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Original Paper

# Beyond limited scenarios: A dynamic framework for adaptive management of nationwide industrial symbiosis under uncertainty

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ABSTRACT

Industrial symbiosis networks, characterized by complex inter-industry resource exchanges, propagate localized disruptions across multiple sectors, thereby generating greater systemic uncertainty than single-industry systems. This inherent complexity undermines reliable energy conservation and emission reduction (ECER) planning in promoting industrial symbiosis and heightens the risk of ineffective policies. In this study, we develop a probabilistic framework integrating Latin hypercube sampling and Sobol sensitivity analysis to assess the impacts of 389 uncertain factors on China's iron and steel–thermal power–cement symbiosis network from 2020 to 2030. Our findings indicate that: (1) Nationwide industrial symbiosis could achieve energy savings of 47.1–61.2 Mtce and significantly reduce emissions of $SO_2$ (170.3–248.9 kt), $NO_x$ (166.7–280.3 kt), and PM (41.8–96.7 kt) by 2030, with required investments ranging from 92.8 to 122.1 billion USD. By balancing ambition and feasibility, we establish policy-actionable ECER targets for the nationwide industrial symbiosis network based on a 75% feasibility threshold across 100,000 uncertain scenarios. (2) Conservation supply curve analysis shows that over 95% of the symbiotic technologies exhibit negative energy conservation costs under uncertainty, yet their cost volatility spans several orders of magnitude. Prioritizing 27 high-potential, low-cost technologies can capture 76.9% of the network's total ECER potential. (3) Technology penetration rates—rather than intrinsic efficiencies—account for 84.5% of the variance in ECER outcomes, underscoring the importance of policies that foster widespread adoption of symbiotic technologies over incremental technological efficiency improvements. This study redefines industrial symbiosis planning from static roadmaps into dynamic adjustment mechanisms, offering robust support for promoting industrial symbiosis under uncertainty.
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## 1. Introduction

Industrial symbiosis represents a key pathway for energy conservation and emission reduction (ECER) in hard-to-abate industries such as iron and steel, cement, and thermal power industries (IEA, 2023). By converting waste and by-products from one industry into energy or alternative raw materials for another, this approach substantially reduces resource consumption and plays a pivotal role in enabling industrial clean transformation (Guo et al., 2020; Liao et al., 2024).

Compared to single-industry systems, cross-sectoral industrial symbiosis networks exhibit broader sources of uncertainty with complex interdependencies among them, resulting in higher systemic uncertainty (Cao et al., 2026; Xie et al., 2024). First, they integrate multiple industries characterized by diverse production processes, wastes, symbiotic technologies, and end-use products, resulting in intricate technical architectures (Fric et al., 2025; Neves et al., 2020). This complexity introduces numerous uncertain parameters, including sector-specific differences in technology adoption, ambiguity about the quantity and composition of waste and by-product inputs, and unstable technology performance under integrated, cross-sectoral conditions (Li and Hanaoka, 2022; Xie et al., 2023; Xu et al., 2023). Second, waste exchange creates tight inter-industry coupling within industrial symbiosis networks (Boom Cárcamo and

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Peñabaena-Niebles, 2022), rendering the system highly sensitive to external shocks (e.g., demand volatility, supply chain disruptions) and endogenous changes (e.g., technology transitions) (Cheng et al., 2024; Zahari and McLellan, 2025). These local shocks are then propagated and magnified through interlinked material flows and feedback mechanisms along symbiotic technology chains, ultimately amplifying uncertainty at the system level (Ji et al., 2020). For instance, a downturn in the real estate market reduces cement production, simultaneously diminishing the sector's capacity to absorb wastes such as steel slag from steel plants and fly ash from thermal power plants. This triggers a chain reaction, leaving steel and thermal power industries grappling with solid waste accumulation and rising disposal costs.

Most importantly, the national scale of the industrial symbiosis network further heightens systemic vulnerability. Compared with industrial symbiosis limited to a single park or city, nationwide networks involve a larger number of enterprises, broader spatial distribution, and more intricate interconnections. Consequently, local disturbances propagate over longer pathways, interacting with multiple interconnected sectors along the network, which causes uncertainty to accumulate and intensify.

Diverse and complex uncertainties pose potential obstacles to the promotion of nationwide industrial symbiosis and may undermine the effectiveness of policy measures (Lamboll et al., 2023; Shafiee Roudbari et al., 2024). Multi-dimensional uncertainties frequently produce order-of-magnitude deviations in environmental-economic output predictions (Scott et al., 2021), causing policy targets to become misaligned with operational realities (Haas et al., 2023). For instance, ambitious targets for emission reduction or recycling may be unrealistic in regions with unstable waste inputs or underdeveloped technologies, leading to implementation failures (Breetz, 2020). Conversely, overly conservative targets may miss cost-effective mitigation opportunities and delay industrial upgrading (Petrović and Ostojić, 2025; Sarkodie, 2021). Moreover, national policies incur amplified risks when disregarding uncertainties, given their mandate to span heterogeneous regional conditions (Wang et al., 2023c). Consequently, establishing a performance assessment framework of nationwide industrial symbiosis under deep uncertainty—evaluating energy conservation, emission reduction, investment cost, etc.—provides a benchmark for setting realistic management objectives and enhancing policy effectiveness. This enables the formulation of tailored risk mitigation strategies, ultimately enhancing policy effectiveness in promoting nationwide industrial symbiosis.

Current uncertainty analysis in industrial symbiosis research mainly relies on scenario analysis, which predicts future developments by defining different plausible scenarios (Zhao et al., 2024). For example, Guo et al. (2023) used scenario analysis to compare continued coal use with early coal phase-out across 850 industrial parks (Guo et al., 2023). Huang et al. (2025) applied it to compare eight sludge processing strategies, quantifying the performance of industrial symbiosis under varying logistical and treatment conditions (Huang et al., 2025). Recent applications demonstrate scenario analysis quantifies environmental-economic performance of large-scale industrial symbiosis networks at city (Xiao et al., 2022), regional (Barrau et al., 2024), and national scales (Kerdlap et al., 2020).

While these studies provide valuable explorations of uncertainty analysis in industrial symbiosis networks, they exhibit two key limitations. First, scenario analysis relies on subjective parameter settings, introducing substantial subjectivity that may compromise prediction accuracy (Dekker et al., 2023). Second, simplified scenario frameworks cannot fully capture the future evolution of complex systems like nationwide industrial symbiosis networks. This may cause significant discrepancies between simulations and reality, undermining robust ECER target-setting and reasonable pathway selection for industrial symbiosis (Cao et al., 2021).

To address these limitations, stochastic sampling has emerged as an effective alternative. By replacing finite scenarios with large-scale probabilistic simulations of uncertain development pathways (Mei et al., 2021), it overcomes subjective limitations. Studies on single industrial sectors (e.g., cement, steel, construction) have employed Latin Hypercube Sampling (LHS) and Monte Carlo simulations to quantify the impacts of techno-economic fluctuations on energy use and pollutant emissions (Prataviera et al., 2022; Wang et al., 2023a).

However, when applied to nationwide industrial symbiosis networks, stochastic sampling methods face critical limitations. Simple stochastic sampling lacks control over the distribution of samples in the parameter space, often leading to clustering in some regions and sparse coverage in others. This severely compromises estimation efficiency and reliability for high-dimensional systems (Helton et al., 2006). As uncertain parameters multiply, the input space volume expands exponentially, demanding prohibitively large numbers of simulations for adequate coverage. Moreover, most existing stochastic sampling practices function as analytical "black boxes": they generate output distributions from numerous random inputs but lack the ability to efficiently and accurately identify which uncertain parameters exert the greatest influence on system-level outcomes. This highlights the necessity for advanced frameworks that combine structured sampling and sensitivity analysis to trace uncertainty transmission and pinpoint key drivers, thereby supporting robust decision-making in complex industrial symbiosis systems.

This study develops an uncertainty-informed management framework to assist ECER in the nationwide iron and steel–thermal power–cement industrial symbiosis network in China. By integrating multidimensional risk tracing, large-scale probabilistic simulations, and sensitivity analysis, we overcome the limitations of traditional static scenario assumptions. The framework provides dynamic ECER target-setting tools and key technology screening criteria for nationwide industrial symbiosis networks. It further identifies cross-sectoral uncertainty transmission mechanisms, enabling the formulation of tailored risk mitigation strategies.

## 2. Methods

### 2.1. Research framework

The research framework is shown in Fig. 1. First, uncertainties in the nationwide iron and steel–thermal power–cement industrial symbiosis network are systematically identified and categorized. Subsequently, LHS is applied to conduct 100,000 large-scale random samplings of these uncertainties to fully simulate future development scenarios of the nationwide industrial symbiosis network. Based on the sampling results, we evaluate the environmental-economic performance of the nationwide industrial symbiosis network and establish reasonable ECER targets for this complex system. Then, a conservation supply curve was employed for cost-benefit analysis to identify key symbiotic technologies under uncertainties. Finally, Sobol sensitivity analysis is introduced to identify critical uncertainties significantly affecting the system's performance to support targeted policy interventions.

The selection of the iron and steel–thermal power–cement sectors as the study boundary is justified by two main factors. First,

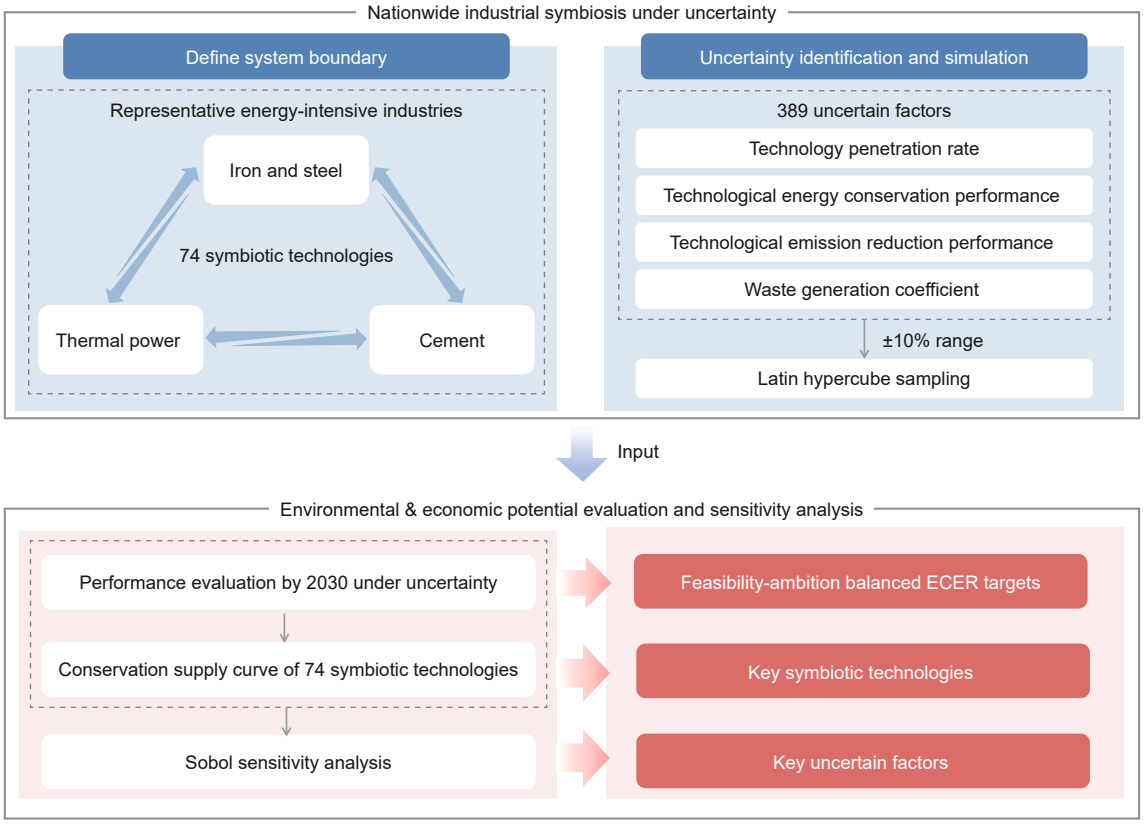



**Fig. 1.** Research framework.

these industries are among the most energy- and pollution-intensive sectors in China. In 2023, they accounted for 37.6% of total industrial energy consumption (NBS, 2025) and contributed 70.6% of industrial $SO_2$ emissions, 82.2% of $NO_x$ emissions, and 39.8% of PM emissions (MEE, 2025), making them critical sectors for China's industrial energy transition and pollution mitigation. Second, there are multiple pathways for material and energy exchange among the three industries, along with close techno-economic linkages, creating significant ECER potential through industrial symbiosis (Cao et al., 2020). For example, steelmaking generates large quantities of by-products such as steel slag and blast furnace slag that can be reused in cement production, while secondary energy streams such as residual heat and by-product gases can be recovered for power generation. At the same time, all three sectors operate large-scale, high-temperature furnaces, enabling the processing and utilization of wastes from other industries.

Focusing on the nationwide iron and steel–thermal power–cement industrial symbiosis network in China, symbiotic technologies within the system are classified into three categories: (1) iron and steel-source technologies (IST), which utilize wastes and by-products from the steel industry, including residual heat and pressure recovery technologies ($IST_{energy}$) and waste material recycling technologies ($IST_{material}$); (2) thermal power-source technologies (PT), which focus on efficient treatment and utilization of by-products and waste from thermal power generation; and (3) cement-sink technologies (CT), which substitute traditional fossil fuels with industrial wastes, biomass, or other alternative fuels in cement production. Based on literature review and in-depth field surveys, a total of 74 symbiotic technologies were identified, comprising 17 $IST_{energy}$, 21 $IST_{material}$, 19 PT, and 17 CT symbiotic technologies (see Supplementary Materials for details). The baseline scenario is set in 2020, with 2030 as the target year for analysis.

This study compiles and organizes parameters across multiple industries, waste types, and geographic regions. By systematically integrating these heterogeneous data sources, we reduce systematic errors caused by cross-regional inconsistencies. The required data are summarized in Table 1, and Tables S1–S4 in the Supplementary Materials.

### 2.2. Uncertainty identification and simulation

Uncertain factors within this nationwide iron and steel–thermal power–cement industrial symbiosis network are categorized into four types: (1) uncertainties in waste and by-product generation coefficients (19 parameters), (2) uncertainties in the penetration rates of symbiotic technologies (74 parameters), (3) uncertainties in the energy conservation performances of symbiotic technologies (74 parameters), and (4) uncertainties in the emission reduction performances of symbiotic technologies (222 parameters).

The 389 uncertain factors are assumed to follow a uniform distribution within a ±10% range of their predicted 2030 values. This interval is widely adopted in uncertainty studies to characterize reasonable variations in techno-economic parameters over medium-term projections (Doh Dinga and Wen, 2021; Wang et al., 2023b). To simulate the system's development under these uncertainties, LHS is employed to generate 100,000 future scenarios. The method divides the high-dimensional sampling space into hypercubes and performs stratified random sampling within each, effectively reducing redundancy and improving estimation accuracy (Olsson et al., 2003).

**Table 1**
Data sources.

| Parameter type | Parameter | Source |
|---|---|---|
| Industrial parameter | Production outputs | Literature review, expert investigation |
| | Industrial structure | Literature review, expert investigation |
| | Types and generation coefficients of wastes and by-products | *"China's Environment Statistical Yearbook", "Annual Report on Prevention and Control of Solid Waste Pollution in Large and Medium Cities of China", "Annual Report on Comprehensive Utilization of China Resources", "Environmental Protection Statistics of China's steel industry"*, literature review |
| Conversion coefficient | Coal equivalent coefficients of different types of energy | *"China's Energy Statistical Yearbook", "General Principles for Calculation of Total Energy Consumption (*GB2589-90)" |
| | Pollutant emission coefficients of energy combustion and product production process | Literature review, *"Annual Development Report for China's Power Industry"* |
| Technical parameter | Energy conservation performance (coal/power/oil/steam); Emission reduction performance ($SO_2$, $NO_x$, PM); Technology penetration rates; Fixed investment; Operational cost; Investment cost; Economic benefit; Discount rate | *"National Catalog of Energy Conservation and Low-Carbon Technologies", "Green Development Plan for the Industrial Sector", "The Guidance Catalog for Advanced and Applicable Energy conservation and Emission-reduction Technologies in the Iron and Steel Industry", "The Guidance Catalog for Advanced and Applicable Energy conservation and Emission-reduction Technologies in the Cement Industry"*, on-site investigation, literature review |

### 2.3. Performance evaluation under uncertainty

The performance evaluation of the nationwide industrial symbiosis network involves two sequential steps. First, we simulate the system-level ECER potential for 2020–2030 under uncertainty, integrating production scale, generation coefficients, technology penetration rates, and other key factors. Second, we disaggregate the system-level results to individual symbiotic technologies. Technology cost-benefit analyses based on a conservation supply curve are then performed to pinpoint key symbiotic technologies offering both significant ECER benefits and economic feasibility.

Energy conservation potential:

$$\mathrm{TEC} = \sum_{st}^{\mathrm{ST}} \mathrm{PO}_{\mathrm{ui}} \times \mathrm{GF}_{\mathrm{bp-ui}} \times \sum_{i}^{I} \mathrm{ECP}_i \times \left(\mathrm{PR}_{st,t+\Delta t} - \mathrm{PR}_{st,t}\right) \quad (1)$$

where TEC denotes the total energy conservation achieved by the nationwide industrial symbiosis network; ST is the set of symbiotic technologies, and $st$ indexes an individual symbiotic technology; PO is the production output; ui represents the upstream industry of a symbiotic technology; GF is the waste generation coefficient; bp − ui is the by-products and wastes generated in the upstream industry; $I$ is the set of energy conservation approaches (i.e., direct energy conservation of a symbiotic technology and indirect energy conservation through reduced material consumption), and $i$ indexes an individual approach; ECP is the energy conservation performance; PR is the penetration rate of a symbiotic technology; $t$ is the year of 2020; and $t + \Delta t$ denotes the year 2030.

Pollutant emission reduction potential:

$$\mathrm{TER}_p = \sum_{st}^{\mathrm{ST}} \mathrm{PO}_{\mathrm{ui}} \times \mathrm{GF}_{\mathrm{bp-ui}} \times \sum_{j}^{J} \mathrm{ERP}_{j,p} \times \left(\mathrm{PR}_{st,t+\Delta t} - \mathrm{PR}_{st,t}\right) \quad (2)$$

where TER denotes the total emission reduction achieved by the nationwide industrial symbiosis network; $p$ is the pollutant (i.e., sulfur dioxide, nitrogen oxides, and particulate matter); $j$ is the set of emission reduction approaches (i.e., direct emission reduction, emission reduction through energy conservation, and emission reduction through material substitution); and ERP represents the emission reduction performance of each symbiotic technology.

We then disaggregate the ECER potential of this nationwide iron and steel–thermal power–cement industrial symbiosis network into individual symbiotic technologies and evaluate their cost-benefit using a conservation supply curve. Three key economic indicators determine the economic performance of each technology: fixed investment, representing the one-time capital expenditure for equipment installation; operation and maintenance cost, covering recurring expenses such as repairs, material consumption, and labor; and economic benefit, which primarily derives from conserved energy and reduced pollutant emissions.

Annualize the fixed investment over the technical lifetime:

$$\mathrm{ANI} = \mathrm{FI} \times \frac{i}{1 - \left(\frac{1}{1+i}\right)^{\mathrm{TL}}} \quad (3)$$

where ANI is the annualized investment cost; FI is the fixed investment cost; $i$ is the discount rate (8% in this study); and TL is the technical lifetime of the symbiotic technology.

Energy conservation cost:

$$\mathrm{EC} = \mathrm{ANI} + \mathrm{OMC} - B \quad (4)$$

$$\mathrm{ECC} = \frac{\mathrm{EC}}{\mathrm{ECP}} \quad (5)$$

where OMC denotes the operation and maintenance cost; and $B$ is the economic benefit; ECC is the energy conservation cost per unit of energy saved; EC denotes the economic cost of a symbiotic technology.

### 2.4. Sensitivity analysis

Based on the 100,000 LHS-generated scenarios described in Section 2.2, we apply Sobol sensitivity analysis to identify the key factors that significantly affect the environmental and economic performance of the nationwide industrial symbiosis network. Sobol sensitivity analysis is a global sensitivity analysis method based on model decomposition and variance analysis (Sobol, 2001). It decomposes the total variance of the model output into contributions from individual input parameters and their interactions. First-order, higher-order, and total sensitivity indices are then calculated by normalizing the variance contributions of each parameter against the total variance (Tsvetkova and Ouarda, 2021). This approach can handle both linear and nonlinear models, and has been widely applied in existing studies to quantify the relative influence of each input variable on model outputs (Crescenzi et al., 2024; Krych and Pettersen, 2025). The specific steps are as follows:

Assuming the model is defined as $Y = f(X)$ where the input parameters $X = (X_1, X_2, \cdots, X_m)$ are independent random variables, the model can be decomposed as Eq. (6):

$$f(X) = f_0 + \sum_{i=1} f_i(X_i) + \sum_{i<j} f_{ij}\left(X_i, X_j\right) + \sum_{i<j<k} f_{ijk}\left(X_i, X_j, X_k\right) + \cdots + f_{1,2,3,\cdots,m}(X) \tag{6}$$

By applying the variance operator to both sides of Eq. (6), we obtain:

$$Var[f(x)] = \sum_{i=1} D_i[f(x)] + \sum_{i<j} D_{ij}[f(x)] + \sum_{i<j<k} D_{ijk}[f(x)] + \ldots + D_{1,2,3,\cdots,m}[f(x)] \tag{7}$$

where $Var[f(x)]$ is the total variance of the model $f(x)$; $m$ is the number of uncertain input parameters; $D_i[f(x)]$ is the first-order variance of input parameter $x_i$; $D_{ij}[f(x)]$ is the second-order variance of $x_i$ and $x_j$, by analogy; $D_{1,2,3,\cdots,m}[f(x)]$ is the $m^{\text{th}}$-order variance of the parameters or sets.

Subsequently, the sensitivity indices of different orders for each parameter are defined as the ratio of the corresponding order-specific variance to the total variance. These yields:

$$S_i = \frac{D_i[f(x)]}{Var[f(x)]} \tag{8}$$

$$S_{ij} = \frac{D_{ij}[f(x)]}{Var[f(x)]} \tag{9}$$

$$S_{1,2,\cdots,m} = \frac{D_{1,2,\cdots,m}[f(x)]}{Var[f(x)]} \tag{10}$$

$$1 = \sum_{i=1}^{m} S_i + \sum_{1\le i<j\le m}^{m} S_{ij} + \sum_{1\le i<j<k\le m}^{m} S_{ijk}\cdots + S_{1,2,\cdots,m} \tag{11}$$

where $S_i$ is the first-order sensitivity index, representing the main effect of a single parameter on the output; $S_{ij}$ is the second-order sensitivity index, which quantifies the interaction effect between two parameters; and $S_{1,2,\cdots,m}$ is the $m^{\text{th}}$ order sensitivity index, reflecting the contribution of the combined interaction of $m$ parameters to the output variance.

Finally, the total sensitivity index of the input parameter $i$ is calculated by summing up the indices in each order, as shown in Eq. (12):

$$\mathrm{ST}_i = S_i + \sum_{i\neq j}^{m} S_{ij} + \sum_{i\neq j, i\neq k}^{m} S_{ijk} + \ldots\ldots \tag{12}$$

Combined with Eq. (11), it can also be written in the following form:

$$\mathrm{ST}_i = 1 - \frac{D_{\sim i}}{Var[f(x)]} \tag{13}$$

where $\mathrm{ST}_i$ is the total sensitivity index of $i$; $D_{\sim i}$ is the variance contribution of all parameters except $x_i$.

However, the calculation of the total sensitivity index is complex if the model has a large number of sensitive parameters. In this situation, a simple method can be adopted to estimate the index value through large number sampling. This estimation is shown in Eqs. (14) and (15):

$$Var[f(x)] = \frac{1}{n}\sum_{m=1}^{n} f^2\left(x_m^{(1)}\right) - E^2 f(x) \tag{14}$$

$$D_{\sim i} = \frac{1}{n}\sum_{m=1}^{n} f\left(x^{(1)m}\right)\cdot f\left(x_{\sim i}^{(1)m}, x_i^{(2)m}\right) - E^2 f(x) \tag{15}$$

where $n$ is the total sample size ($n$ = 100,000 in this study); $x^{(1)m}$ represents the $m^{\text{th}}$ sample vector from the first sampling; and $x_{\sim i}$ denotes the subset of all input parameters except $x_i$. The superscripts (1) and (2) indicate two independent sampling matrices generated during the simulation process.

## 3. Results

### 3.1. Probabilistic ECER target-setting balances ambition and feasibility for the nationwide industrial symbiosis network

To account for long-term development uncertainties, the LHS method is employed to sample 389 uncertain factors 100,000 times. The 100,000 feasible sampling results represent 100,000 distinct long-term development scenarios (2020–2030) for the nationwide industrial symbiosis network that comply with realistic conditions and policy requirements.

Results show that the nationwide industrial symbiosis network's environmental and economic performance metrics exhibit markedly different sensitivities to future scenario uncertainties. Specifically, the magnitude of fluctuations in the simulated outcomes ranks as follows: PM reduction (24.2%) > $NO_x$ reduction (15.5%) > $SO_2$ reduction (11.4%) > investment cost (8.3%) > energy conservation (7.9%) (Fig. 2). This ranking demonstrates that the system's energy conservation performance is the most stable under varying conditions, while its effectiveness in reducing PM emissions is the most susceptible to change. Consequently, achieving robust and cost-effective ECER outcomes—particularly for the highly sensitive PM reduction target—requires explicitly accounting for uncertainty in the nationwide industrial symbiosis network.

Given uncertainties in future development scenarios, we simulate the 5th–95th percentile range (i.e., the central 90% interval) of the nationwide industrial symbiosis network's performance from 2020 to 2030. This network is expected to achieve energy savings of 47.1–61.2 Mtce, reduce $SO_2$ emissions by 170.3–248.9 kt, $NO_x$ emissions by 166.7–280.3 kt, and PM emissions by 41.8–96.7 kt, while requiring technological investment costs of 92.8–122.1 billion USD.

Reasonable ECER target-setting for the nationwide industrial symbiosis network should balance ambition with feasibility.

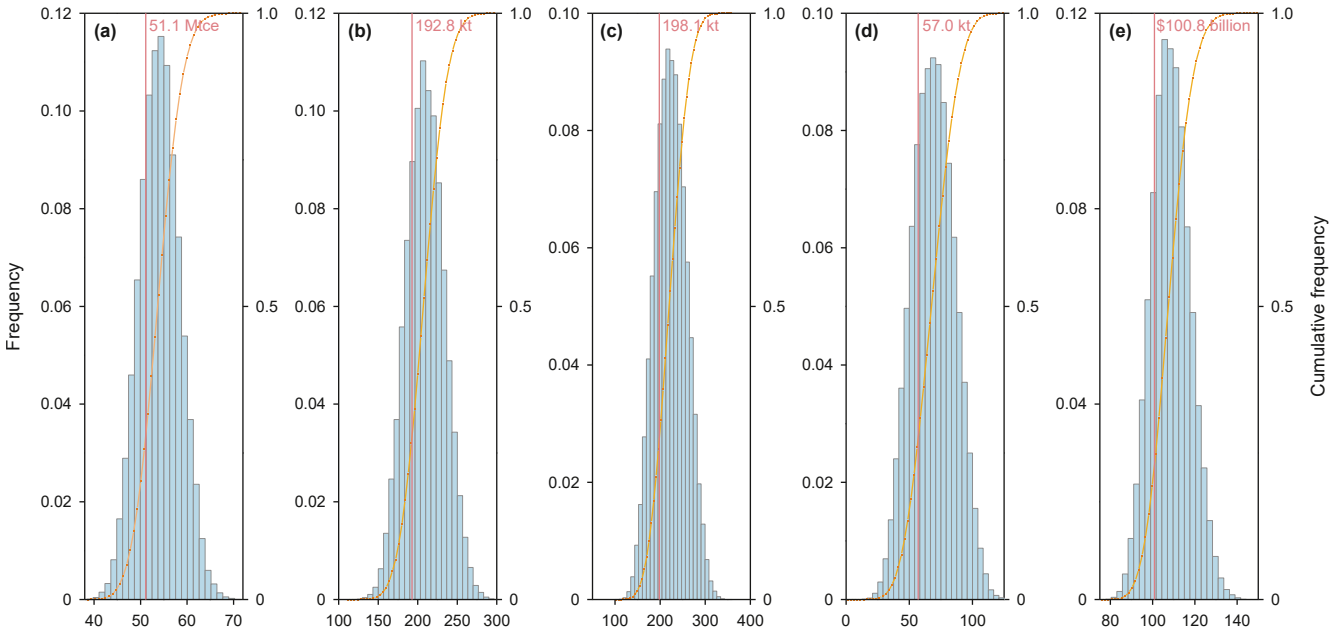



**Fig. 2.** Probability distributions of the environmental and economic performance of the nationwide industrial symbiosis network, 2020–2030. **(a)** Energy conservation potential, **(b)** $SO_2$ reduction potential, **(c)** $NO_x$ reduction potential, **(d)** PM reduction potential, and **(e)** investment cost.

Accordingly, we establish 2020–2030 targets based on a 75% feasibility threshold across 100,000 simulated scenarios (Wen et al., 2018), avoiding targets that are either unattainable or insufficiently ambitious. The specific targets include: achieving energy savings of 51.1 Mtce, reducing $SO_2$ emissions by 192.8 kt, $NO_x$ emissions by 198.1 kt, and PM emissions by 57.0 kt, while keeping the total investment costs below 100.8 billion USD. Benchmarked against IEA projections, the energy-saving target established in this study is expected to reduce China's total energy consumption by 1.2% in 2030 (IEA, 2024). This result underscores the network's capacity to reliably deliver a significant contribution to the nation's energy transition, even amidst future uncertainties.

### *3.2. Environmental and economic performance of the symbiotic technologies varies widely, calling for targeted and differentiated promotion policies*

The above presents a comprehensive analysis of the nationwide industrial symbiosis network's achievable energy conservation, emission reductions, and associated investment costs under uncertain development scenarios. To identify the critical technological pathways for achieving these targets, we disaggregate the system-wide results to individual symbiotic technologies and assess their cost-effectiveness using energy conservation supply curves.

Meeting nationwide ECER targets depends on the coordinated contributions of multiple types of symbiotic technologies. As shown in Fig. 3, according to the mean estimates derived from the 100,000 simulated scenarios, $IST_{material}$ symbiotic technologies make prominent contributions to ECER, accounting for 37% of national energy savings (20.0 Mtce), 46% of $SO_2$ reduction (95.3 kt), and 34% of $NO_x$ reduction (76.6 kt), highlighting their central role in the industrial symbiosis network. In contrast, PM reduction is primarily driven by CT technologies, contributing 60% of total potential (41.4 kt). This dominance stems from the fact that CT technologies directly target particulate emission sources—such as fly ash and desulfurization gypsum generated by the power industry—by repurposing these loose powders into stable

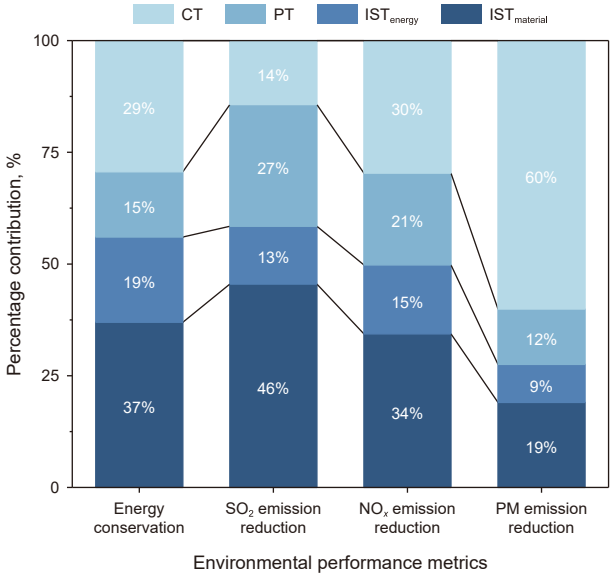



**Fig. 3.** Contributions of different symbiotic technologies to energy conservation and emission reduction. CT, cement–sink technologies; PT, thermal power–source technologies; $IST_{energy}$, waste heat and pressure recovery technologies in the iron and steel industry; $IST_{material}$, material recycling technologies in the iron and steel industry.

resources (e.g., cement raw materials), effectively preventing particulate release into the atmosphere at the source. These results demonstrate that no single type of symbiotic technology is capable of meeting all environmental targets effectively, underscoring the need for integrated deployment of multiple symbiotic technologies to maximize system-wide ECER outcomes.

Approximately 95.9% of symbiotic technologies exhibit negative energy conservation costs under uncertainty (Fig. 4), indicating that most symbiotic technologies deliver energy benefits and remain economically viable. Collectively, these technologies offer a cumulative average energy conservation potential of 52.7

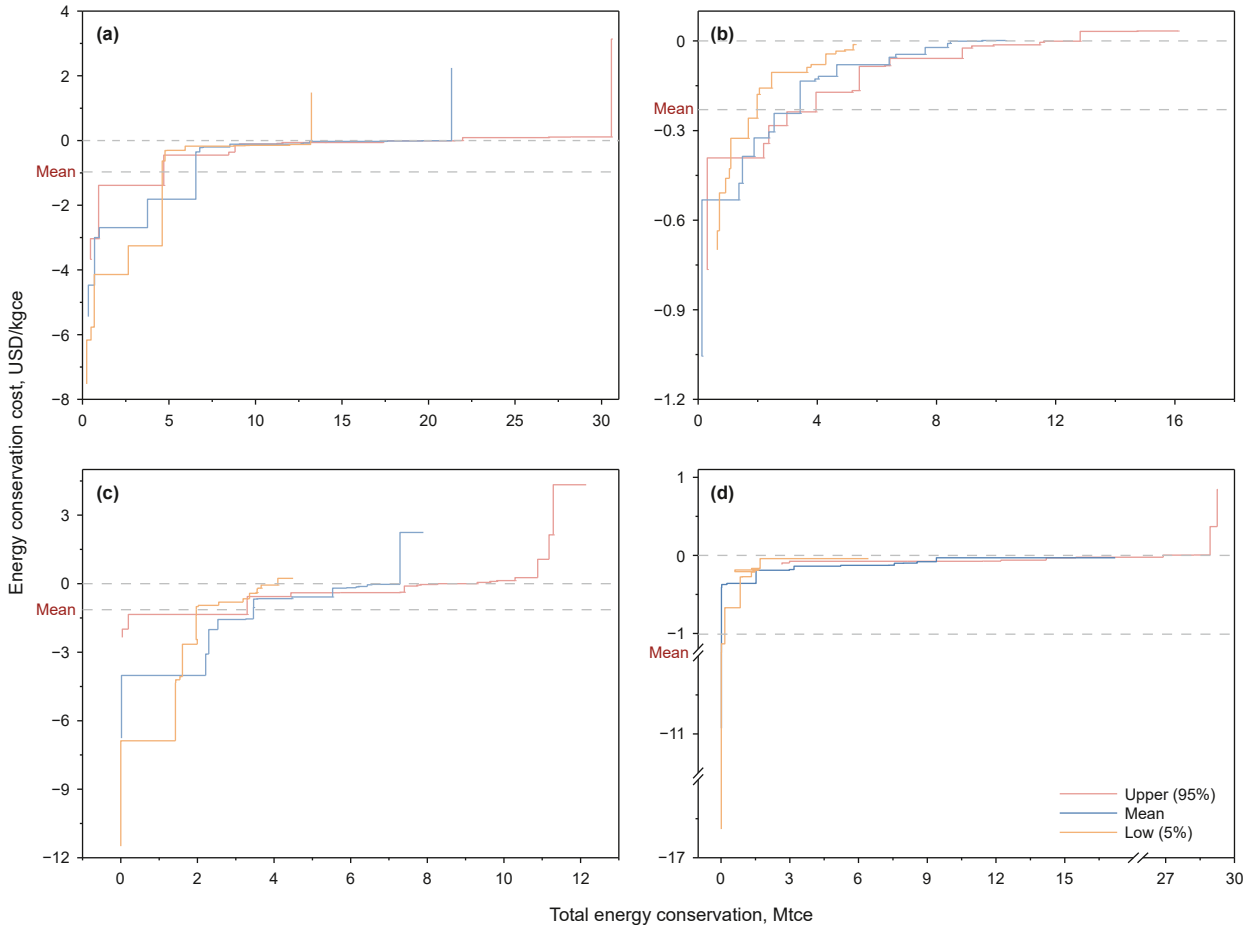



**Fig. 4.** Energy conservation supply curves for four types of symbiotic technologies. **(a)** $IST_{material}$, material recycling technologies in the iron and steel industry; **(b)** $IST_{energy}$, waste heat and pressure recovery technologies in the iron and steel industry; **(c)** PT, thermal power–source technologies; **(d)** CT, cement–sink technologies. Two gray dashed lines indicate: the zero-level reference line, and the average energy conservation cost of each technology category, calculated by first averaging the sampled values for each individual technology, and then averaging across all technologies in the category.

Mtce, which could reduce national energy consumption by about 1.3% by 2030.

However, notable differences emerge across different types of symbiotic technologies in both the mean values and stability of energy conservation costs. PT symbiotic technologies have the lowest average energy conservation cost (−1.1 USD/kgce). However, their substantial variability across the 100,000 simulated scenarios (average standard deviation > 10 USD/kgce) suggests that the economic advantage of these technologies may not be reliable under uncertainty, posing potential challenges for investment and policy decisions. In contrast, $IST_{energy}$ symbiotic technologies demonstrate slightly higher average energy conservation costs (−0.2 USD/kgce), while exhibiting much lower variability across scenarios (average standard deviation = 0.1 USD/kgce). Only a few cases exhibit slightly positive costs, indicating that most $IST_{energy}$ technologies remain economically advantageous under uncertainty. Notably, while the average energy conservation costs of $IST_{material}$ and PT symbiotic technologies are both negative, some individual technologies exceed 2 USD/kgce, highlighting the need for careful technology selection.

Significant heterogeneity in emission reduction costs—both between technology categories and across pollutants within a specific category—compounds the complexity of technology selection. For example, PM reduction costs range from −67.3 USD/g for CT technologies to −0.4 USD/g for $IST_{energy}$ technologies. The standard deviation of PM reduction costs across simulated scenarios differs by as much as 840.2 among the four technology categories, indicating that some symbiotic technologies may face substantial economic uncertainty in practical applications. Even within the same category, cost-effectiveness can diverge significantly across pollutants. For instance, within $IST_{material}$ symbiotic technologies, the average $SO_2$ and $NO_x$ reduction costs across simulated scenarios are positive, whereas the average PM reduction cost is negative. This divergence suggests that $IST_{material}$ symbiotic technologies are more suitable for PM control but may require complementary technologies or policy support when addressing $SO_2$ and $NO_x$ mitigation.

Furthermore, cost results for individual technologies reveal trade-offs between ECER targets. In the $IST_{material}$ category, some technologies achieve negative energy conservation costs (e.g., −4.5 USD/kgce) while exhibiting extremely high PM reduction costs (e.g., 1.1 USD/g). This indicates that prioritizing energy conservation alone may lead to disproportionately high costs for pollutant abatement. In contrast, $IST_{energy}$ symbiotic technologies achieve more balanced performance across environmental objectives, displaying relatively consistent and well-aligned cost profiles.

Taken together, the pronounced heterogeneity in both energy conservation and emission reduction costs across the four technology categories highlights the need to reclassify the 74 symbiotic

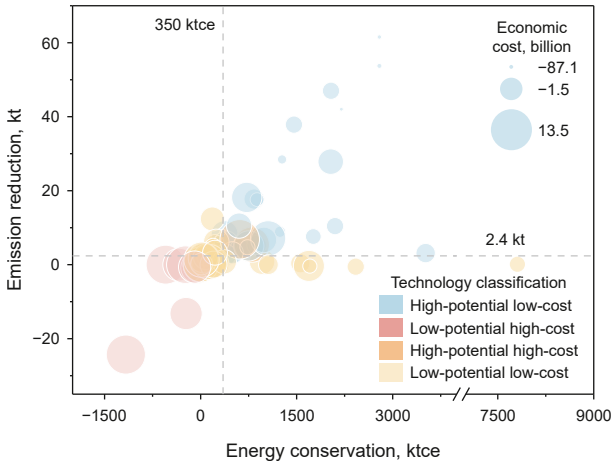



**Fig. 5.** Classification of symbiotic technologies based on their energy conservation potential, emission reduction potential, and economic cost. The technologies are categorized into four distinct groups: high-potential low-cost (priority promotion), high-potential high-cost (policy intervention), low-potential low-cost (need technological upgrade), and low-potential high-cost (non-priority promotion).

technologies using a multi-objective perspective. Such a refined classification framework can support differentiated deployment strategies, reduce the risk of biased decisions arising from single-metric evaluations, and enhance the likelihood that the industrial symbiosis network will achieve stable and efficient ECER outcomes under future uncertainties.

Based on the 2030 energy conservation potential, emission reduction potential, and economic cost of each symbiotic technology under uncertainty, this study classifies the 74 symbiotic technologies into four groups (see Fig. 5). Specifically, for each technology we calculate the mean energy conservation and emission reduction potential across 100,000 scenarios. The medians of these two indicators are then used as thresholds to distinguish "high-potential" from "low-potential" technologies. Economic cost is classified using zero as the threshold: technologies with negative costs (i.e., net economic benefits) are defined as "low-cost", whereas those with positive costs are categorized as "high-cost". This framework results in four groups of symbiotic technologies.

**High-potential low-cost group (priority promotion):** This cohort comprises 27 symbiotic technologies (6 $IST_{material}$, 10 $IST_{energy}$, 4 PT and 7 CT) with exceptional energy conservation potential (>350 ktce), emission reduction potential (>2.4 kt), and cost advantages (negative economic cost), demonstrating strong feasibility for widespread adoption. $IST_{energy}$ technologies account for 37% of this group, highlighting their pivotal role in this nationwide industrial symbiosis network. Collectively, these 27 technologies can deliver 76.9% of the network's total ECER potential. Therefore, we recommend inclusion of these 27 symbiotic technologies in the 2020–2030 *National Catalog of Energy Conservation and Low-Carbon Technologies*, supported by industry benchmarking and targeted green finance.

**High-potential high-cost group (policy intervention):** 2 symbiotic technologies (1 $IST_{energy}$ and 1 PT) show significant ECER potential but face adoption barriers due to elevated costs. As demonstrated by Cao et al. (2025), differentiated and targeted interventions—subsidies, tax incentives, and risk compensation—are necessary in enhancing economic viability and nationwide promotion of this type of symbiotic technology. Therefore, we recommend a government-led two-tier incentive scheme: baseline subsidies coupled with performance-based ECER rewards to alleviate enterprise adoption costs.

**Low-potential low-cost group (need technological upgrade):** 37 symbiotic technologies (11 $IST_{material}$, 6 $IST_{energy}$, 14 PT and 6 CT) demonstrate strong economic returns but relatively limited ECER contributions. The government should take measures to guide enterprises toward technological upgrades, improving overall network effectiveness.

**Low-potential high-cost group (non-priority promotion):** 8 symbiotic technologies (4 $IST_{material}$ and 4 CT) show limited ECER potential with poor economic performance. They should be excluded from the 2020–2030 *National Catalog of Energy-Saving and Low-Carbon Technologies*. This group of symbiotic technologies can be further categorized into two sub-groups: (1) technologies nearing saturation (limited further diffusion potential), and (2) those processing minimal waste/byproducts (inherently low ECER scalability). Resource reallocation to higher-efficiency alternatives is recommended.

### *3.3. Technology penetration rates serve as the primary leverage point for enhancing multi-objective performance in industrial symbiosis networks*

Sobol sensitivity analysis shows that technology penetration rates contribute the largest share of variance in ECER outcomes, accounting for 84.5% of the total variance across the evaluated targets. Given the large number of uncertain inputs (389), the differences between the first-order ($S$) and total sensitivity (ST) indices are generally small. Therefore, this study focuses on ST values, which capture both the direct and interaction effects of each parameter and thus provide a comprehensive measure for identifying the dominant contributors to uncertainty (Vuillod et al., 2023). As shown in Fig. 6, technology penetration rates exhibit the highest ST across all environmental targets—particularly for PM (accounting for 94.9% of variance) and $NO_x$ (accounting for 91.8% of variance) reduction. This indicates that ECER outcomes are highly sensitive to changes in technology penetration rates.

In contrast, uncertainty in the technical performance of symbiotic technologies contributes relatively little to system-level ECER outcomes. Specifically, variability in energy conservation and emission reduction performance across technologies explains only 6.2% of the total variance in environmental benefits (ST = 0.30), while having a negligible impact on investment costs (ST = 0). This indicates that, under uncertainty, improvements in individual technology performance alone are unlikely to substantially alter the overall system-level ECER outcomes.

Uncertainties in emission reduction performance have a relatively greater effect on total $SO_2$ reduction (ST = 0.10) than on $NO_x$ (ST = 0.05) or PM (ST = 0.04). This predominance arises because $SO_2$ mitigation exhibits greater dependency on symbiotic technologies. Symbiotic technologies critically enable high-sulfur byproduct substitution and desulfurization residue valorization—constituting primary $SO_2$ mitigation approaches (Uali et al., 2025). Consequently, fluctuations in the emission-reduction effects of symbiotic technologies induce pronounced impacts on nationwide $SO_2$ mitigation outcomes. In contrast, $NO_x$ and PM reduction follows more decentralized pathways with diversified approaches, rendering it less susceptible to symbiotic technology variations (Su et al., 2025). Thus, even with technological performance fluctuations, their systemic mitigation effects remain marginal.

Fluctuations in total investment costs of the nationwide industrial symbiosis network are largely driven by technology penetration rates (accounting for 73% of variance) and by-product/waste generation coefficients (accounting for 27% of variance).

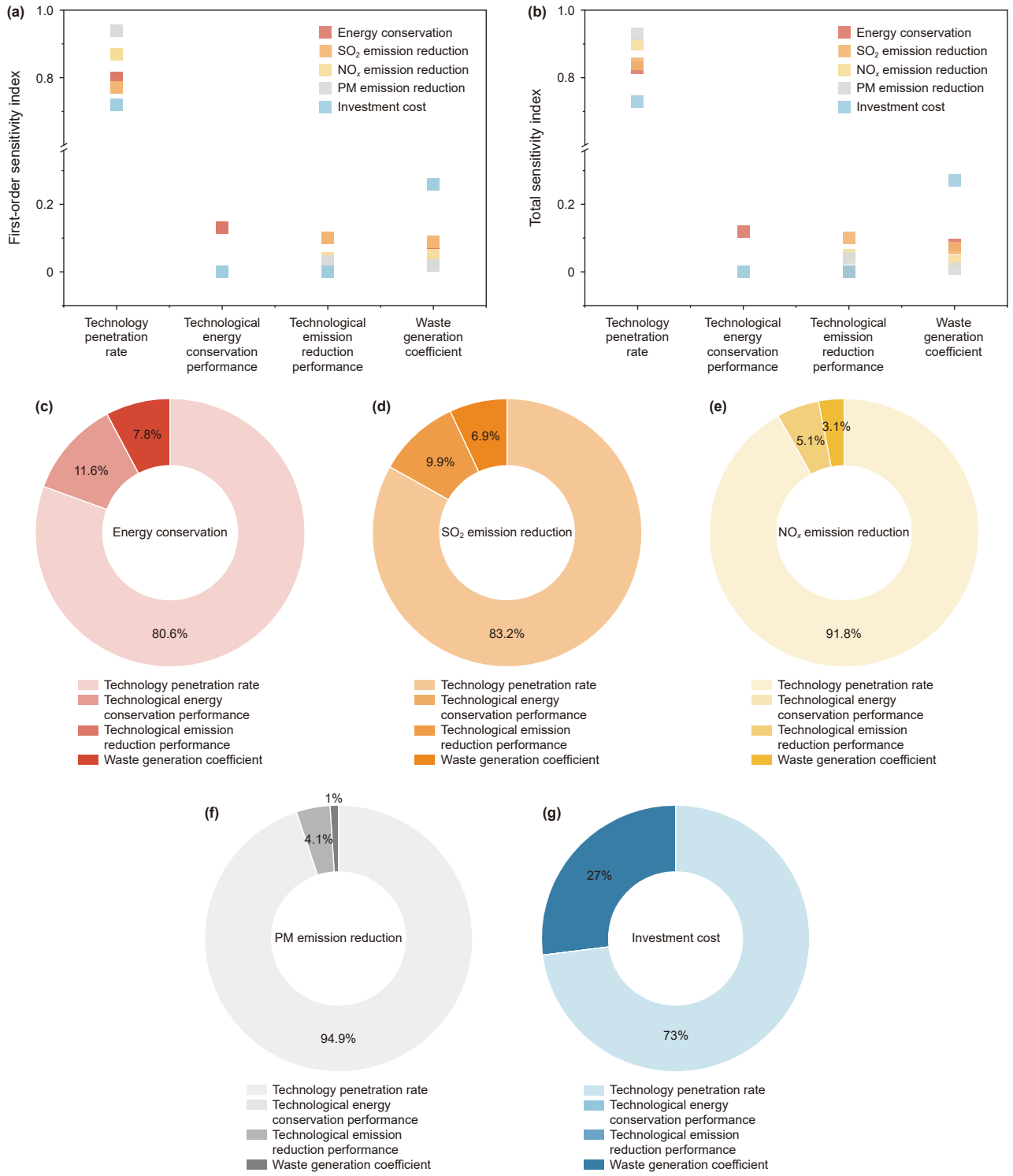



**Fig. 6.** Results of Sobol sensitivity analyses. **(a)** First-order sensitivity indices, **(b)** total sensitivity index for the four categories of uncertain factors, **(c)** relative contribution of each category to the total variance of specific targets: energy conservation, **(d)** $SO_2$ emission reduction, **(e)** $NO_x$ emission reduction, **(f)** PM emission reduction, **(g)** investment cost. Contributions are calculated by normalizing the total sensitivity indices across all factor categories for each target.

This indicates that investment requirements are most sensitive to the scale and pace of technology deployment, while variability in waste generation introduces secondary, but meaningful, effects. These results emphasize that accurate forecasting of technology adoption and careful assessment of waste generation are critical for reliable economic planning and risk management in nationwide industrial symbiosis under future uncertainties.

## 4. Conclusions

Nationwide industrial symbiosis networks face broader, more interconnected uncertainty sources than single-industry systems, leading to greater systemic unpredictability. Accurately modeling these intricate uncertainty relationships and quantifying their impacts is critical, as it not only provides benchmarks for setting

appropriate ECER management targets, but also enables the formulation of tailored risk mitigation strategies. This study employs Latin Hypercube Sampling to simulate 100,000 feasible development scenarios for the nationwide iron and steel–thermal power–cement industrial symbiosis network during 2020–2030, enabling in-depth analysis of systemic uncertainties.

To ensure that nationwide ECER targets are both ambitious and achievable, we define policy-actionable target ranges for energy, emissions, and investment costs based on a 75% feasibility threshold. Unlike traditional rigid "one-size-fits-all" goals, this threshold creates a buffer zone between environmental urgency and technological and economic feasibility, supporting adaptive management under uncertainty. For China's nationwide iron and steel–thermal power–cement industrial symbiosis network, the 2020–2030 targets are: achieving energy savings of 51.1 Mtce, reducing $SO_2$ emissions by 192.8 kt, $NO_x$ emissions by 198.1 kt, and PM emissions by 57.0 kt, while keeping the total investment costs below 100.8 billion USD.

Through conservation supply curve analysis, we pinpoint key symbiotic technologies delivering significant ECER benefits with economic feasibility under uncertainty. Symbiotic technologies exhibit substantial heterogeneity in ECER potential and cost-effectiveness. Therefore, 74 symbiotic technologies are classified into four categories for targeted management. Among them, 27 high-potential, low-cost symbiotic technologies were prioritized for government promotion. These insights indicate that policy design should move beyond uniform incentives and adopt a differentiated approach guided by technology performance, enabling efficient allocation of resources and ensuring robust achievement of energy conservation and emission reduction targets under uncertainty.

Through Sobol sensitivity analysis, we identify critical leverage points—particularly technology diffusion over pure technical performance—for maximizing systemic performance resilience. Sobol sensitivity analysis reveals that technology penetration rates dominate ECER outcome variance of the nationwide industrial symbiosis network. It drives 84.5% of outcome variability, far exceeding other factors. This indicates its critical leverage effect on energy conservation, emission reduction, and cost control. By contrast, merely improving technical parameters (e.g., energy conservation effect of a single symbiotic technology) makes a limited systemic contribution. Policymakers should shift focus from R&D investment to optimizing technology diffusion. First, they should increase investment in cross-sector infrastructure, such as residual heat pipeline networks and by-product transfer stations, to remove physical bottlenecks that constrain resource sharing between industries. Second, differentiated incentive schemes and demonstration programs should be implemented to accelerate the diffusion of key symbiotic technologies across regions and sectors. In addition, dynamic monitoring and phased evaluation mechanisms targeting technology penetration rates should be established to enable timely policy adjustments, thereby enhancing overall system resilience under uncertainty.

This study advances industrial symbiosis governance by establishing a probabilistic decision framework that navigates multi-source uncertainties inherent in national-scale industrial symbiosis networks. Beyond overcoming static scenario limitations, this study reconceptualizes industrial symbiosis planning from deterministic roadmaps to dynamic uncertainty-adaptive frameworks. However, limited by insufficient data, this research focuses on the nationwide iron and steel–thermal power–cement industrial symbiosis network, potentially underestimating the ECER potential of industrial symbiosis. As data accumulates, the framework could expand to include additional industrial sectors and incorporate the residential consumption sector, enabling ECER potential assessment of production–consumption–society meta-coupling systems under uncertainty.

## CRediT authorship contribution statement

**Xuan Wang:** Writing – original draft, Visualization, Validation, Methodology, Data curation, Conceptualization. **Xin Cao:** Writing – review & editing, Supervision, Data curation. **Yi-Han Wang:** Writing – original draft, Methodology. **Ming-Xuan Wu:** Data curation. **Ze-Chen Zhang:** Data curation.

## Data availability

All data used for this research are provided or available from publicly accessible sources cited. Source data are provided with this research.

## Declaration of competing interest

The authors declare no competing interests.

## Acknowledgments

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## Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.petsci.2026.07.007.

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