Received: 13 August 2026 | Revised: 21 October 2026 | Accepted: 28 October 2026

https://doi.org/10.56946/jeee.v5i2.966
Volume 5 (2): 29-40

Journal of Environmental and Energy Economics

Research Article

Coordinated Economic Growth and Decarburization in Jiangsu Using an Integrated MOO–CCD Framework

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Abstract

Economic growth, carbon reduction, and environmental stewardship may all be achieved at once via the use of an optimization technique that takes trade-offs and multiple target progressions into account. Without fully grasping the complex interplay of financial, climatic, environmental, and resource implications, many current regional MOO studies aim for compromise solutions. The creation of a MOO and CCD framework in the Jiangsu Province, China, is the main subject of this study. From 2018 to 2030, we can see potential pathways for energy transition and company reorganization by analyzing eleven indicators: GDP, employment, water consumption, CO_2, sulfur dioxide, NOx, PM, CO_2, chemical oxygen demand, ammonia nitrogen and solid waste rounding it off. The study's basis is an input-output model with 47 components. Numerous factors are considered, including electricity-related situations, resource and emission coefficients from the past, and more. As a starting point for coordination, CCD ranks and evaluates potential MOO solutions once the optimal-point method has standardized the reduction and maximization objectives. All three scenarios put yearly GDP growth at 6.8%, with the precise number falling anywhere from 6.7% to 7.0%. We need to be more transparent about the moral judgments and assumptions that drive these changes because of the potential impact they have on the environment. There will be major shifts in the energy mix and the make-up of the industrial sector, and we need to be prepared for that. A more appropriate use of this method would be in scenario analysis rather than in making an exact forecast. Adaptive methods, such as sustainable alternatives, higher industrial advancements, and integrated governance, may replace strict annual requirements in policymaking.

Keywords: coupling coordination degree; decarburization; energy transition; industrial restructuring; multi-objective optimization; regional sustainability

1. Introduction

Achieving economic growth while reducing carbon emissions and environmental pollution has become a major challenge for regions undergoing rapid industrial and economic transformation. Economic development is closely associated with energy consumption, industrial production, employment generation, and natural resource utilization. However, continued dependence on energy-intensive production systems can increase carbon dioxide (CO_2) emissions and other environmental pressures, potentially undermining the long-term sustainability of economic growth. Therefore, regional development strategies increasingly need to consider economic performance alongside energy efficiency, resource conservation, and environmental protection. Previous research has examined the relationships between economic growth, human capital, energy consumption, and environmental degradation across different national and regional contexts [1-4].

Previous studies have provided evidence that economic development and environmental performance are closely interconnected. Research has highlighted the influence of fossil energy consumption, foreign direct investment, and economic development on CO_2 emissions, while other studies have examined the effects of economic and structural changes on carbon emissions [2, 5]. Environmental degradation has also been associated with natural resource utilization, economic growth, and human capital development in different regions [6, 7]. In addition, research on renewable energy technologies and green economic growth has emphasized the potential contribution of energy diversification, technological development, and sustainable resource management to environmental improvement [8–10]. Studies focusing on carbon emissions, natural resources, and green growth

further demonstrate the importance of considering environmental objectives within broader economic development strategies [11–13]. Collectively, these findings indicate that economic growth, energy use, and environmental sustainability should not be considered independently when developing regional policies.

Despite this growing body of research, achieving balanced progress across multiple development objectives remains difficult. Industrial restructuring and the transition towards cleaner energy sources may reduce emissions and resource consumption, but they can also affect production costs, employment, industrial output, and the demand for other resources. Similarly, prioritizing one environmental objective does not necessarily guarantee improvements in other environmental dimensions. For example, reducing carbon emissions may involve changes in the electricity-generation structure, while the resulting energy transition may create additional requirements for water, infrastructure, and industrial investment. Conventional multi-objective optimization (MOO) methods can identify compromise solutions among competing objectives; however, a solution with a favorable overall performance may still contain substantial imbalances among individual objectives. Consequently, evaluating both optimization performance and the coordination among economic, resource, climate, and environmental dimensions is important.

Although previous studies have investigated green economic growth, environmental efficiency, carbon emissions, and regional sustainability [9, 10, 19, 23], there remains a need for an integrated analytical approach that incorporates coordination assessment into the selection of multi-objective optimization solutions. In particular, conventional optimization approaches and coupling coordination degree (CCD) assessments are often used separately. This limits the ability to determine whether an optimization solution achieves balanced development across interconnected economic, resource, climate, and environmental subsystems. Furthermore, the simultaneous consideration of economic growth, employment, energy use, water consumption, CO_2 emissions, conventional air pollutants, wastewater pollutants, and solid waste within a sector-based regional optimization framework requires further investigation. Addressing this gap can improve the assessment of trade-offs and provide a more comprehensive basis for regional development planning.

Jiangsu Province, China, provides an important regional context for examining these interactions because its economic development and industrial structure require consideration of production, energy consumption, resource utilization, and environmental performance simultaneously. In this study, an integrated multi-objective optimization and coupling coordination degree (MOO–CCD) framework is developed using a 47-sector input–output structure for Jiangsu Province. The framework considers eleven objectives covering economic growth, employment, resource use, carbon emissions, and conventional environmental pollution. It combines objective normalization and ideal-point optimization with CCD-based assessment to evaluate the coordination of alternative development pathways. Three coordinated scenarios are considered: air pollution and carbon emissions (MOO-CA), solid waste and carbon emissions (MOO-CS), and water pollution and carbon emissions (MOO-CW). Their results are compared with conventional multi-objective optimization to examine how coordination criteria influence the selection of regional development pathways.

Accordingly, this study aims to: (1) develop a multi-objective optimization framework incorporating eleven economic, social, resource, and environmental objectives for Jiangsu Province; (2) identify alternative energy transition and industrial restructuring pathways under competing development and environmental constraints; (3) integrate CCD assessment into the optimization solution-selection process and compare the resulting solutions with conventional ideal-point optimization; and (4) examine the sensitivity of the selected pathways to changes in objective weights, input–output coefficients, economic growth requirements, technological constraints, and CCD parameters. The working hypothesis is that integrating CCD into multi-objective optimization will favor development pathways with a more balanced performance across economic, resource, climate, and environmental objectives than conventional ideal-point optimization, although trade-offs among individual objectives will remain.

2. Methods and materials

2.1. Model description

Figure 1 summarizes the analytical sequence. First, the 47-sector production system and resource and emissions accounts define the feasible set. Second, each of the eleven objectives is optimized separately to establish its ideal and anti-ideal values. Third, all

objectives are converted to dimensionless benefit scores and combined through an ideal-point distance. Fourth, subsystem indices and the CCD are calculated for every feasible candidate. In this study CCD is not merely reported after optimization: it is used in the solution-selection stage as a minimum coordination requirement and as a ranking criterion among candidates with comparable ideal-point distance. Finally, scenarios are compared using common indicators and sensitivity dimensions [6].

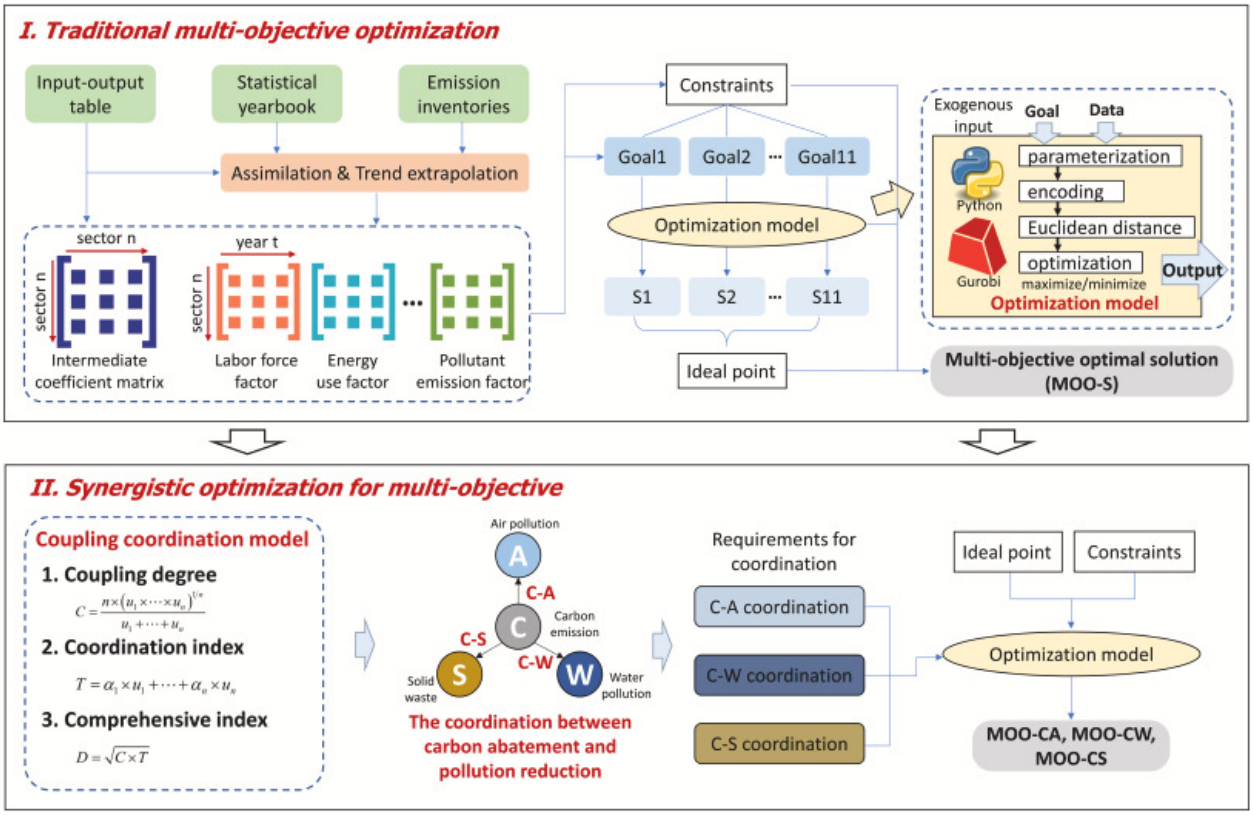


Figure 1. Integrated MOO–CCD workflow from data inputs and sectoral constraints to normalized objectives, ideal-point solutions, CCD screening, scenario comparison, and sensitivity analysis.

2.2. Establishing traditional MOO

2.2.1. Data requirements, assumptions, and constraints

The production framework makes use of the 47-sector-generated 2017 Jiangsu input-output table to achieve increased computational efficiency and prioritize energy- and pollution-intensive industries. We may find Table 1 that demonstrates the links between the main input-output industries and the 47 analytical sectors. The fundamental model's input coefficients remain unchanged from 2018 to 2030. The point is not to suggest that technological progress has stalled, but to provide the groundwork for future comparisons. It is critical to get numerical estimates from the authors' initial model files before submission. We employ instances with low efficiency coefficients and examples with high efficiency coefficients to conduct hypothetical impact analysis [7].

Energy usage, water consumption, value addition, employment, carbon dioxide emissions, and output were some of the metrics tracked by He et al. [8] the Jiangsu statistics yearbooks from 2002 to 2017. Coefficients are calculated for each unit of sectoral production. Make use of the past data for each linear, log-linear, or exponential coefficient to construct a trend model. Changes to R^2, information criteria, residual diagnostics, and, where available, out-of-sample or rolling-origin error should be used for model selection when the data allows it. For sensitivity analysis to be reliable, prediction intervals, not point predictions, must be used. Important construction methods, materials, units, time, and sectorial scope are detailed in Table 1.

The six pillars of electrical production are: thermal power; hydroelectricity; nuclear power; wind power; solar power; and natural gas output. Lastly, the discrepancy between the six sectors and the five that really exist may be resolved. The reliability of installed capacity as a measure of real energy use is called into question. Even though an allocated energy meter records both consumption and output simultaneously, the capacity data is kept separate from and not connected to either.

First, there are limitations on practicality and capability; second, there are yearly changes in reference framework sectoral output; and finally, there are regulations that limit GDP growth and sectoral allocations. Assumptions regarding the feasibility of the restructuring in the modeling process are the source of the non-defined targets of a 5% minimum GDP growth, ±20% volatility in sector-share, and ±5% annual output variation. The only way to find out how resilient the model is to re-evaluate it under various conditions, including varying GDP levels. Numerical sensitivity findings cannot be obtained from baseline tables alone; the original optimization dataset and code are also required. Table 1. Data dictionary and construction of the eleven optimization objectives. Exact yearbook editions, table numbers, price deflator, missing-value treatment, and forecast diagnostics should be supplied from the authors' source files before resubmission.

Table 1. Each of the eleven Jiangsu MOO-CCD framework goals contains data, units, coverage, construction methods, optimization criteria, etc.

Objective/variable	Unit	Primary source	Period	Coverage	Construction and direction
GDP	CNY, constant prices	Jiangsu statistical yearbooks; IO table	2002–2017; projected 2018–2030	47 sectors	Sectoral value-added coefficient × output; maximize
Employment	persons	Jiangsu statistical yearbooks	2002–2017; projected 2018–2030	47 sectors	Employment coefficient × output; maximize
Energy use	standard coal equivalent or stated energy unit	Jiangsu energy statistics	2002–2017; projected 2018–2030	47 sectors; 6 power categories	Energy-intensity coefficient × output; minimize
Water use	m^3	Jiangsu statistical yearbooks	2002–2017; projected 2018–2030	47 sectors	Water-intensity coefficient × output; minimize
CO_2	tones CO_2	Energy balance and emissions inventory	2002–2017; projected 2018–2030	47 sectors	Activity × emission factor; minimize
SO_2, NOx, PM	tones	Environmental statistical records	2002–2017; projected 2018–2030	47 sectors	Pollutant coefficient × output; minimize
COD, ammonia nitrogen	tones	Environmental statistical records	2002–2017; projected 2018–2030	47 sectors	Wastewater pollutant coefficient × output; minimize
Solid waste	tones	Environmental statistical records	2002–2017; projected 2018–2030	47 sectors	Waste coefficient × output; minimize

2.2.2. Construct the optimization functions

There are four main categories into which the model's eleven objectives fall. An increase in GDP and the addition of new employment are indicators of progress in society and the economy. Less energy and water are among the few resources. Reducing emissions of greenhouse gases is essential for better climatic performance. Environmental performance standards are many and

varied, but some examples include: air pollution, chemical oxygen demand, solid waste, ammonia nitrogen, nitrogen oxides, and sulfur dioxide levels. While standardized weights make comparisons easier, the old-fashioned practice of equal weighting does not ensure impartiality. Therefore, multiple focal frameworks, such as economic/social, climate, and pollution control, are important characteristics that people pay attention to Ren et al. [9].

2.2.2.1 Economic and social objectives

With output balanced, capacity controlled, resources accessible, and regulatory constraints satisfied, economic productivity and job creation are maximized. At fixed prices, capturing value added is the goal for achieving GDP goals. Job quality and allocation are not analyzed by Li et al. [10] the employment objective, which is based on jobs that are supported by industry performance criteria.

2.2.2.2 Resource-use objectives

Water and electricity are handled cautiously since they might slow down growth in certain areas. All evaluations are based on industry-specific performance and intensity metrics. We start with three separate quantitative and conceptual ideas: power production, energy consumption, and installed capacity [11].

2.2.2.3Climate and environmental objectives

Reducing emissions of carbon dioxide is the central tenet of any strategy to mitigate climate change. Environmental protection activities aim to reduce sulfur dioxide, organic matter, nitrogen oxides, chemical oxygen demand, ammonia nitrogen, and solid waste. When many measures are considered independently, it is not always the case that one ecological trait is improved [12].

2.2.2.4 Objective summary and notation

The output of industry, a variable x^k, t, may represent me in year t. As for objective k, $f_k(x)$ is the adjusted annual total broken down by sector. Employment and GDP are used to measure the benefits, whereas the other nine factors are used as spending benchmarks. The symbols used in these editable equations are listed in Table 2.

Table 2. Mathematical notation.

Symbol	Definition
x_i,t	Output of sector i in year t
a_{ij}	Intermediate input coefficient from sector i to sector j
v_i,t	Value-added coefficient
q_{ki},t	Coefficient for resource, carbon, or pollutant objective k
z_k	Normalized benefit score for objective k
w_k	Weight assigned to objective k; $\Sigma w_k = 1$
U_m	Comprehensive development index for subsystem m
C	Coupling coefficient
T	Weighted comprehensive development index
D	Coupling coordination degree

2.2.3. Model solving with ideal point method

Applying single-objective optimization to each goal k yields a feasible set that includes both the optimal and suboptimal values of $f*$. Goals with varied units and orientations may be more easily compared by normalizing the range of values to [0,1]. Applying the formula $z_k(x) = [f_k(x) - f_k^-] / [f_k* - f_k^-]$ is one approach to accomplishing a useful goal. An example of a financial parameter's formula is $z_k(x) = [f_k\cdot\cdot - f_k(x)] / [f_k - f_m*]$. A goal-oriented ideal criterion is represented by a value of one, whereas the inverse criterion is zero. We are dealing with word sheets, not graphical equations, when we reduce the weighted Euclidean distance $L(x) = \{\{_k w_k[1 - z_k(x)]$ ^ $^1\ddot{O}^2\}$ in order to meet production and regulatory standards.

Benefit normalization: $z_k(x) = [f_k(x) - f_k^-] / [f_k* - f_k^-]$

Cost normalization: $z_k(x) = [f_k^- - f_k(x)] / [f_k^- - f_k*]$

Ideal-point distance: $L(x) = \{\Sigma_k w [1 - z_k(x)]^2\}^{1/2}$

Reference weights: $w_k = 1/11$ and $\Sigma_k w_k = 1$

2.3. Integrating MOO with the CCD model

The mixing procedure is initiated by choosing a solution. The first step is to use the standard objective assessments to produce indices for the economic-social, resource, climatic, and environmental subsystems. The coupling coefficient, C, may be expressed as the equation of the four subsystem scores U_1, U_4, where each score corresponds to the range [0,1]. The total development index may be expressed as $T = o_m\alpha_m U_m$, where α_m is an integer and $o_m\alpha_m$ is 1. One way to describe the amount of coordination is as $D = \sqrt{(C \times T)}$. The crucial need is shown by consistent α_m values. First, a minimum D is specified and all possible MOO solutions are compared to it. Finding out how effective they are will be done by comparing their boosted D to their dropped ideal-point distance. In addition to being a descriptive statistic generated after the MOO solution has been found, CCD changes the choice of the practical compromise.

$$\text{Subsystem index: } U_m = \Sigma_{k \in m}\, \beta_{k|m}\, z_k, \text{ with } \Sigma_{k \in m}\, \beta_{k|m} = 1$$

$$\text{Coupling coefficient: } C = [4^4(U_1U_2U_3U_4)/(U_1 + U_2 + U_3 + U_4)^4]^{1/4}$$

$$\text{Comprehensive development index: } T = \Sigma_m\, \alpha_m U_m, \text{ with } \Sigma_m \alpha_m = 1$$

$$\text{Coupling coordination degree: } D = \sqrt{(C \times T)}$$

$$\text{Integrated selection rule: minimize } L(x) \text{ and maximize } D(x), \text{ subject to } D(x) \geq D\min \text{ and } x \in \Omega$$

$$\text{Material balance: } x_t \geq A\, x_t + y_t$$

$$\text{Output adjustment: } (1 - g_i^L)\, x_i,\, t{-}1 \leq x_i,\, t \leq (1 + g_i^U)\, x_i,\, t{-}1$$

$$\text{Policy constraints: GDP growth} \geq \text{gGDP and sector-share change} \leq \text{smax}$$

3. Results

Using CCDs, traditional ideal-point multi-objective optimization criteria, and goal-specific metrics, the research differentiates three options. The full list of acronyms is shown in Table 3. We have something closer to model predictions than to actual evidence. Percentages, not changes in percent, are used to depict share fluctuations. There is no variation in the units, denominators, or base year used for comparison.

Table 3. Scenario and abbreviation definitions. Labels should be cross-checked against the authors' optimization code and supplementary tables before submission.

Label	Scenario	Definition
MOO-S	Conventional MOO reference solution	Ideal-point MOO without CCD screening
MOO-CA	Coordinated air-pollution and carbon pathway	CCD-integrated solution emphasizing air pollutants and CO_2
MOO-CS	Coordinated solid-waste and carbon pathway	CCD-integrated solution emphasizing solid waste and CO_2
MOO-CW	Coordinated water-pollution and carbon pathway	CCD-integrated solution emphasizing water pollutants and CO_2
SOO-G2	Single-objective employment solution	Maximizes employment
SOO-G3	Single-objective energy solution	Minimizes energy use
SOO-G5	Single-objective water solution	Minimizes water use

3.1. Energy transition pathways for sustainable development

Figure 2 compares the electricity-generation mix under MOO-CA, MOO-CS, and MOO-CW. The scenarios replace part of coal- and gas-fired generation with wind and solar generation, but the magnitude differs because each pathway gives different priority to air pollution, solid waste, or water pollution while retaining carbon coordination. All shares in Figure 2 must use total electricity

generation as the denominator. Installed capacity values, if retained, should be displayed in a separate panel and identified by Rehman et al. [13].

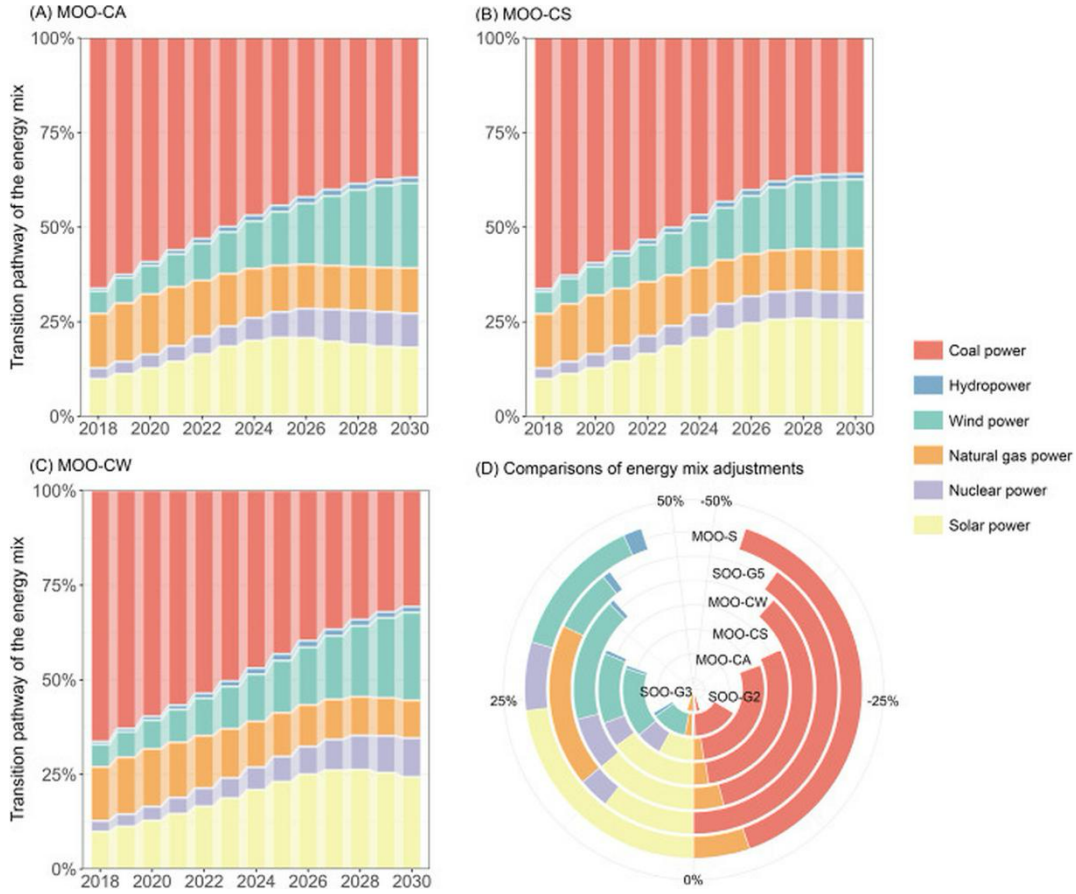


Figure 2. Comparative Analysis of Energy Mix Transition Pathways under MOO-CA, MOO-CS, and MOO-CW Scenarios, and Their Corresponding Energy Mix Adjustments (2018–2030).

Alternative manufacturing procedures are not viable in the present economic climate. Emissions from direct combustion might be reduced by the quick adoption of sustainable resource substitution; however, this could be challenging to achieve owing to limitations in capacity, finance, predictability, and sectoral efficiency. It is more accurate to see the discrepancies between the three coordinated solutions as limitations of the model than evidence of causation.

In order to adapt to the evolving energy scene, traditional thermal energy sources and new renewable energy sources must work together. Attempts to multitask run the risk of depleting renewable energy sources or good ol' fossil fuels. So that we may understand the inclusion of MOO, we will examine MOO-S in relation to SOO-G2, SOO-G3, and SOO-G5. The energy transfer channels for SOO-G2, SOO-G3, SOO-G5, and MOO-S are shown in Figure S2. In order to assess how the CCD module affects the best energy transition, we include MOO-CA, MOO-CS, and MOO-CW in these analyzes. Harmonizing the eleven goals to improve the energy composition will require more work due to the disparities among MOO-S and SOO-G2, SOO-G3, and SOO-G5. With just a 5% shift in the energy mix over the allotted time, SOO-G3 prioritizes labor-intensive, fossil-fuel-based energy generation to optimize job prospects. On the other hand, SOO-G5 prioritizes expanding renewable energy use to cut water usage by 22.8%. To achieve all goals in the SOO-G5 framework, it is necessary to decrease natural gas energy consumption by 24.6%, increase wind energy by 7%, and increase solar energy by 13% (as shown in Figure 2) [14].

Earlier assertions of a 29.3%-35.7% drop are untenable if the baseline year, energy category, and denominator are different from the 92.3%, 91.8%, and 89.3% coal percentages. Prior to resubmitting, compare these data with the first results. Until the validation process is complete, it will not be recognized as evidence of outstanding achievement in the document. Figure 2 and the following table should make it quite obvious whether the data is for generation, final consumption, or installed capacity Alam et al. [15].

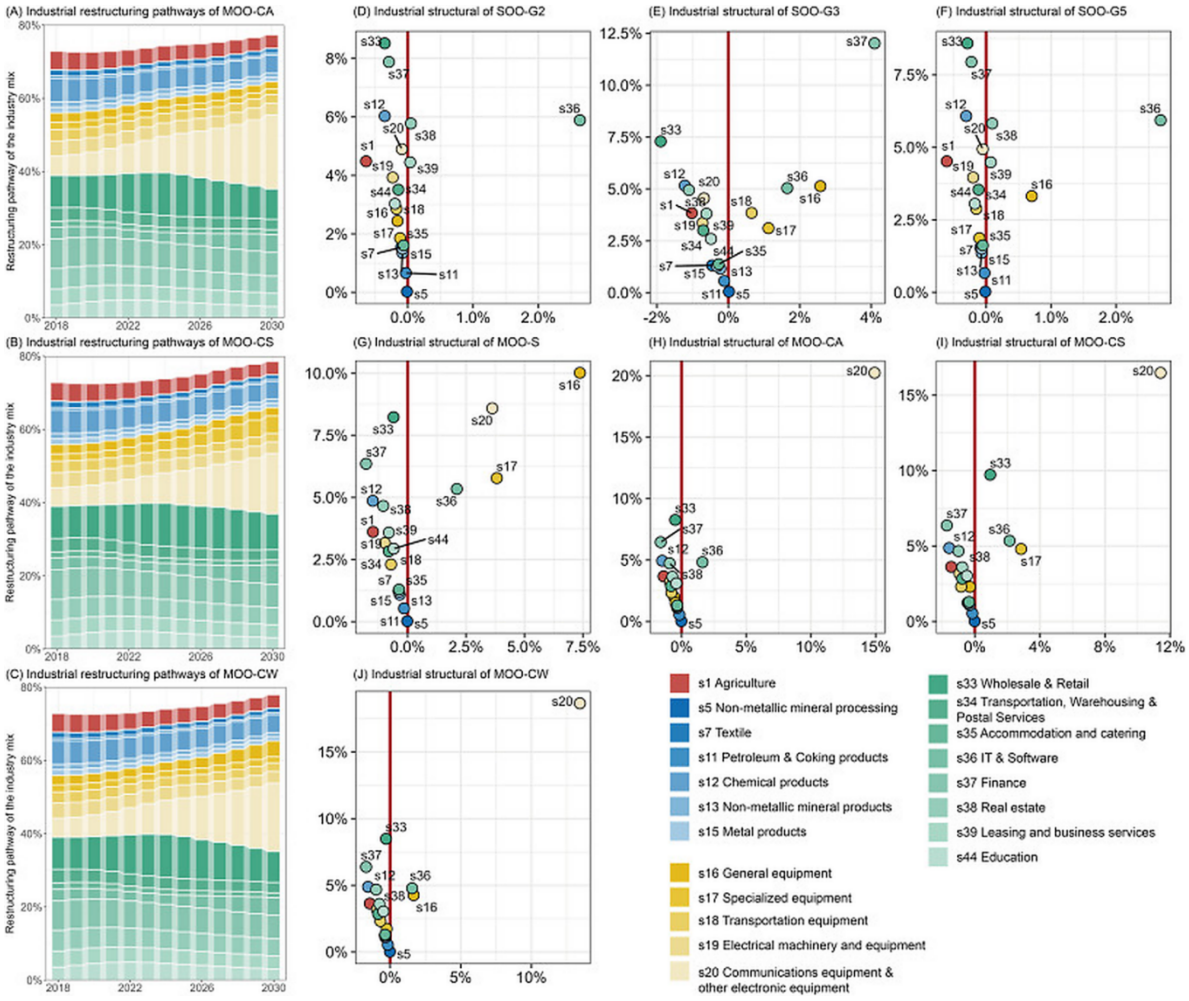


Figure 3. Pathways for industrial reorganization according to various options. The outcomes produced by the multi-objective optimization model, after the integration of the CCD module, highlight the synchronized advancement of carbon emission reduction alongside air contaminants, solid waste, and water pollutants. Every solution emphasizes a harmonious progression among these ecological goals. Adjustments of sectors and their proportions of SOO-G2, -G3, -G5, MOO-S, MOO-CA, MOO-CS, and MOO-CW. The X-axis illustrates the modifications of sectors during the whole planned duration (2018–2030), whilst the Y-axis denotes the sector proportions in 2030.

3.2. Industrial restructuring pathways for balanced growth

Figure 3 compares changes in industrial output shares under the three coordinated pathways. The recurring mechanism is reallocation away from resource-intensive activities toward higher-value manufacturing and services, subject to the annual output and sector-share constraints. This pattern supports GDP and employment while lowering selected intensities; however, total impacts depend on scale effects, supply-chain requirements, and the assumed stability of technical coefficients [16].

3.3. Coordinated advancement of the eleven objectives

Figure 4 compares normalized objective trajectories, so the panels should report dimensionless scores or clearly stated physical units consistently. A formal comparison should include, for every scenario, ideal-point distance L, coordination coefficient C, comprehensive index T, coordination degree D, and the minimum normalized objective score. These indicators reveal whether a solution improves overall proximity to the ideal point by allowing one objective to deteriorate. The reported annual GDP result is expressed consistently as a 6.8% average, corresponding to the 6.7%–7.0% range across coordinated scenarios [17].

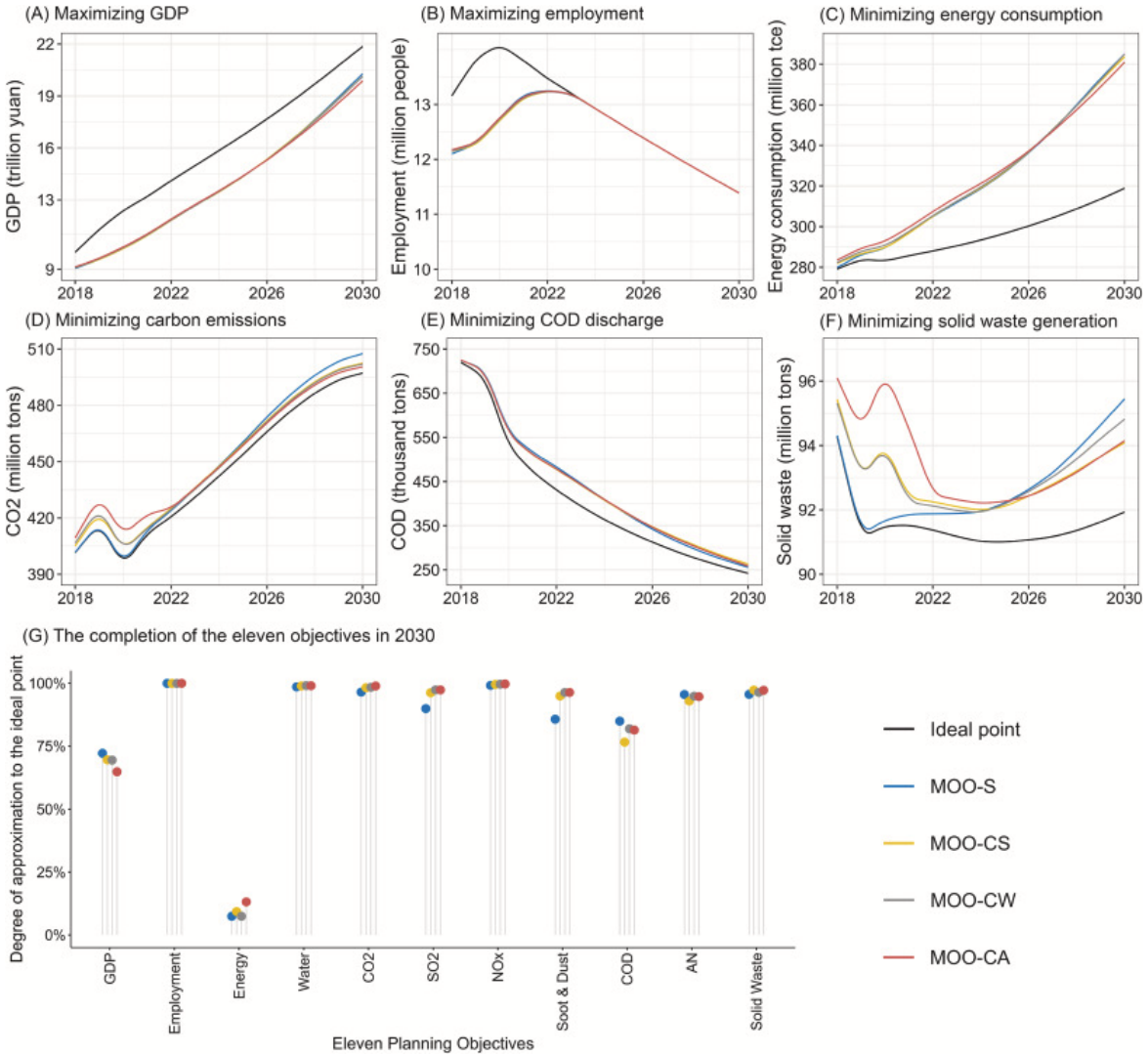


Figure 4. Comparison of normalized objective performance and coordination indicators for MOO-S, MOO-CA, MOO-CS, and MOO-CW. Panels should identify units, baselines, denominators, and scenario labels; the accompanying data table should report L, C, T, D, and the minimum objective score.

The initial phrasing does not identify the denominator, numerator, or measure; hence, the assumption that the model's efficacy increases by 'less than 1%' as a general performance indication is rejected. After reviewing the initial model and determining the relevant statistic, any such ratio has to be restored. Despite these caveats, the research did reach a valid conclusion: CCD changes solution selection by penalizing inconsistent subsystem scores, but only the officially defined metrics that have been previously developed can measure the degree of improvement [18].

4. Discussions

4.1. Marginal contributions

That compromise and collaboration are different qualities is the main conclusion from the process. It is possible for an ideal solution to have an extra component while accomplishing one's highest aspirations. Although CCD offers parameter choices, it incorporates balancing data; hence, it cannot be considered a value-free, unbiased metric. Displaying all the relevant measurements and ideal parameters at once, together with their corresponding weights and cutoffs, is when the comprehensive technique really shines. A correlation between energy substitution and industrialization advances has been shown empirically. Changes to the make-up of different businesses impact pollution levels, water and electricity use, and better energy generation lessens the emissions intensity of expanding industries. Even if the Ruhr revolution had grasped the need for significant industrial diversity, it would not have been able to preserve the Jiangsu model because of historical and institutional differences. Only structural change as it relates to employment, infrastructure, and adaptation at the regional level will be included in our assessment [19].

4.2. Policy implications

It is often more prudent to propose policy reforms rather than impose stringent restrictions. Renewable energy options, efficiency improvements, and industrial development timing may be better understood with the use of coordinated monitoring in Jiangsu. In order to monitor the model's renewable adoption or sectoral development, scenario analyzes need annual measurements. Considering that these goals are contingent on technical components, energy costs, capacity limitations, regulatory restrictions, and objective criteria, they are not crucial [20].

Energy accounting and capacity planning must remain distinct throughout the implementation. One only shows future production, while the other changes depending on things like demand, storage, infrastructure, curtailment, consumption, and installed solar or wind capacity. It would be more accurate to publish these figures in various units and categories to avoid overstating the effect of capacity additions on emissions [21].

Indicators such as the normalized aim, total GDP, emissions, employment repercussions, and sector-specific adjustment costs shouldn't be controlled by legislators. If a less-than-ideal approach helps keep water quality, waste management, or job opportunities from drastically declining, it may be worth it. Responsible policy frameworks may influence the final decision by revealing inconsistencies, which is the practical goal of the CCD display [22].

5. Conclusion, Limitations and future perspectives

The absence of structure-specific information is the main limitation. With the static intermediate coefficients from 2017, it will be challenging to account for the changing dynamics of reliance on imports, replacement of technologies by endogenous means, and reconfiguration of the supply chain till 2030. A number of factors may influence the forecast coefficient, including functional configurations, structural disturbances, incomplete or missing data, and limited historical datasets. A number of important variables, such as expected economic growth, energy tariffs, technology pricing, natural disasters, changes in regulations, and national industrial plans, might push realistic possibilities beyond the given limits. To tackle these uncertainties, the original model files must be updated with various technical-coefficient techniques, forecasting intervals, and GDP-growth scenarios [23].

Wang et al. [24] objectives and subsystem weights; iii baseline GDP weights; vi the coordination standard's structural features and the paths of fixed, efficiency-enhancing, and harmful technical coefficients; and iv annual production limits and sector allocation caps are the components of an all-inclusive robustness framework. To differentiate between changes brought about by CCD integration and those induced by ordinary MOO secularization, it could be helpful to use an ε-constraint or Pareto-front evaluation technique. To ensure consistency, we will need an optimization solver, variant, parameters, convergence criteria, scenario files, and machine-readable graphical data, a panel with objective coefficients, forecasting methods, diagnostics, and support from 47 different industries. Going to a different place during the procedural phase is technically possible, but it would be quite difficult to do so in line with Jiangsu's norms and procedures.

Consent to participate: Not applicable.

Consent for publication: Not applicable.

Author Contributions: Muhammad Zohaib: Conceptualization, Supervision, Methodology, Project Administration, and Writing – Review and Editing. Abdul Ghaffar: Resources, Investigation, Data Curation, Writing – Original Draft Preparation, and Writing – Review and Editing. Muhammad Asif: Software, Data Analysis, Visualization, and Formal Analysis, Writing – Review and Editing. Kashif Raza: Writing – Review and Editing, Validation, Investigation, and Data Verification. All authors contributed to the interpretation of the results, critically reviewed the manuscript, and read and approved the final version of the manuscript.

Funding: Not Applicable

Data Availability Statement: Not Applicable

Acknowledgments: The authors gratefully acknowledge the Department of Economics, Ghazi University, Dera Ghazi Khan, Punjab, Pakistan, for providing institutional support and resources during the completion of this research.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Fukao, K., Makino, T., & Settsu, T. (2021). Human capital and economic growth in Japan: 1885–2015. Journal of Economic Surveys, 35(3), 710–740. https://doi.org/10.1111/joes.12419
2. Ali, M. U., Gong, Z., Ali, M. U., Wu, X., & Yao, C. (2021). Fossil energy consumption, economic development, inward FDI impact on CO_2 emissions in Pakistan: Testing EKC hypothesis through ARDL model. International Journal of Finance & Economics, 26(3), 3210–3221. https://doi.org/10.1002/ijfe.1958
3. Jiao, Y., Xiao, X., & Bao, X. (2022). Economic policy uncertainty, geopolitical risks, energy output and ecological footprint—Empirical evidence from China. Energy Reports, 8, 324–334. https://doi.org/10.1016/j.egyr.2022.03.105
4. Danish, Ulucak, R., & Baloch, M. A. (2023). An empirical approach to the nexus between natural resources and environmental pollution: Do economic policy and environmental-related technologies make any difference? Resources Policy, 81, Article 103361. https://doi.org/10.1016/j.resourpol.2023.103361
5. Cai, Y., Duan, H., Luo, Z., Duan, Z., & Wang, X. (2022). Dynamic driving mechanism of dual structural effects on the correlation between economic growth and CO_2 emissions: Evidence from a typical transformation region. International Journal of Environmental Research and Public Health, 19(7), Article 3970. https://doi.org/10.3390/ijerph19073970
6. Nathaniel, S. P. (2021). Environmental degradation in ASEAN: Assessing the criticality of natural resources abundance, economic growth and human capital. Environmental Science and Pollution Research, 28(17), 21766–21778. https://doi.org/10.1007/s11356-020-12034-x
7. Ayad, H., Sari-Hassoun, S. E., Usman, M., & Ahmad, P. (2023). The impact of economic uncertainty, economic growth and energy consumption on environmental degradation in MENA countries: Fresh insights from multiple thresholds NARDL approach. Environmental Science and Pollution Research, 30(1), 1806–1824. https://doi.org/10.1007/s11356-022-22256-w
8. He, B., Ismail, N., Leng, K. K. K., & Chen, G. (2023). Techno-economic analysis of an HRES with fuel cells, solar panels, and wind turbines using an improved Al-Biruni algorithm. Heliyon, 9(12), Article e22828. https://doi.org/10.1016/j.heliyon.2023.e22828
9. Ren, S., Li, L., Han, Y., Hao, Y., & Wu, H. (2022). The emerging driving force of inclusive green growth: Does digital economy agglomeration work? Business Strategy and the Environment, 31(4), 1656–1678. https://doi.org/10.1002/bse.2975
10. Li, Z., Li, L., & Hui, M. (2024). Fostering green economic growth through sustainable management of natural resources. Resources Policy, 91, Article 104867. https://doi.org/10.1016/j.resourpol.2024.104867
11. Rehman, A., Ulucak, R., Murshed, M., Ma, H., & Işık, C. (2021). Carbonization and atmospheric pollution in China: The asymmetric impacts of forests, livestock production, and economic progress on CO_2 emissions. Journal of Environmental Management, 294, Article 113059. https://doi.org/10.1016/j.jenvman.2021.113059
12. Huang, J. (2024). Resources, innovation, globalization, and green growth: The BRICS financial development strategy. Geoscience Frontiers, 15(2), Article 101741. https://doi.org/10.1016/j.gsf.2023.101741
13. Rehman, A., Ma, H., Ozturk, I., & Ulucak, R. (2022). Sustainable development and pollution: The effects of CO_2 emission on population growth, food production, economic development, and energy consumption in Pakistan. Environmental Science and Pollution Research, 29(12), 17319–17330. https://doi.org/10.1007/s11356-021-16998-2

14. Haroon, M., & Hayyat, M. (2025). Assessing the dual impact of gold mining on local communities: Socio-economic benefits and environmental challenges. Resources Policy, 103, Article 105559. https://doi.org/10.1016/j.resourpol.2025.105559
15. Alam, M. S., Rabbani, M. R., Tausif, M. R., & Abey, J. (2021). Banks' performance and economic growth in India: A panel cointegration analysis. Economies, 9(1), Article 38. https://doi.org/10.3390/economies9010038
16. Yang, L., Zhou, X., & Feng, X. (2022). Renewable energy-led economic growth hypothesis: Evidence from novel panel methods for N-11 economies. Renewable Energy, 197, 790–797. https://doi.org/10.1016/j.renene.2022.07.025
17. Momoh, H. (2021). The impact of human capital development on economic growth in Germany (1991–2018). Journal of Economics and Sustainable Development, 12(22), 37–47. https://doi.org/10.7176/jesd/12-22-05.
18. Zheng, X., Wang, L., Hou, J., & Nepal, R. (2024). Capacity utilization rate and company performance before the COVID-19 economic crisis: Evidence from listed companies in China's electricity industry. Energy Economics, 131, Article 107348. https://doi.org/10.1016/j.eneco.2024.107348
19. Zhao, X., Ma, X., Shang, Y., Yang, Z., & Shahzad, U. (2022). Green economic growth and its inherent driving factors in Chinese cities: Based on the Metafrontier-global-SBM super-efficiency DEA model. Gondwana Research, 106, 315–328. https://doi.org/10.1016/j.gr.2022.01.013
20. Trammell, P., & Korinek, A. (2023). Economic growth under transformative AI. SSRN. https://doi.org/10.2139/ssrn.4616883
21. Bonsay, J. O., Cruz, A. P., Firozi, H. C., & Camaro, P. J. C. (2021). Artificial intelligence and labor productivity paradox: The economic impact of AI in China, India, Japan, and Singapore. Journal of Economics, Finance and Accounting Studies, 3(2), 120-139. https://doi.org/10.32996/jefas.2021.3.2.13
22. Rahim, S., Murshed, M., Umarbeyli, S., Kirikkaleli, D., Ahmad, M., Tufail, M., & Wahab, S. (2021). Do natural resources abundance and human capital development promote economic growth? A study on the resource curse hypothesis in Next Eleven countries. Resources, Environment and Sustainability, 4, Article 100018. https://doi.org/10.1016/j.resenv.2021.100018
23. Jiang, Y., Sharif, A., Anwar, A., The Cong, P., Lelchumanan, B., Thi Yen, V., & Thi Thuy Vinh, N. (2023). Does green growth in E-7 countries depend on economic policy uncertainty, institutional quality, and renewable energy? Evidence from quantile-based regression. Geoscience Frontiers, 14(6), Article 101652. https://doi.org/10.1016/j.gsf.2023.101652
24. Wang, G., Sharma, P., Jain, V., Shukla, A., Shahzad Shabbir, M., Tabash, M. I., & Chawla, C. (2022). The relationship among oil prices volatility, inflation rate, and sustainable economic growth: Evidence from top oil importer and exporter countries. Resources Policy, 77, Article 102674. https://doi.org/10.1016/j.resourpol.2022.102674

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