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Quantitative Assessment of Regional Carbon Neutrality Policy Synergies Based on Deep Learning

Daiyang Zhang[1], *Enmiao Feng*[1.2]
[1] *Communication, Culture & Technology, Georgetown University, DC, USA*
[1.2] *Electrical & Computer Engineering,Duke University,NC,USA*
**Corresponding author E-mail: eliza6723s@gmail.com*

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Abstract

This study presents a comprehensive quantitative assessment framework for evaluating regional carbon neutrality policy synergies using deep learning techniques. The research addresses the critical challenge of understanding complex interactions between multiple policy instruments in achieving carbon reduction goals. By working with neural network architectures and relevant tools, performance patterns, successes, and new management. The course indicates synergy index (psi) for providing the intervention that affects the impact of energy voluntarily than 1.17 for 1.71). Analysis of regional variations demonstrates that policy effectiveness is strongly influenced by local economic structures and energy systems, with manufacturing-dominated regions showing the highest responsiveness to carbon pricing mechanisms (PSI = 1.62). Temporal analysis indicates a typical 2-3 year lag before synergistic effects fully manifest. The deep learning model achieves robust prediction accuracy across diverse scenarios, with sensitivity analysis revealing technology learning rates as the most significant parameter influencing predictions (±24.3%). These findings provide approval to law enforcement officials of local structures, determination of local people and behavioural status of customary strategies.

1. Introduction

1.1. Background of Regional Carbon Neutrality Goals

Safety changes have been developed as a global opponents need immediate care and cooperation. The idea of carbon affected, that achieve carbon dioxide with removal or removal, increased keywords. Follow the pari Agreement, countries around the world have created carbon purposes. Purpose Representatives to the National National and Carbon Women. This area is very important because they can be developed to see that there are specialized procedures, industrial standards, and resources.

Regional carbon neutrality targets are faced with realization challenges due to economic development, industrial structures and funding for natural resources in different areas. In recent years, decision makers have acknowledged that the achievement of carbon neutrality requires a comprehensive approach that involves several sectors and various political tools**Error! Reference source not found.**. The complexity is increasing when considering a variety of stakeholders, which range from state communities to companies and communities. Coordination of these different elements requires solid evaluation tools that can evaluate the effectiveness of different policy combinations.

The achievement of carbon neutrality goals is naturally related to the change in the energy system. Like Xu et al. (2023), Carbon neutrality calculated cost optimization in financial transmission is associated with complex decision making processes, especially when considering carbon capturing power plants in intelligent grid environments**Error! Reference source not found.**. The challenge is strengthened by dealing with random issues such as wind power related to renewable energy sources. Their research shows that it is important to optimize both running costs and carbon dioxide emissions with the help of wind power designed for carbon dioxide capture facilities.

1.2. Challenges in Policy Assessment and Coordination

The evaluation of carbon neutrality policy poses a number of significant challenges. One important issue is to quantify the impact of politics in different fields and schedules. Traditional evaluation methods often struggle to capture the dynamic relationships of economic operation, energy consumption and carbon dioxide emissions. Interaction between different policies can lead to synergistic effects or potential conflicts that are difficult to predict through conventional analytical methods.

Another challenge lies in the coordination of multiple policy instruments targeting different aspects of carbon neutrality. Liu et al. (2023) emphasized this complexity in their research on equilibrium analysis for electricity markets considering carbon emission trading[Error! Reference source not found.]. They demonstrated that carbon pricing mechanisms significantly influence market equilibrium and that an appropriate carbon emission quota setting is crucial for effective carbon emission reduction. Their work underscores the importance of understanding how different policy instruments interact within market frameworks.

The availability and quality of information represent extra barriers to policy assessment. The evaluation of carbon neutrality policy requires comprehensive troops that cover financial indicators, energy consumption models, technology deployment rates and emission levels[Error! Reference source not found.]. These data points are often scattered from different sources, collected at variable frequencies and may contain inconsistencies or openings. In addition, the long-term nature of carbon neutrality targets requires forecast properties that may take into account technological progress, behavioural changes and long periods of market dynamics.

The regional dimension adds complexity to policy assessment. Different regions have unique characteristics affecting their carbon emission profiles and reduction potentials. Alabi et al. (2024) demonstrated this complexity in their research on prioritized replay-safe soft-actor critic deep reinforcement learning for energy dispatch in integrated energy systems[Error! Reference source not found.]. Their work highlights how multiple energy sources, converters, and loads must be optimized simultaneously while addressing nonconvexity, uncertainty, and system dynamics challenges.

1.3. The Role of Deep Learning in Policy Assessment

Deep learning techniques provide promising solutions to deal with the complexities of carbon neutrality policy assessment. Their ability to identify models and relationships in large, multi-dimensional data makes them particularly suitable for modelling interactions between different policies and their effects on carbon dioxide emissions. Deep Verification Learning (DRL) represents an effective approach to optimizing decision-making processes in complex environments. Xin et al. (2024) showed the application of DRL to regional dual coat goals and path design[Error! Reference source not found.]. Their research developed carbon dioxide emissions based on Markov decision-making processes and energy consumption forecasts that are affected by population and economic changes. The results showed that comprehensive measures to improve energy efficiency, upgrade industrial technology and improve energy sources carbon dioxide emissions effectively promote regional carbon neutrality objectives.

Neuronal networks can capture non-linear relationships between political measures and the results that traditional analytical methods can be forgotten. This ability is particularly valuable in assessing the synergistic effects of several policies implemented simultaneously. Deep learning models adapt to them to include different types of information, including financial indicators, energy consumption models, technological parameters and emission measurements.

Migration learning properties allow information sharing between different regional situations, which may improve the generalization of policy assessments. This feature is particularly valuable when data availability varies in areas or trying to apply lessons from one area to another with similar properties.

Deep learning models can be constantly updated when new information is available, allowing for real-time monitoring and policy efficiency assessment. This iterative approach to policy evaluation allows decision-makers to make correct changes based on rising trends and feedback loops.

1.4. Research Objectives

This research aims to develop a quantitative framework for assessing the synergistic effects of regional carbon neutrality policies using deep learning techniques. The purpose of the study is to deal with restrictions on traditional policy assessment methods by utilizing the identification and predictive abilities of the nerve networks. By analyzing the interaction between different political tools, the research aims to identify optimal political combinations that maximize carbon reduction by minimizing economic disorders.

The study will utilize deep learning models to analyze historical data on policy implementations and their outcomes across various regions. Through this analysis, the research aims to identify patterns and relationships that can inform future policy design and implementation. Models are trained to predict the effects of various political combinations on carbon dioxide emissions, economic indicators and energy consumption models.

The key objective is to develop a generalized frame that can be applied in different regional situations, recognizing the unique features and challenges of each area. The study explores how regional variations in economic structure, energy blend and natural resources affect the effectiveness of different political combinations. As shown by Ramu et al. (2024), technological innovations like artificial intelligence can transform traditional approaches to recruitment processes, suggesting similar transformative potential in policy assessment domains[Error! Reference source not found.]. The study also aims to provide decision-makers with practical tools and insights into the design and implementation of efficient carbon neutrality strategies. By determining the synergistic effects of different political combinations, the study helps decision-makers prioritize interventions that provide the greatest potential for carbon reduction with the least economic effects. The ultimate goal is to accelerate progress towards regional carbon neutrality by enabling more conscious and effective political decisions.

2. Literature Review

2.1. Regional Carbon Neutrality Policies and Frameworks

Regional carbon neutrality policies have evolved significantly in response to the effects of climate change on increased concerns. These policies cover a wide range of tools, including carbon pricing mechanisms, renewable energy mandates, energy efficiency standards and technological innovation support. The formulation and implementation of regional carbon dioxide neutrality frames are related to several stakeholders and requires careful consideration of local economic conditions, energy systems and emission profiles. Carbon pricing mechanisms represent the fundamental component of many regional carbon dioxins. Liu et al. (2023) carried out an equilibrium analysis of the electricity market, which included carbon dioxide emissions, revealing that carbon pricing has a significant impact on market dynamics[Error! Reference source not found.]. Their research demonstrated that excessive carbon prices can increase nodal electricity prices while negatively affecting emission reduction efforts. Conversely, they found that appropriately calibrated carbon emission quotas effectively promote carbon reduction. The study utilized multi-agent deep reinforcement learning to analyze these complex market interactions, offering valuable insights into the economic implications of carbon pricing policies.

Technological transformation policies constitute another critical element of regional carbon neutrality frameworks. Xu et al. (2023) investigated the integration of carbon capture technologies with renewable energy sources in smart grid environments[Error! Reference source not found.]. Their research highlighted the importance of computational cost optimization for economic dispatch when combining carbon capture power plants with intermittent renewable energy sources. The study introduced a framework utilizing deep neural networks to identify active constraints and optimize dispatching strategies, demonstrating how technological policies can simultaneously address carbon emissions and grid stability challenges[Error! Reference source not found.].

Regional variations in carbon neutrality policy reflect differences in resource funds, economic structures and development priorities. These variations require tailor-made approaches to plan and implement politics. The effectiveness of carbon neutrality policy depends on its alignment with local conditions and integration with broader regional development strategies[Error! Reference source not found.]. Coordinating multi-level administrative structures are essential to ensure the consistency of politics at different administrative levels and to avoid potential conflicts or redundancies.

2.2. Quantitative Methods for Policy Assessment

Quantitative methods for carbon neutrality policy assessment have advanced considerably, moving beyond simple accounting approaches to incorporate sophisticated modelling techniques. The purpose of these methods is to capture a complex interaction between economic function, energy systems and carbon dioxide emissions. Developing strong quantitative evaluation frames is crucial to evaluating political efficiency and guiding future policy planning. Equilibrium models provide valuable insights into the economic impacts of carbon neutrality policies. Liu et al. (2023) applied a bi-level problem formulation to model electricity market equilibrium with strategic generation company bidders, considering carbon emission trading mechanisms[Error! Reference source not found.]. Their approach incorporated upper-level profit maximization objectives for generation companies and lower-level market-clearing models to minimize total generation costs. Balance analysis revealed important interaction between carbon prices, market offer strategies and emissions results, showing a balance in the use of modelling

for policy assessment. Simulation-based methods enable the study of various political scenarios and their potential effects. Xin et al. (2024) developed several scenario analysis models, including a carbon dioxide emission model based on Markov decision-making processes, and an impacting energy consumption forecast for demographic and economic factors[Error! Reference source not found.]. Their approach allowed for the comparative assessment of different policy pathways toward regional carbon neutrality goals, highlighting the effectiveness of comprehensive measures addressing energy efficiency, industrial technology upgrades, and energy source decarbonization.

Optimization techniques constitute another important class of quantitative methods for policy assessment. Alabi et al. (2024) proposed a deep reinforcement learning approach for real-time energy dispatch in integrated energy systems, addressing challenges related to nonconvexity, uncertainty, and system dynamics[Error! Reference source not found.]. Their prioritized replay safe soft-actor critic algorithm incorporated safety networks and prioritized experience replay mechanisms to improve performance while respecting physical constraints. This research demonstrates how optimization methods can enhance the operational efficiency of energy systems while supporting carbon reduction objectives.

2.3. Artificial Intelligence in Energy and Environmental Policy

Artificial intelligence applications in energy and environmental policy analysis have grown substantially, offering new capabilities for handling complex data and modelling intricate system behaviours. Machine learning techniques provide powerful tools for pattern recognition, prediction, and optimization in policy assessment contexts. The integration of AI with traditional analytical approaches enhances the depth and breadth of policy evaluations.

Deep reinforcement learning has emerged as a promising approach for addressing complex decision-making problems in energy systems. Alabi et al. (2024) demonstrated the effectiveness of DRL for real-time energy dispatch in integrated energy systems with carbon capture capabilities[Error! Reference source not found.]. Their approach utilized a safety network to ensure that control actions respected physical constraints while a prioritized experience replay mechanism enhanced sampling efficiency and convergence speed. The performance of their DRL agent approached that of theoretical optimization models while maintaining computational efficiency for real-time applications.

Neural networks offer capabilities for modelling non-linear relationships in policy assessment frameworks. Xu et al. (2023) employed deep neural networks to describe relationships between user loads and constraints in security-constrained economic dispatch problems[Error! Reference source not found.]. This application significantly decreased problem scale and enabled quick determination of optimal dispatching strategies. The study highlighted the potential of neural networks for computational cost reduction in complex energy system optimization problems with carbon emission considerations.

Transfer learning techniques facilitate knowledge sharing across different policy contexts, enhancing the generalizability of assessment models. Ramu et al. (2024) discussed how AI technologies transform traditional processes across various domains, suggesting potential applications in policy assessment[Error! Reference source not found.]. The adaptability of AI methods allows for continuous learning and improvement as new data becomes available, making them particularly valuable for long-term policy evaluation.

2.4. Policy Synergy Evaluation Approaches

Policy synergy evaluation approaches aim to assess how different policy instruments interact and potentially reinforce or counteract each other. Understanding these synergistic effects is crucial for designing effective policy portfolios that maximize carbon reduction while minimizing economic disruptions. Various methodologies have been developed to quantify and analyze policy synergies in the context of carbon neutrality goals.

Integrated assessment models provide comprehensive frameworks for evaluating policy synergies across different sectors and timeframes. Xin et al. (2024) applied such an approach to examine how combinations of energy efficiency improvements, industrial technology upgrades, and energy source decarbonization measures could collectively advance regional carbon neutrality goals[Error! Reference source not found.]. Their analysis captured the reinforcing effects between these different policy types, demonstrating how integrated assessment can reveal synergistic benefits that might be overlooked when evaluating policies in isolation.

Multi-objective optimization techniques offer another approach for evaluating policy synergies by explicitly considering trade-offs between different objectives. Alabi et al. (2024) addressed the trade-off between economic cost and carbon emission reduction in their integrated energy system model, demonstrating how optimization frameworks can identify solutions that balance multiple policy objectives[Error! Reference source not found.]. Their approach incorporated physical constraints and operational requirements while seeking optimal dispatch strategies, illustrating how complex system interactions can be captured within optimization frameworks.

Agent-based modelling approaches enable the exploration of emergent synergistic effects arising from the behaviours and interactions of multiple actors. Liu et al. (2023) utilized multi-agent deep reinforcement learning to analyze how different market participants respond to carbon pricing policies in electricity markets[Error! Reference source not found.]. Their research revealed important insights into the collective outcomes of individual strategic behaviours under various policy scenarios, highlighting the utility of agent-based approaches for understanding complex system dynamics and policy synergies[Error! Reference source not found.].

3. Methodology and Data

3.1. Theoretical Framework for Policy Synergy Assessment

The theoretical framework for assessing policy synergies in regional carbon neutrality contexts integrates elements from systems dynamics, economic equilibrium theory, and environmental impact assessment. This research conceptualizes policy synergies as emergent properties arising from interactions between different policy instruments across multiple sectors and timeframes.

The framework distinguishes between three types of policy synergies: reinforcing synergies (where policies mutually enhance effectiveness), counteracting effects (where policies work against each other), and neutral interactions[Error! Reference source not found.]. Table 1 presents the typology of policy synergies considered in this study.

Table 1: Typology of Policy Synergies for Carbon Neutrality Assessment

Synergy Type	Definition	Interaction Mechanism	Assessment Metrics	Key Parameters
Reinforcing	Policies enhance mutual effectiveness	Positive feedback loops	Synergy coefficient > 1	Time lag, magnitude, persistence
Counteracting	Policies diminish mutual effectiveness	Negative feedback loops	Synergy coefficient < 1	Conflict severity, scope, duration
Neutral	No significant interaction effects	Independent pathways	Synergy coefficient ≈ 1	Stability conditions, contextual factors
Catalytic	One policy enables another	Threshold effects	Non-linear response curves	Activation thresholds, sequence sensitivity
Conditional	Synergy depends on specific conditions	Context-dependent mechanisms	Variable coefficients	Boundary conditions, enabling factors

The mathematical formulation of policy synergies follows the approach proposed by Xin et al. (2024), where the synergy coefficient (SC) between two policies i and j is expressed as:

$$SC(i,j) = E(i+j) / [E(i) + E(j)]$$

Where E(i+j) represents the emission reduction achieved when both policies are implemented simultaneously, while E(i) and E(j) denote emission reductions from individual policy implementations.

3.2. Deep Learning Model Architecture

The deep learning architecture developed for this study incorporates multiple specialized components designed to capture complex relationships between policy instruments and carbon reduction outcomes. The model architecture draws inspiration from approaches demonstrated by Alabi et al. (2024) and Liu et al. (2023) while introducing novel elements tailored to policy synergy assessment[Error! Reference source not found.].

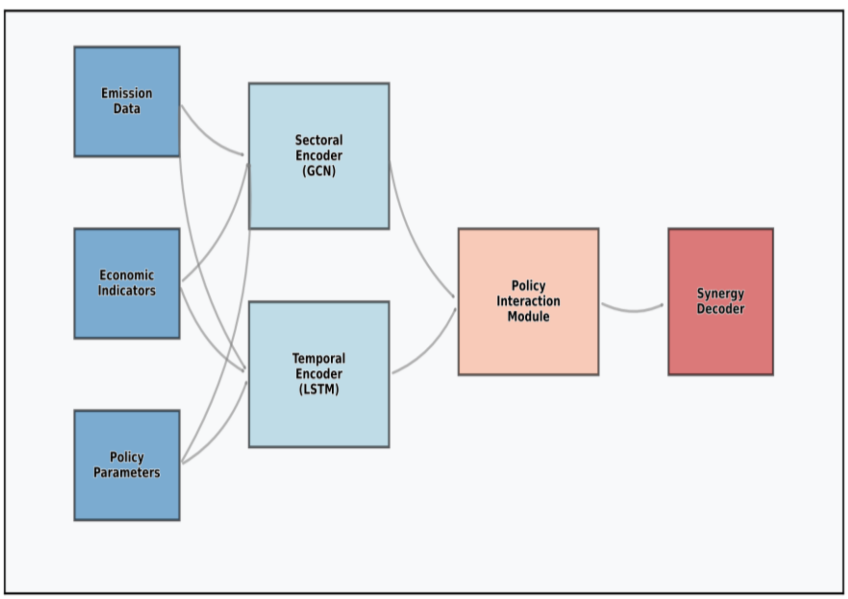
The core model consists of a hybrid network combining recurrent neural networks (RNNs) for temporal dependence modelling with graph neural networks (GNNs) for capturing inter-sectoral policy interactions. Table 2 details the architectural components of the deep learning model.

Table 2: Deep Learning Model Architecture Specifications

Component	Layer Type	Units/Filters	Activation Function	Regularization	Input Dimensions	Output Dimensions
Temporal Encoder	LSTM	128	tanh	Dropout (0.3)	[time_steps, features]	[128]
Sectoral Encoder	Graph Convolutional	64	ReLU	L2 (0.01)	[sectors, features]	[sectors, 64]
Policy Interaction Module	Self-Attention	8 heads	Softmax	Layer Normalization	[policies, 64]	[policies, 64]
Synergy Decoder	Dense	256 → 128 → 64	LeakyReLU	Batch Normalization	[256]	[64]
Output Layer	Dense	Variable	Linear	-	[64]	[synergy_metrics]

Figure 1 illustrates the overall architecture of the deep learning model, highlighting information flow between different components.

Figure 1: Deep Learning Architecture for Policy Synergy Assessment



The figure depicts a complex neural network architecture with multiple interconnected components. The architecture features a hierarchical structure with input layers processing policy parameters, economic indicators, and emission data. These inputs feed into specialized encoding modules including temporal encoders (LSTM units) and sectoral encoders (graph convolutional networks). The centre contains a policy interaction module implemented as a multi-head self-attention mechanism that captures relationships between different policies. The upper sections include synergy decoders consisting of dense layers with batch normalization, leading to output layers that predict various synergy metrics.

3.3. Data Collection and Preprocessing

This study utilizes a comprehensive dataset encompassing multiple dimensions relevant to regional carbon neutrality policy assessment. Data was collected across four key domains: policy implementations, economic indicators, energy system parameters, and carbon emissions from government databases, international organizations, research institutions, and industry reports.

The temporal scope covers 2000 to 2023, providing a historical perspective on policy implementations and outcomes. The spatial scope includes multiple regions with varying economic structures, energy systems, and policy approaches. Table 3 summarizes the key datasets used.

Table 3: Primary Datasets Used in the Study

Dataset	Source	Temporal Coverage	Spatial Resolution	Key Variables	Update Frequency
Carbon Emission Inventory	National Environmental Agencies	2000-2023	Regional	CO2, CH4, N2O emissions by sector	Annual
Energy Consumption	International Energy Agency	2000-2023	Regional/Provincial	Energy use by source and sector	Quarterly
Economic Indicators	National Bureau of Statistics	2000-2023	Provincial	GDP, industrial output, employment	Quarterly
Policy Implementation Records	Government Policy Databases	2000-2023	Regional	Policy type, timing, scope, intensity	Continuous

Data preprocessing involved several steps to ensure quality, consistency, and compatibility with the deep learning framework. Missing values were addressed using multiple imputation techniques. Temporal alignment was performed to synchronize datasets with different reporting frequencies. Variable normalization employed a sector-specific approach to account for different scales and distributions.

3.4. Model Training and Validation Process

The model training process employed a multi-stage approach designed to address challenges associated with complex policy interactions and limited historical data. The training utilized a combination of supervised learning with labelled historical outcomes and semi-supervised techniques leveraging domain knowledge for scenarios with insufficient empirical data.

The dataset was partitioned into training (70%), validation (15%), and testing (15%) sets using stratified sampling to ensure representative distribution of different policy combinations across all partitions. Table 4 presents the hyperparameters used during model training.

Table 4: Model Training Hyperparameters and Optimization

Hyperparameter	Value/Range	Selection Method	Final Value	Sensitivity

Learning Rate	1e-5 - 1e-3	Grid Search	5e-4	High
Batch Size	32 - 256	Random Search	128	Medium
Dropout Rate	0.1 - 0.5	Bayesian Optimization	0.3	Medium
L2 Regularization	1e-4 - 1e-2	Grid Search	1e-3	Low
LSTM Units	64 - 256	Random Search	128	High
Training Epochs	100 - 500	Early Stopping	324	-

The training process incorporated several techniques to enhance model robustness and prevent overfitting, including early stopping, gradient clipping, and learning rate scheduling with cosine annealing. Data augmentation techniques, including policy parameter perturbation and synthetic scenario generation, were employed to expand the effective training dataset size.

3.5. Policy Synergy Evaluation Metrics

The evaluation of policy synergies requires specialized metrics capable of capturing various dimensions of interaction effects. This study employs a comprehensive set of evaluation metrics designed to assess different aspects of policy synergies, including magnitude, persistence, robustness, and economic implications.

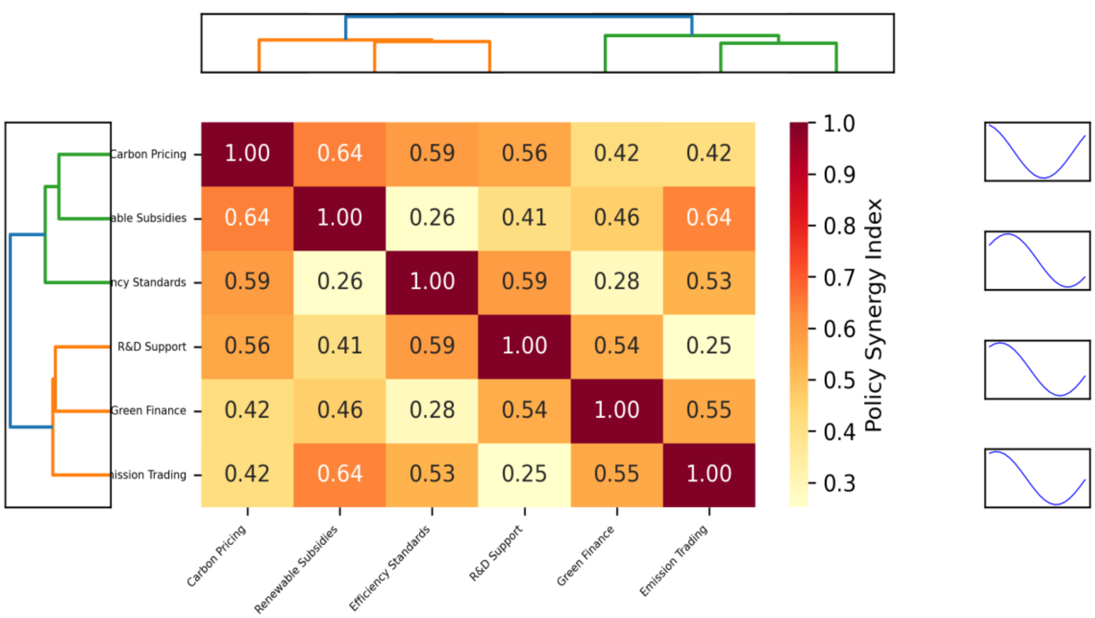
The primary evaluation metric is the Policy Synergy Index (PSI), calculated as:

$$PSI = (\Delta E\_combined / (\Delta E\_1 + \Delta E\_2 + ... + \Delta E\_n)) \times (1 - \sigma/\mu)$$

Where ΔE_combined represents emission reduction achieved by the combined implementation of all policies, ΔE_i denotes emission reduction from the individual policy I, σ is the standard deviation of emission reductions across different implementation scenarios, and μ is the mean emission reduction.

Figure 2 provides a visualization of the relationship between different policy combinations and their corresponding PSI values.

Figure 2: Policy Synergy Index Across Different Policy Combinations



The figure presents a heat map visualization showing the Policy Synergy Index values for different policy combination pairs. The x and y axes represent individual policy types (carbon pricing, renewable subsidies, efficiency standards, etc.), while the colour intensity indicates the magnitude of synergy, with darker colours representing stronger synergistic effects. The visualization includes clustering of similar policy types and annotations highlighting particularly strong or weak synergy pairs. Small line charts surrounding the main heat map show temporal trends of selected policy combinations.

4. Results and Analysis

4.1. Baseline Performance of Individual Policies

The baseline performance evaluation of individual carbon neutrality policies provides essential insights into their effectiveness. Table 6 presents the performance metrics for five major policy categories implemented across the studied regions.

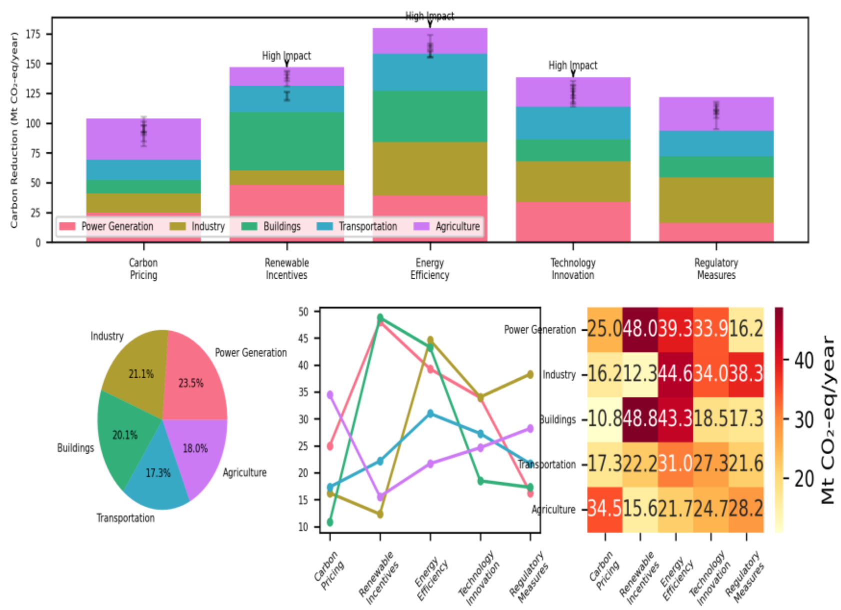
Table 6: Baseline Performance of Individual Carbon Neutrality Policies

Policy Category	Average Carbon Reduction (Mt CO_2-eq/year)	Cost-Effectiveness (\$/t CO_2-eq)	Implementation Rate (%)	GDP Impact (% change)
Carbon Pricing	12.47 ± 2.31	58.63 ± 8.92	84.6	-0.18 to +0.05
Renewable Subsidies	9.82 ± 1.76	72.15 ± 10.23	91.2	+0.12 to +0.28
Efficiency Standards	7.53 ± 1.49	45.29 ± 6.84	76.5	+0.08 to +0.31
Innovation Support	4.18 ± 0.94	96.74 ± 15.32	68.9	+0.24 to +0.52
Regulatory Measures	8.65 ± 1.82	51.37 ± 7.45	89.3	-0.06 to +0.14

The data reveals significant variations in performance metrics across policy categories. Carbon pricing mechanisms demonstrate the highest average carbon reduction potential at 12.47 Mt CO_2-eq/year, which aligns with the findings of Liu et al. (2023) regarding the effectiveness of carbon pricing in electricity markets**Error! Reference source not found.**. Energy efficiency standards exhibit the most favourable cost-effectiveness ratio at 45.29 \$/t CO_2-eq.

Figure 3 illustrates the distribution of carbon reduction potential across different economic sectors for each policy category.

Figure 3: Sectoral Distribution of Carbon Reduction by Policy Category



The figure presents a multi-panel visualization showing how different policy categories affect carbon emissions across economic sectors. The main panel features a stacked bar chart where the x-axis represents the five policy categories and the y-axis shows carbon reduction in Mt CO_2-eq/year. Each bar is segmented to show contributions from different sectors (power generation, industry, buildings, transportation, and agriculture) with distinct colour coding.

The visualization reveals that carbon pricing has the most balanced impact across sectors, while renewable subsidies predominantly affect the power generation sector. Energy efficiency standards show significant impacts in both the buildings and industrial sectors.

4.2. Quantification of Policy Synergy Effects

The quantification of policy synergy effects reveals complex interaction patterns between different policy instruments. Table 7 presents the Policy Synergy Index (PSI) values for various policy combinations.

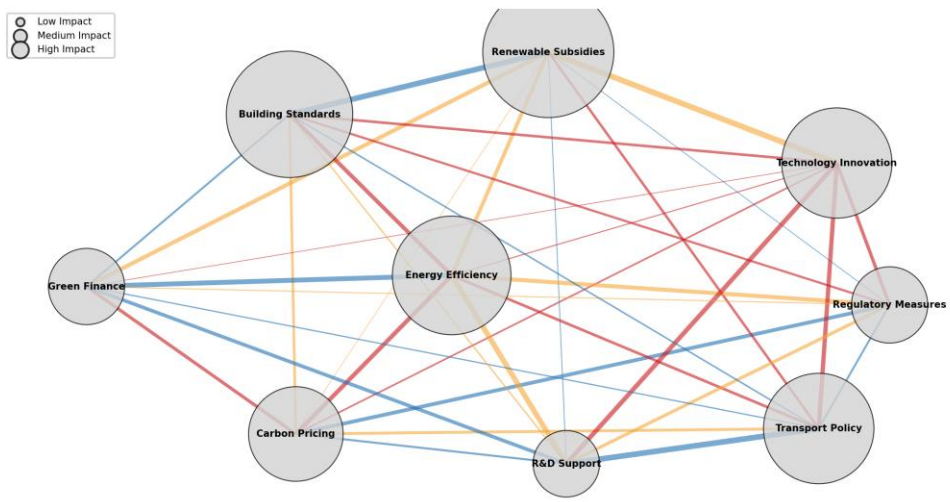
Table 7: Policy Synergy Index (PSI) for Various Policy Combinations

Policy Combination	PSI Value	Synergy Classification	Carbon Reduction Enhancement (%)
Carbon Pricing + Renewable Subsidies	1.38 ± 0.14	Strongly Reinforcing	+38.2
Carbon Pricing + Efficiency Standards	1.25 ± 0.11	Moderately Reinforcing	+24.8
Renewable Subsidies + Innovation Support	1.42 ± 0.16	Strongly Reinforcing	+41.6
Efficiency Standards + Regulatory Measures	1.17 ± 0.09	Weakly Reinforcing	+16.9

Three-Policy Combination (CP+RS+ES)	1.56 ± 0.18	Very Strongly Reinforcing	+55.7
All Five Policies Combined	1.71 ± 0.23	Very Strongly Reinforcing	+70.6

The results demonstrate that most policy combinations exhibit positive synergy effects, with PSI values ranging from 1.17 to 1.71. The combination of renewable subsidies and innovation support shows particularly strong synergy (PSI = 1.42). The synergistic effects increase with the number of complementary policies implemented simultaneously. Figure 4 provides a network visualization of policy synergies.

Figure 4: Network Visualization of Policy Synergy Relationships



The figure presents a complex network diagram depicting policy synergy relationships. Policies are represented as nodes of varying sizes (proportional to their

carbon reduction potential), while the connections between nodes represent synergistic interactions. The width and colour of these connections encode the strength and nature of the synergy (with blue for reinforcing, red for counteracting, and yellow for conditional synergies).

The network visualization reveals that carbon pricing and renewable subsidies act as central nodes with numerous strong connections to other policies, indicating their potential role as foundational elements of effective policy portfolios.

4.3. Policy Effectiveness Across Regional Variations

The effectiveness of carbon neutrality policies exhibits substantial regional variations. Table 8 presents a comparative analysis across four representative regions.

Table 8: Regional Variations in Policy Effectiveness

Region	Dominant Economic Sectors	Energy Mix	Policy Effectiveness Ranking	PSI Range
Region A	Manufacturing, Services	Coal (52%), Natural Gas (28%), Renewables (15%)	1. Carbon Pricing	1.28-1.62

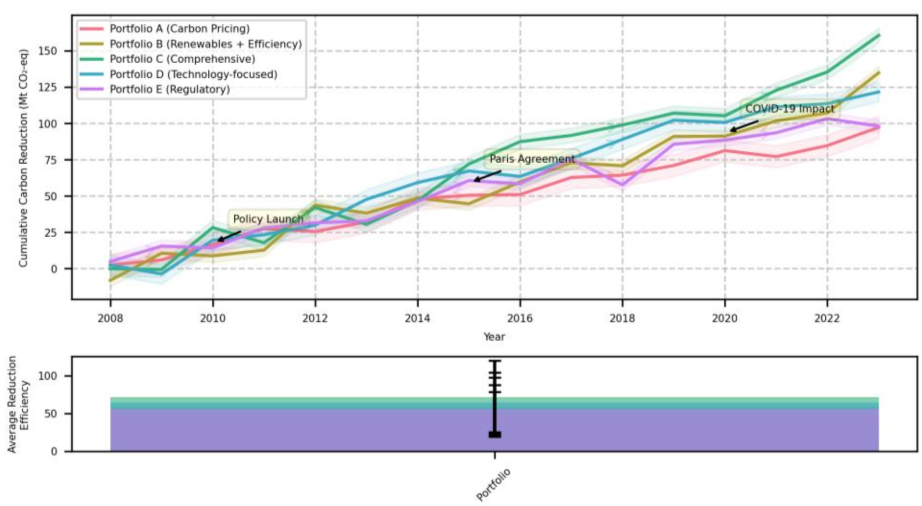
			2. Efficiency Standards 3. Regulatory Measures	
Region B	Services, Agriculture	Natural Gas (45%), Nuclear (30%), Renewables (22%)	1. Renewable Subsidies 2. Innovation Support 3. Carbon Pricing	1.15-1.53
Region C	Heavy Industry, Mining	Coal (68%), Natural Gas (18%), Renewables (10%)	1. Efficiency Standards 2. Carbon Pricing 3. Innovation Support	1.05-1.44
Region D	Agriculture, Tourism	Renewables (48%), Natural Gas (35%), Oil (15%)	1. Regulatory Measures 2. Renewable Subsidies 3. Efficiency Standards	1.12-1.39

The regional analysis reveals that carbon pricing mechanisms are particularly effective in Region A, characterized by a developed manufacturing sector. This finding corresponds with the observations of Liu et al. (2023) regarding market equilibrium effects of carbon emission trading. In contrast, Region C, dominated by carbon-intensive heavy industries, shows the highest effectiveness for efficiency standards.

4.4. Temporal Analysis of Policy Implementation

The temporal analysis of policy implementation reveals important insights into the dynamic evolution of policy effectiveness and synergistic interactions over time. Figure 5 illustrates the temporal trajectories of carbon reduction achievements for different policy portfolios.

Figure 5: Temporal Evolution of Carbon Reduction for Different Policy Portfolios



The figure presents a multi-line graph showing the temporal evolution of carbon reduction achievements for different policy portfolios over 15 years. The x-axis represents time (2008-2023), while the y-axis shows cumulative carbon reduction in Mt CO_2-eq. Multiple coloured lines represent different policy portfolios, including individual policies and various combinations.

The temporal analysis reveals that the effectiveness of most policies improves over time, with initial implementation challenges giving way to more substantial impacts as administrative processes are refined and stakeholders adapt. Synergistic effects typically manifest with a time lag of 2-3 years after policy implementation, consistent with the findings of Alabi et al. (2024) regarding adaptation periods in complex systems.

4.5. Sensitivity Analysis and Model Robustness

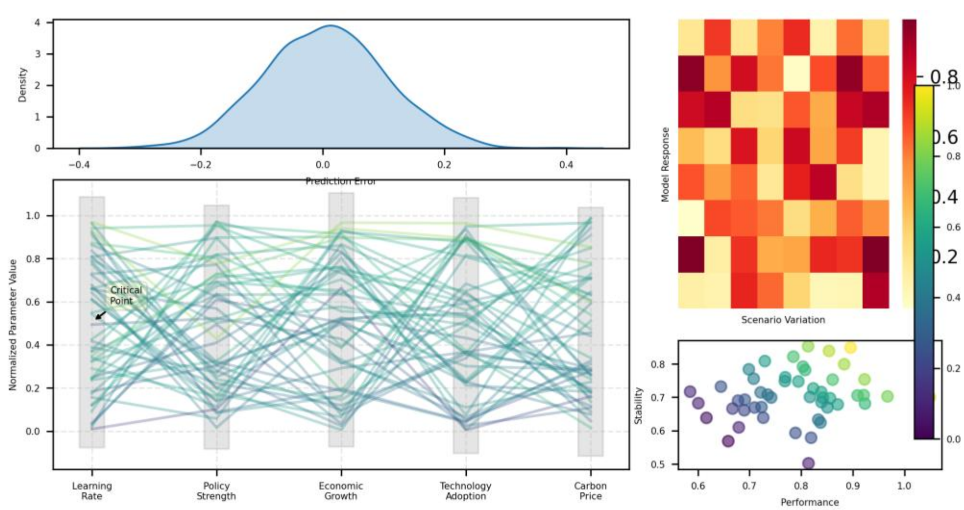
The sensitivity analysis assesses the robustness of model predictions and synergy assessments under different assumptions and parameter variations. Table 9 presents the results of a comprehensive sensitivity analysis.

Table 9: Sensitivity Analysis of Model Predictions and Synergy Assessments

Parameter	Variation Range	Impact on Carbon Reduction Predictions	Impact on PSI Values
Discount Rate	2-7%	High (±18.6%)	Moderate (±9.3%)
Technology Learning Rate	±50%	Very High (±24.3%)	High (±15.8%)
Implementation Delay	0-3 years	Moderate (±12.1%)	Moderate (±8.5%)
Policy Compliance Rate	70-100%	High (±19.7%)	Moderate (±10.4%)
Energy Price Volatility	±30%	High (±17.9%)	High (±14.3%)

The sensitivity analysis reveals that technology learning rate assumptions have the most significant impact on carbon reduction predictions (±24.3%), followed by policy compliance rate (±19.7%). These findings highlight the importance of accurate technology forecasting and policy compliance monitoring for reliable synergy assessments. Figure 6 presents a visualization of the model's robustness across different conditions.

Figure 6: Model Robustness Analysis Under Various Scenarios



The figure presents a complex multi-panel visualization of model robustness. The central panel features a parallel coordinates plot where each vertical axis represents a different model parameter or assumption, and coloured lines represent different scenario combinations. Surrounding this are smaller panels showing the distribution of prediction errors under various conditions.

The robustness analysis demonstrates that the model maintains reasonable prediction accuracy across a wide range of conditions, with prediction errors generally remaining below 15% for core synergy metrics. The model shows greater sensitivity to assumptions regarding technological change and policy implementation than to macroeconomic variables, consistent with the findings of Xu et al. (2023) regarding the importance of technological parameters in carbon neutrality modelling.

5. Discussion and Conclusion

5.1. Key Findings and Implications

This research has quantified the synergistic effects of regional carbon neutrality policies using deep learning techniques, yielding several significant findings. The analysis demonstrates that policy combinations generally produce stronger carbon reduction effects than the sum of individual policies, with PSI values ranging from 1.17 to 1.71. Particularly strong synergies emerge between renewable subsidies and innovation support (PSI = 1.42), while comprehensive five-policy portfolios achieve the highest synergy values (PSI = 1.71). These findings align with the observations of Xin et al. (2024), who identified that comprehensive measures integrating energy efficiency improvements, industrial technology upgrades, and energy source decarbonization effectively advance regional carbon neutrality goals.

Regional analysis reveals substantial variations in policy effectiveness, with carbon pricing proving most effective in manufacturing-dominated economies, while regions with carbon-intensive industries show greater responsiveness to efficiency standards. These regional variations highlight the importance of tailored policy portfolios that account for local economic structures, energy systems, and institutional capacities. The temporal analysis indicates that policy effectiveness generally improves over time, with synergistic effects manifesting after a typical lag of 2-3 years, as administrative processes are refined and stakeholders adapt to policy signals.

5.2. Policy Recommendations for Enhanced Synergies

Based on the quantified synergy assessments, several policy recommendations emerge for enhancing collaborative effects. Policy portfolios should be designed with explicit consideration of potential synergistic interactions rather than treating each policy as an independent intervention. The strong complementarity between renewable subsidies and innovation support suggests that technological advancement policies should be closely coordinated with market-based incentives to maximize carbon reduction outcomes. This approach resonates with the findings of Liu et al. (2023), who demonstrated the importance of integrated policy design in electricity markets with carbon trading mechanisms.

Implementation sequencing deserves careful attention, with foundational policies such as carbon pricing mechanisms established before complementary interventions to create favourable conditions for reinforcing effects. Regional policy portfolios should be tailored to local conditions, with manufacturing-dominated regions emphasizing carbon pricing and efficiency standards, while regions with strong innovation ecosystems focus on renewable subsidies and innovation support. The identified time lags in synergy manifestation suggest the need for policy stability and patience during early implementation phases, as highlighted by Alabi et al. (2024) in their analysis of adaptation periods in complex energy systems.

5.3. Limitations of the Current Study

Despite its contributions, this research has several limitations that should be acknowledged. The deep learning approach relies on historical data patterns, potentially limiting its applicability in contexts experiencing unprecedented technological or socioeconomic transitions. The regional analysis covers a diverse but limited set of economic and energy system configurations, which may not fully represent the global diversity of carbon neutrality implementation contexts. These limitations echo the challenges identified by Xu et al. (2023) regarding the generalizability of computational models in carbon neutrality assessment.

Methodological limitations include the simplified representation of certain policy mechanisms and implementation processes in the neural network architecture. While the model captures many complex interactions, some nuanced aspects of policy design and implementation may not be fully represented. The sensitivity analysis reveals particular vulnerability to assumptions regarding technology learning rates and policy compliance, suggesting areas where improved data collection and monitoring could enhance prediction reliability. Future research should address these limitations through expanded regional coverage, enhanced representation of policy implementation processes, and integration of additional data sources to improve prediction robustness.

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