used in AEDM simulations for Massachusetts and Seoul

Input Parameter	Massachusetts (2025)	Seoul (2025)	Source/Justification
Baseline CO2, Emissions	70 $MtCO_2$	120 $MtCO_2$	Regional energy plans OECD (2023)
Carbon Tax (if active)	$50/ton	$50/ton	Scenario design (generated by author)
Energy Demand Growth Rate	+1.2% per year	+0.8% per year	Literature based assumptions (generated by the author)
Infrastructure Maturity	Mid-level (non-smart grid)	Advanced (smart grid)	Qualitative index (generated by author)
Price Elasticity (Low-Income)	-0.2	-0.3	Croson & Treich (2014); Shogren (2012)
Discount Rate	3% real	3% real	IPCC (2021); U.S. Office of Management and Budget (2003)

Source: generated by the authors.

Figure 2. Simulated CO_2 emissions reductions (%) in Massachusetts and Seoul under three policy scenarios: Business-as-Usual (BAU), Carbon Tax, and AI-Adaptive Policies. Results show improved outcomes under adaptive governance driven by AI feedback mechanisms



Source: generated by the authors.

4.2 Cost-Effectiveness and Policy Precision

AEDM's evaluation engine assessed cost-effectiveness in terms of marginal abatement cost—the cost of avoiding one additional ton of CO_2 emissions. The AI-adaptive scenario consistently achieved lower costs than its static-policy counterparts. In Massachusetts, the adaptive model yielded an average abatement cost of \$78/ton, compared to \$104/ton under a fixed carbon tax. In South Korea, dynamic adjustments enabled by AI lowered the average cost to \$65/ton, attributed to centralised policy coordination and integrated data feedback.

Policy precision, defined as the ability to target interventions where they have the greatest impact, improved by 22-31% as measured through reductions in energy inequality indexes and peak demand volatility.

Table 2. Average marginal abatement cost (\$/ton CO_2 reduced) across three policy scenarios in Massachusetts and Seoul. AI-adaptive policies consistently achieved lower costs compared to static interventions

Policy Scenario	MA (\$/ton CO_2)	Seol (\$/ton CO_2)
BAU	-	-
Carbon Tax	104	93
AI-Adaptive	78	65

Source: generated by the authors.

4.3 Systemic Resilience and Infrastructure Adaptability

Infrastructure simulations showed improved adaptive capacity in both regions under AI-informed scenarios. In Massachusetts, transitions in electric vehicle (EV) adoption were smoother—characterised by fewer demand spikes, more consistent tech uptake, and stable investment cycles. Peak load flattening and coordinated household energy retrofits helped mitigate grid stress and blackout risks.

Seoul, with its strong digital infrastructure baseline, exhibited even greater systemic resilience, achieving a 25% reduction in blackout probabilities and faster recovery from simulated disruptions.

These gains were enabled not only by technical optimisation but also by behavioural feedback mechanisms embedded at the micro level—for example, consumer responsiveness to dynamic pricing and community-based solar participation.

4.4 Social Equity Outcomes

Distributive equity—measured using a composite energy justice index—also improved significantly. In Massachusetts, low-income households experienced a 14% reduction in energy cost burden due to targeted subsidies and adaptive pricing. In Seoul, the equity index improved by 18%, supported by real-time targeting and broad access to efficiency upgrades.

These outcomes underscore that AI-informed policy models, when designed with equity in mind, can simultaneously enhance environmental and social performance—consistent with the welfare economics framework underpinning AEDM.

4.5 Interpretation and Policy Implications

The comparative results highlight several key insights:

- **AI integration** enhances policy flexibility, enabling real-time alignment with shifting behavioural and infrastructural dynamics.
- **Governance context matters**: While Seoul's centralised system produced slightly better outcomes, Massachusetts showed that adaptive models can effectively compensate in decentralised environments.
- **Behavioural realism** is critical: Models that omit behaviourally responsive mechanisms miss substantial potential from demand-side interventions.
- **Equity** is not optional: Properly designed AI-driven models can prioritise fairness without sacrificing efficiency.

Taken together, these findings reinforce the need to embed AI systems within broader economic policy frameworks, not just technical energy planning. AEDM demonstrates the value of multi-level, adaptive modelling to support more holistic, resilient, and just approaches to climate governance.

5. Conclusions

This research developed and implemented the AI-Enhanced Decarbonisation Model (AEDM) to simulate adaptive, policy-driven energy transitions in two innovation- intensive, high-emission regions: Massachusetts (USA) and Seoul (South Korea). The model integrates artificial intelligence with behavioural and welfare economics to evaluate decarbonisation pathways at the micro (behavioural), meso (infrastructure), and macro (governance) levels.

Three policy scenarios were examined: Business-as-Usual, a static Carbon Tax, and an AI-adaptive policy regime. The AI-enhanced adaptive scenario outperformed static models across all evaluation criteria, including emissions reductions, cost-effectiveness, systemic resilience, and equity outcomes. AI-driven feedback mechanisms enabled more precise and responsive policy targeting, reducing marginal abatement costs while supporting fairer distribution of decarbonisation benefits.

These findings support the hypothesis that AI can significantly enhance the responsiveness and effectiveness of decarbonisation frameworks, particularly when embedded in economic models that reflect real-world behaviours and institutional complexity. This reinforces a growing consensus in sustainability economics: that climate policy must move beyond deterministic or technocratic optimisation toward more adaptive, context-sensitive approaches. Prior models identified in literature focus either on a single level (e.g., household behaviour or grid optimisation) or lack real-time feedback capability. By contrast, AEDM demonstrates that integrating artificial intelligence with behavioural economics and welfare trade-offs allows for more adaptive and equitable policy targeting. The emissions reductions achieved in the AI-adaptive scenario—up to 42% in Seoul and 36% in Massachusetts—are comparable or greater than outcomes reported in studies using fixed carbon tax or subsidy-based approaches.

The model's architecture also enables the direct simulation of regionally distinct policy environments. This feature is particularly novel compared to larger-scale integrated assessment models (IAMs), which tend to generalise institutional behaviour. AEDM's flexibility and modularity position it as a valuable complement to such macro-scale models, especially for national or urban-level climate policy experimentation. The most significant contribution lies not just in its performance metrics, but in its design philosophy: a shift from top-down optimisation toward context-aware, multi-level governance simulation.

However, the study is not without limitations. AEDM simulations are based on modelled scenarios rather than real-time deployment, and several assumptions—such as behavioural elasticity and infrastructure turnover—are derived from literature rather than localised empirical data. While the two case studies provide meaningful contrasts, broader applications across varying governance systems and economic contexts are needed to further validate the model's scalability and robustness.

Future research could expand the AEDM architecture by incorporating dynamic labour market impacts, transnational energy trade, and co-benefits such as public health and innovation spillovers—indirect advantages that arise when new technologies developed in one region benefit others. The governance component may also be deepened to account for institutional inertia, political feasibility, and the ethical challenges associated with using AI in public decision making.

In conclusion, AEDM demonstrates the potential of integrating AI with economic modelling to support adaptive, equitable, and evidence-based climate policy. By aligning technological capability with social and institutional realities, it provides a practical framework as a foundation for implementing adaptive and effective climate governance in response to accelerating climate risks.

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