Journal of Environmental Management 392 (2025) 126699

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

Carbon allowance decision optimization with multi-agent simulation: Incorporating behavioral drivers

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ARTICLE INFO

Keywords:
Carbon emission allowance allocation
Carbon allowance auction mechanism
Carbon emission reduction
Multi-agent simulation
Risk attitude
Information feedback

ABSTRACT

Carbon trading markets play a vital role in reducing emissions, with the initial allocation of carbon allowances being a key issue. As many emerging markets shift from free allocation to auction mechanism, this study develops a carbon allowance decision optimization model based on multi-agent simulation under two commonly used auction mechanisms. The model considers both government's auction effectiveness and total companies' carbon compliance cost, and incorporates behavioral factors influencing corporate bidding behavior: risk attitude and information feedback. This paper further assesses how key auction parameters like reserve price, allowance supply, and secondary market transaction price affect auction efficiency, corporate compliance costs, and carbon reduction outcomes. The multi-objective particle swarm optimization (MOPSO) algorithm is used to solve the model, and the TOPSIS method helps select ideal solutions from the Pareto set. The main results include: (1) Risk-seeking companies are more likely to win bids, highlighting the impact of bidding attitudes; (2) Under trusted social network, as the density of corporate social networks increases, auction information feedback helps improve auction efficiency, but excessive bid adjustments may lead to convergence and reduce efficiency; In contrast, the existence of false underreporting information will lead to a decrease in auction efficiency and total enterprise costs, which is particularly evident under the uniform-price auction mechanism. (3) The increase in auction reserve price and secondary market transaction price can both encourage companies to reduce carbon emissions; (4) Increasing allowance supply reduces compliance costs but may weaken companies' emission reduction incentives. This study provides insights for governments in designing carbon allowance auction mechanisms that balance auction efficiency and corporate compliance costs, as well as emission reduction outcomes. It also offers decision-making guidance for enterprises in optimizing carbon compliance strategies.

1. Introduction

As one of the most promising market-based tool for reducing emissions (Cheng et al., 2025), the carbon emission trading system has been adopted by many countries and regions, including the European Union, California, RGGI, China, and Australia (Yuan et al., 2024). The carbon allowance allocation mechanism is one of the core components in the design of the system (Xiong et al., 2017) and a key issue in the construction of an effective carbon market (Jiang et al., 2016). Currently, there are two ways to allocate carbon allowance: free allocation and paid allocation (Khezr and MacKenzie, 2018). Paid allocation is primarily conducted through auctions. Zhang et al. (2022) points out that allowance auctions not only achieve environmental benefits, but also bring about economic welfare improvements through revenue reuse. Schmalensee and Stavins (2017) noted that free allocation can gradually transition to auctions, as seen in practice of California. Today, most mature carbon markets, such as the EU ETS, California, and RGGI, primarily adopt auction-based allocation (Carratù et al., 2020). Additionally, policies indicate that emerging carbon markets, such as China's National Carbon Trading Market and the Kazakhstan Carbon Market, are also introducing the auction mechanism (China, State Council, 2024; ICAP, 2024). The commonly used carbon auction formats in the international market are uniform-price and discriminatory-price sealed-bid auctions. Given current trends, carbon allowance auction is expected to become the dominant allocation method (Jiang et al., 2016). Therefore, this study focuses on the auction mechanism.

The International Energy Agency (IEA) pointed out that the introduction of the carbon emission mechanism aims to encourage

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https://doi.org/10.1016/j.jenvman.2025.126699
Received 5 May 2025; Received in revised form 10 July 2025; Accepted 20 July 2025
Available online 24 July 2025
0301-4797/

enterprises to reduce emissions, improve environmental benefits, and provide government financial sources for the investment and deployment of clean energy (IEA, 2024); but at the same time, it inevitably increases the carbon compliance costs of enterprises. Scholars conducted multi-dimensional research on the design of auction mechanisms from a macro perspective. Zhao et al. (2010) studied the design of carbon allowance allocation systems in the power market, especially the impact of different allocation methods such as auction and grandfather allocation on market equilibrium. Yu et al. (2024) uses system dynamics simulation to study the optimal timing and appropriate policy intensity for introducing a bidding mechanism in three regions of China. Esmaeili Avval et al. (2022) studied the impact of uniform-price and discriminatory sealed-bid auctions on carbon price control and supply chain profits under both constrained and unconstrained price and quantity settings in carbon emission allowance auction design. Wang et al. (2022) analyzed the bidding mechanisms in China's carbon emission trading system, such as bidding models, bidding scales, and pricing models, and used the market linkage index to analyze the operating trends and effects of the carbon bidding mechanism. Chen et al. (2023) established a blockchain-based carbon auction allocation mechanism suitable for China's carbon market, considering different scenarios and the technical characteristics of blockchain. Sun and Li (2020) proposed a pollution permit allocation mechanism based on multi-unit double auctions in the context of the Beijing Environment Exchange in China. Based on economic experiments, Cong and Wei (2012) analyzed carbon prices, auction efficiency, demand suppression, and power supply fluctuations in three forms: uniform-price, discriminatory-price auction, and English clock auctions.

Meanwhile, some scholars also conducted research from the perspective of enterprises. As the main participants in the auction, companies' decision-making behavior has a great impact on the results of the carbon allowance auction. For example, Wang and Yang (2016) developed a carbon auction model with asymmetric private valuations, relaxing the independent and identically distributed assumption, and analyzed how reserve prices influence bidding strategies and equilibrium outcomes. Qu et al. (2018) established a decision model for optimal production of enterprises, government penalties or subsidies, and cost minimization of integrated energy service providers. Wei et al. (2018) used experimental economics to analyze how firms' bidding strategies and production decisions affect the carbon market, finding that short-sighted behavior by firms can intensify market volatility. Liu et al. (2019) used a mathematical model to describe the behaviors and strategies of three entities in the steel industry: state-owned enterprises, private enterprises, and carbon emission rights exchanges, and simulated the dynamic game process of the three entities in the carbon auction in Netlogo. As policymakers, government need to assess the efficiency of carbon auctions in resource allocation and transactions. As key participants, Companies need to evaluate compliance costs and make effective decisions on bidding, emission reduction, etc. While both parties influence the operation effect of auction outcomes, few studies integrate these factors into a unified optimization framework.

In addition, bidding behavior directly influences companies' auction results, so it constitutes an important part of the research on carbon allowance auction mechanisms. Traditional auction theories and research are often based on rational people assumption, but in reality, bidders generally have limited rationality, and their behavior is often affected by factors such as risk attitude, price information, and social networks(Li, 2017). Some scholars paid attention to the impact of risk attitude on bidding behavior. For example, Liu et al. (2018) studied the role of risk preference in construction bidding decisions, and the results showed that bidders with higher risk preferences tend to make higher price increase decisions. Chen and Wang (2019) introduced buyer risk attitude in multi-attribute reverse auctions and constructed a two-stage auction model considering fuzzy efficiency and supplier capabilities. However, in the field of carbon allowance auction, research on the impact of bidders' risk attitude on bidding behavior is still relatively lacking.

Beyond internal factors such as risk attitudes, bidding behavior is also influenced by external environmental factors. In real society, economic entities establish relationships through information interaction, and judge the market situation based on this, so as to choose the optimal strategy. In the auction market, auction information, quotation information, etc., will affect the allocation outcomes, auction efficiency, seller revenue, etc. (Adomavicius et al., 2013; Gretschko and Rajko, 2015). Some scholars studied information feedback for different auction types or information types. For example, Zheng et al. (2019a) used experimental methods to evaluate how different types of feedback affect allocation efficiency, firm revenue, and government income in emission rights auctions. Liu et al. (2016) employed a regression model to analyze the impact of real-time and historical prices on bidding behavior in repeated auctions. Zhan and Bai (2014) studied how bidders adjust their bidding strategies in an information-incomplete market when the number of transactions and historical prices are known. Engin and Vetschera (2020) conducted empirical research in the context of electronic auctions and found that providing bidders with more information feedback significantly influences firms' bidding behavior. In the carbon allowance single-round sealed auction, most participants are companies with high carbon emissions and similar businesses. They are familiar with each other and exchange information frequently, which may have an impact on the bidding behavior of companies. However, few studies have incorporated information feedback into the carbon auction format.

Therefore, based on the current research status, this paper develops a carbon allowance decision optimization model from both governmental and corporate perspectives, and incorporates the risk attitude and information feedback that affect corporate bidding behavior. Focusing on the internationally commonly used uniform-price and discriminatory-price sealed auction formats, the impact of corporate risk attitudes and different information feedback structures on bidding strategies and results is studied. Moreover, this paper assesses how changes in critical auction parameters, such as reserve prices and allowance supply, affect auction performance and emission reductions. The main innovations and contributions of this paper are as follows.

(1) Develop a carbon allowance decision-making optimization model that accounts for the objectives of both governments and companies. The model can provide some theoretical insights for designing auction systems that balance market efficiency and corporate compliance costs, while also supporting companies in formulating effective compliance strategies.
(2) Integrate companies' risk attitudes and information feedback into the carbon auction framework. Three types of risk attitudes are defined and embedded into the model as static characteristics of firms to capture behavioral heterogeneity. A social network-based bidding feedback mechanism is established to simulate information exchange and strategy adjustments among firms under both trusted and misinformation network structures. This makes up for the problem that existing studies are insufficient in characterizing corporate heterogeneous decisions, and also makes the model as close to the actual auction situation as possible.
(3) Evaluate the impact of the carbon allowance auction reserve price, total supply, and secondary market transaction price on auction efficiency, corporate costs, and carbon emission reductions. It further reveals how different auction mechanism settings incentivize corporate emission reduction behavior, thereby enabling carbon allowance auctions to more effectively achieve their emission reduction targets.
(4) Apply the multi-agent approach to represent autonomous decision-making and interactions among companies, avoiding the influence of subjective bias of participants in the economic experimental method on the experimental results.

The remainder of this paper is organized as follows. Section 2 develops the company bidding model by incorporating risk attitudes and establishing an information feedback mechanism. Then this section constructs the carbon allowance decision optimization framework, introduces the heuristic algorithm used for solving the model, and describes the method for selecting the ideal solution. Section 3 presents the agent characteristics, algorithm parameters, and simulation scenarios. This section also analyzes the optimization results and conducts a sensitivity analysis of key parameters. Section 4 presents the conclusions and provides corresponding policy recommendations.

2. Models and methodology

This section first introduces the commonly used international carbon allowance auction process, defines the objective functions, and then establishes the company social network-based information feedback mechanism. The optimization framework is illustrated in Fig. 1.

The model is based on uniform-price and discriminatory-price sealed-bid auctions (Beijing Municipal Ecology and Environment Bureau, 2023; RGGI, 2024). The auction process includes: (1) the government publishes the total allowance and reserve price before the auction; (2) sets a maximum bidding amount limit; (3) companies submit bids in a single round; (4) the platform aggregates bids into a demand curve and determines the clearing price; (5) allowances are allocated based on the results. The government has the responsibility to monitor the performance of companies and impose fines on companies that have deficiencies.

Fig. 1 shows the optimization model established in this paper. The government takes auction efficiency as the goal, because this indicator is not only the main criterion for measuring the auction effectiveness (Hu et al., 2019), but also the main goal of some carbon markets to implement carbon auction mechanism (Mougeot et al., 2011). The companies (multi-agents) participating in the auction minimize the total carbon compliance cost through interaction. This goal can not only reflect the cost status of the enterprise, but also reflect the overall situation of the market, avoid the market imbalance that may be caused by individual cost optimization, and maintain market fairness. In the model, the company will generate an initial bid based on its own valuation, reserve price and risk attitude, and exchange initial bids in good faith with neighbors in social networks of different densities, and then readjust the bid range to participate in the auction. The optimization model solution method in this paper is the MOPSO combined with TOPSIS, which will be described in detail in Section 3.

2.1. Company's bidding model

Before the carbon allowance auction begins, the government announces the auction reserve price (α) and the total supply (ts). All participating companies are assumed to be fully informed of the auction rules. Each company i has a unit valuation v_i. The bid price b_{pi} is randomly generated within the range between α and its v_i, as shown in formula (1). The allowance E_i required by each company is generated using Zipf's law, following (Wang and Duan, 2022). In international carbon markets such as South Korea, RGGI, California, and Beijing, quantity caps are often imposed on participants to prevent market dominance and ensure liquidity and competition. Therefore, this study sets the upper limit of bidding quantity for each company at 15 % of the total supply. The bid quantity b_{qi} is defined in formula (2).

$$b_{pi} \sim U(\alpha, v_i) \tag{1}$$

$$b_{qi} \in [E_i, 0.15ts) \tag{2}$$

After bidding ends, the government collects all submitted prices and quantities, sorting them in descending order of bid price. If prices are identical, bids are further sorted by quantity in descending order (the matrix B_{sorted} can is shown in formula 3). The intersection of the aggregated demand curve and the supply curve determines the clearing price, which is also the bid price b_{pk} of the last winning company. For simplicity, transaction fees are not considered in this study.

$$B_{sorted} = \begin{pmatrix} b_{p\ \max} & b_{qi} \\ \vdots & \vdots \\ b_{p\ \min} & b_{qj} \end{pmatrix} \tag{3}$$

After the auction is over, the actual price paid (b_{ai}) by a company under the uniform-price format is given by formula (4), and under the discriminatory format by formula (5).

$$b_{ai} = \begin{cases} b_{pk}, i \leq k \\ 0, i > k \end{cases} \tag{4}$$

$$b_{ai} = \begin{cases} b_{qi}, i \leq k \\ 0, i > k \end{cases} \tag{5}$$

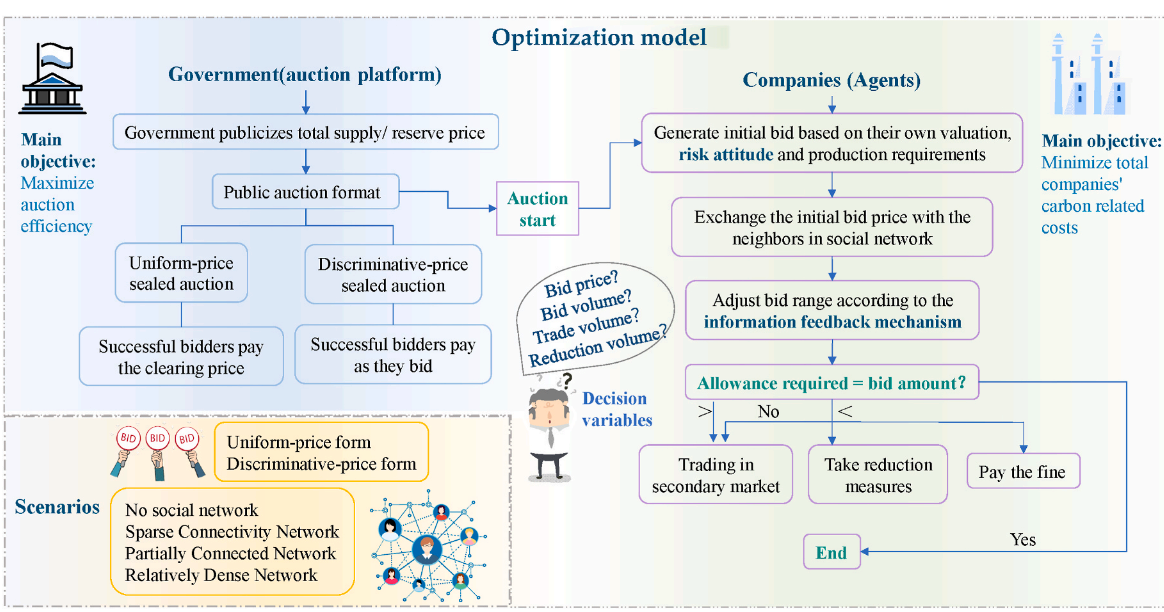

Fig. 1. Framework of optimization model.

For company i, the number of carbon allowance w_i obtained in the primary auction market is shown in formula (6).

$$w_i = \begin{cases} b_{qi}, b_{pi} > b_{pk} \\ \dfrac{b_{qi}}{\sum_{i=j}^{k} b_{qi}} \left(ts_j - \sum_{i=1}^{j-1} b_{qi} \right), b_{pj} = b_{pi} = \ldots = b_{pk}, j \le i \le k \\ 0, b_{pi} < b_{pk} \end{cases} \tag{6}$$

This formula indicates that when $b_{pi} > b_{pk}$, company i wins the auction and the amount won is b_{qi}. When the bids from company j to company k are equal $(b_{pj} = b_{pi} = \ldots = b_{pk})$, and the companies distribute the remaining carbon amount in proportion to ts_j. When $b_{pi} < b_{pk}$, the company fails in the auction.

2.2. Company's bidding risk attitude

In real auctions, companies exhibit different bidding attitudes. Some are risk-seeking, believing that higher risk brings higher returns and thus tend to bid higher; some are risk-averse, fearing uncertainty and bidding more conservatively; while some adopt a moderate stance between the two(Wang and Liu, 2010). Following previous studies (Rao et al., 2012; Wang et al., 2014), this paper classifies bidders into three types: risk-seeking (σ), risk-moderate (β), and risk-averse (γ). Risk-seeking companies aim for higher returns by bidding aggressively to increase their winning chances. Risk-averse companies prefer safer strategies and lower bids to minimize potential losses. Risk-moderate companies balance risk and return, bidding neither too high nor too low. Their bidding behavior is defined in formula (7).

$$\begin{aligned} & b_{pi_\sigma} \sim U[a + 2(v_i - a)/3, v_i] \\ & b_{pi_\beta} \sim U[a + (v_i - a)/3, a + 2(v_i - a)/3) \\ & b_{pi_\gamma} \sim U[a, a + (v_i - a)/3) \end{aligned} \tag{7}$$

2.3. Company's information feedback mechanism

Famous auction scholars Milgrom and Weber pointed out that in the auction, bidders' bids will change according to the signals of other bidders (Milgrom and Weber, 1982). The signal refers to the value-related information each bidder observes about the auction item, also known as a value estimate. For example, in the second-price sealed auction and English auction, the adjustment of the bidder's equilibrium bid is affected by its own signal and the bids of other bidders. Many articles prove that the bidding strategy of bidders depends on the bids of other bidders. For example, Zheng et al. (2015) stated that the classical expected utility theory does not consider the impact of the psychological factors of the subject on decision-making, while the prospect theory believes that people's perception of wealth is not the absolute value of wealth, but the relative value of wealth compared to a reference point, and constructs the value function based on the relative value to make decisions Li et al. (2025) applied the anchoring effect from behavioral finance to construct an expected bid adjustment for rival power generators in the monthly electricity bidding market. The logic is: if a strategic generator anticipates higher bids from competitors, it shifts its bid steps toward higher prices; if it anticipates lower bids, it covers more low-price intervals. Zhan and Bai (2014) studied bidding strategies in continuous double auction markets and proposed a bidding model based on the dynamic Hurwicz criterion. In this model, the buyer's bid adjustment is related to the historical lowest and highest prices, see Appendix B-1 for details. Wang (2017) studied the bid information feedback mechanism in continuous double auctions. See Appendix B-2 for details.

Studies above show that bidders' bids are influenced by competitors. High-emission firms often share similar businesses and may interact frequently, so the information exchange may affect their bidding strategies. In a single-round sealed carbon auction format, companies can only access bids from other participants in the same auction. This paper focuses on that type of feedback. Given the lack of research on feedback in this specific context, we built an information feedback model.

Before the auction begins, company i randomly generates an initial bid b_{pi}^0 within its own bidding range $\left[b_{p0}^{min}, b_{p0}^{max}\right]$ based on its bidding attitude. Let N_i be the set of neighbors of company i with $A_{ij} = 1$. $N_h(i)$ and $N_l(i)$ represent the number of neighbors with bids higher and lower than b_{pi}^0, respectively. The total number of neighbors is $N_t(i) = N_h(i) + N_l(i)$. If $N_t(i) = 0$, company i receives no information and does not adjust its bid. The adjusted bidding range $\left[b_{pi}^{min}, b_{pi}^{max}\right]$ is determined based on the feedback from other bidders.

Referring to the studies(Li et al., 2025; Zheng et al., 2015), company i focuses on relative rather than absolute bid values, and the size of the differences Gong (2016). If all others bid higher than company i, it will raise its bid to increase winning chances; if all bid lower, it will reduce the bid to cut costs. When both higher and lower bids exist, company i adjusts its bid based on the average relative difference, as shown in formulas (10–11).

$$AV_h = \frac{1}{N_h(i)} \sum_{j \in \mathcal{N}_i, b_{pj} > b_{pi}^0} \left(b_{pj} - b_{pi}^0 \right) \tag{8}$$

$$AV_l = \frac{1}{N_l(i)} \sum_{j \in \mathcal{N}_i, b_{pj} < b_{pi}^0} \left(b_{pi}^0 - b_{pj} \right) \tag{9}$$

AV_h and AV_l represent the average values above and below company i's initial bid, respectively. If $N_h(i)$ or $N_l(i)$ is 0, the corresponding average is set to 0. The proportion of higher bids is $P_h(i) = N_h(i)/N_t(i)$, and the proportion of lower bids is $P_l(i) = 1 - P_h(i)$.

Next, a risk attitude coefficient λ is introduced to represent the adjustment range based on different risk attitudes. A high-price weight factor w_h is added to the lower bound adjustment to reduce the influence of high-price neighbors, while a low-price weight factor w_l is included in the upper bound adjustment to weaken the impact of low-price neighbors. These factors capture how different risk attitudes affect responsiveness. Additionally, $P_h(i)$ and $P_l(i)$ indicate signal trends. For instance, a high proportion of high bids suggests increasing the upper limit even if AV_h is small. See formulas (10–11).

$$b_{pi}^{min} = b_{p0}^{min} + \lambda(w_h \cdot P_h(i) \cdot AV_h - P_l(i) \cdot AV_l) \tag{10}$$

$$b_{pi}^{max} = b_{p0}^{max} + \lambda(P_h(i) \cdot AV_h - w_l \cdot P_l(i) \cdot AV_l) \tag{11}$$

However, when adjusting their bid ranges based on neighbors' bids, companies must also consider the auction reserve price and their own maximum valuation, and thus must follow the constraints below:

$$b_{pi}^{min} \ge a \tag{12}$$

$$b_{pi}^{max} \le v_i \tag{13}$$

To capture how information spreads among companies and influences bidding behavior, it is essential to build a network model that reflects their communication structure. Social networks effectively describe how bidding information circulates among firms before carbon allowance auctions and provide a research framework for feedback mechanisms. A social network consists of nodes (companies) and edges (connections), with common types including random networks, scale-free networks, and small-world networks(Zhou Q. et al., 2023).

This study assumes n companies participate in the auction and defines a $N \times N$ neighbor matrix $A \in \{0,1\}$. If $A_{ij} = 1$, companies i and j know each other and share bid information before the auction. If $A_{ij} = 0$, they are unconnected and do not exchange information. After receiving bid data from neighbors, each company adjusts its bidding range accordingly.

To explore how connectivity affects information diffusion and bid adjustment, three types of social networks are constructed using random network models: Sparse Connectivity Network (N1): Few companies are connected; Partially Connected Network (N2): Most companies have neighbors, but overall connectivity is moderate; Relatively Dense Network (N3): Every company has at least one neighbor, and the network is more interconnected. Parameter settings for these networks are shown in Appendix A Table 1, and their structures are visualized in Fig. 2: subfigures (a), (b), and (c) represent N1, N2, and N3, respectively. Each node denotes a company, with color indicating risk attitude (pink: risk-seeking, green: risk-moderate, blue: risk-averse). Edges between nodes represent neighbor relationships, more edges indicate more accessible bid information. The length of edges carries no specific meaning. We assume that bid information shared among firms is truthful and trust-based, with no false data involved in the exchange. In this paper, we assume that companies are in a trusted social network (T) and misinformation social network (F), respectively.

2.4. Carbon allowance decision-making optimization model

For the government, auction efficiency is the main criterion for measuring the effectiveness of auctions and an important dimension that reflects government revenue. Therefore, auction efficiency is the objective function. Auction efficiency (eff) is defined as the ratio of actual auction revenue to the theoretical maximum possible revenue in the auction (Bresky, 2013; Cong and Wei, 2012).

$$\max eff = V1/V2 \tag{14}$$

$V1$ represents the actual revenue the government receives from auctioning carbon allowances, while $V2$ is the maximum possible revenue if all allowances were allocated to the highest bidders based on their valuations.

$$V1 = \sum_{i=1}^{k} b_{ai} {}^{*} w_i \tag{15}$$

$$V2 = \sum_{i=1}^{k} v_i {}^{*} w_i \tag{16}$$

From the government's perspective, total enterprise cost reflects market efficiency and helps prevent monopolistic behavior from individual cost optimization. Literature suggests that minimizing total cost better balances efficiency and fairness (Ma et al., 2018; Zhou et al., 2025; Zhu et al., 2023). From the enterprise perspective, total companies' carbon compliance cost (hereinafter referred to as "companies' cost") includes compliance through primary auctions, secondary trading, emission reduction, and penalties. Given the compliance requirement, the lower the total cost, the better. This study sets formula (19) as another optimization objective, this formula is essentially the result of multi-agent strategy interaction, as shown in the following formula:

$$\min \sum_{i=1}^{n} Cost_i \tag{17}$$

$$Cost_i = \begin{cases} w_i {}^{*} b_{ai} - (w_i - E_i){}^{*} p_{2c}, w_i > E_i \\ w_i {}^{*} b_{ai}, w_i = E_i \\ w_i {}^{*} b_{ai} + q_{2ci} {}^{*} p_{2c} + q_{pi} {}^{*} \theta + p_{si} {}^{*} q_{si}, w_i < E_i \end{cases} \tag{18}$$

In the formula, E_i is the carbon allowance required for compliance, and w_i is the amount obtained in the primary auction. If $w_i > E_i$, the company can sell the surplus in the secondary market. If $w_i = E_i$, no further action is needed. If $w_i < E_i$, the company must cover the shortfall via secondary purchases, emission reduction, or paying penalties, subject to constraint (19). The meanings of the main variables involved in the article are shown in Appendix A Table 2.

$$w_i + q_{2ci} + q_{pi} + q_{si} = E_i \tag{19}$$

2.5. Model solution algorithm

Unlike single-objective optimization with a clear optimal solution, multi-objective problems require the Pareto optimality concept (Mohd Zain et al., 2018). A set of non-dominated solutions forms the Pareto front, representing trade-offs for decision-makers. This study involves two conflicting objectives and uses the (MOPSO) algorithm. MOPSO maintains PSO's simplicity and fast convergence while improving solution distribution via crowding distance, outperforming algorithms like NSGA-II (Xiang et al., 2022). The detailed algorithm framework is shown in Fig. 3.

When applying the algorithm, each particle encodes four decision variables: bid price, bid quantity, secondary market allowance, and emission reduction, forming a potential solution. Variables are indexed and mapped to company attributes. Particle positions are updated based on velocity, which is determined by inertia, personal best, and a global best selected via roulette wheel from the archive. To enhance global search, a mutation mechanism with decreasing probability introduces diversity by occasionally generating new solutions. Algorithm parameters are shown in Appendix A Table 3.

After obtaining the Pareto set, the TOPSIS method is used for solution selection. It ranks solutions by computing weighted distances to the ideal and negative-ideal solutions. Key steps include matrix normalization, weight assignment, and closeness calculation. The procedure for

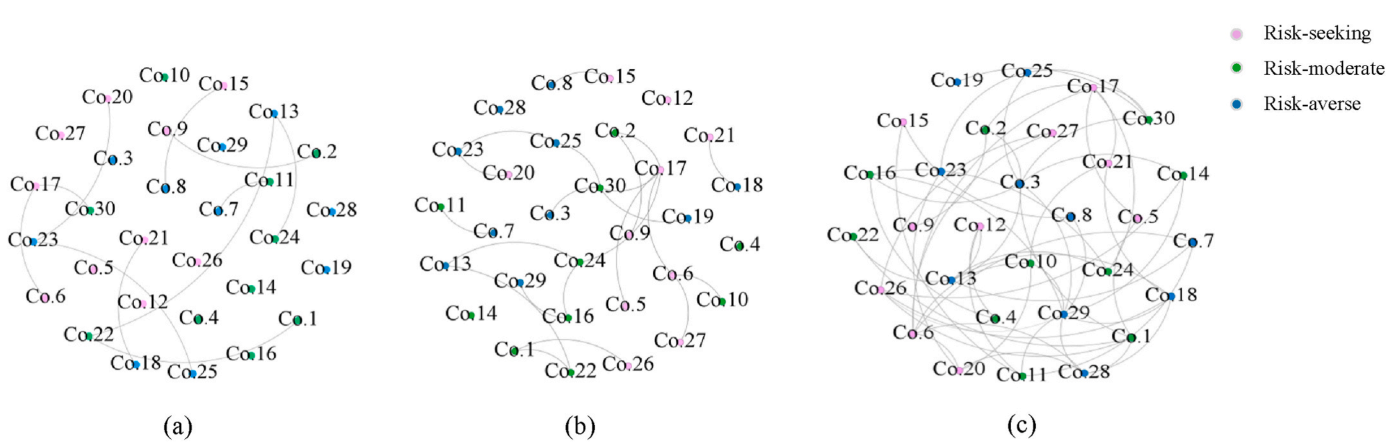

Fig. 2. Three types of social networks.

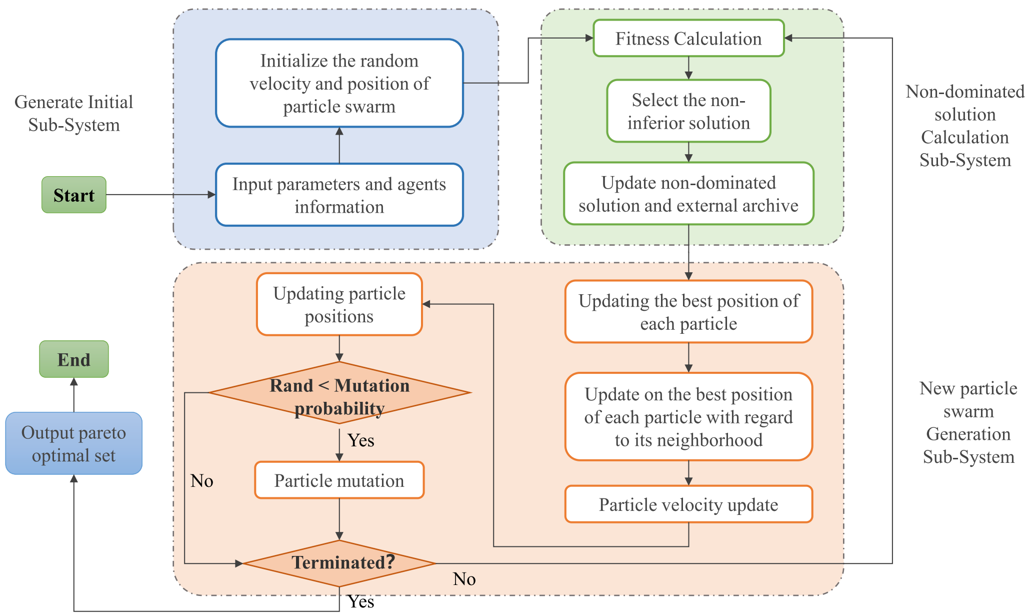

Fig. 3. The framework of MOPSO.

MOPSO and TOPSIS follows the research (Zhang et al., 2025).

3. Simulation analysis

Based on the optimization model in Section 2, this section uses multi-agent simulation to explore the information feedback mechanism under different social networks and risk attitudes, and its impact on auction efficiency and companies' cost.

3.1. Setting of agents, parameters and scenarios

Each agent represents a company with static attributes such as allowance valuation, requirement, abatement cost, and risk attitude. Agents can dynamically adjust their bidding range based on neighbors' bids. This section defines the attributes, variables, and algorithm parameters.

One of the basic characteristics of market clearing is that market supply is less than or equal to market demand (Zheng et al., 2017), *ts* is set to 3000 tons. α is set as 45 yuan/ton. Based on the actual situation of China's fully operational Guangzhou pilot, the transaction price in the secondary market is set higher than the auction reserve price (Wang et al., 2022), and the setting range is referenced by (Tang et al., 2017; Zhou D. et al., 2023), so it is set at 55 yuan/ton. The tradable volume in the secondary market is limited to the excess amount of auction winners. Cause companies with valuations below the reserve price do not participate, while those with valuations above the secondary market transaction price prefer direct trading, we assume companies' valuations are randomly generate from (45,55]. In addition, companies with unit abatement costs below the reserve price choose to reduce emissions, so the unit abatement costs are set from (45,80], and ensure costs are not lower than valuations. Risk attitudes are evenly assigned. Details are provided in Appendix A Table 4.

To prevent market monopoly, there is a bidding amount limit according to formula (2). To encourage emission reduction, the penalty for each unit shortfall is set at five times the secondary market transaction price (Government publication). In the information feedback mechanism, in order to match the bidding attitude, the high price weight factor of risk-seeking companies is higher than that of low price and verse vice. This paper sets two adjustment strengths. Strength 1: $\lambda = 0.7, 0.5, 0.3$ for risk-seeking, risk-moderate, and risk-averse companies, respectively; corresponding weights (w_h, w_l) are (0.7, 0.3), (0.5, 0.5), (0.3, 0.7). Strength 2: $\lambda = 0.3, 0.2, 0.1$; (w_h, w_l) are (0.3, 0.1), (0.2, 0.2), (0.1, 0.3). The experimental scenarios are listed in Table 1.

3.2. Analysis of optimization results

In this section, the MOPSO algorithm is used to obtain a Pareto solution set for each scenario. Then, the TOPSIS method selects the optimal solution from the set. This approach allows decision-makers to flexibly adjust weights based on their preferences and practical needs. In the following analysis, both objective functions are assigned equal weights to determine the ideal solution.

3.2.1. Results without information feedback mechanism

When there is no information feedback mode, companies participating in the auction do not exchange bidding information during the auction, the Pareto solution set under the uniform-price sealed auction and the discriminatory-price sealed auction is shown in Fig. 4(a) and (b), respectively.

In Fig. 4, the horizontal axis represents the auction efficiency, and the vertical axis represents the companies' cost. When there is no information feedback, the auction efficiency of the ideal solution under the uniform price sealed auction is 0.9204, and the companies' cost is 167,013 yuan (the result rounded to the nearest integer). The auction efficiency of the ideal solution under the discriminatory-price sealed auction is 0.9573, and the companies' cost is 175,469 yuan. The results of the successful companies are shown in Fig. 5 below.

The horizontal axis shows bid prices, and the vertical axis indicates the allocated allowance. The area of each circle reflects the bid quantity.

Table 1
Scenario setting.

Auction format	Adjustment strength	Network
Uniform-price format	Strength 1	Net 0
		Net 1
		Net 2
		Net 3
Discriminatory-price format	Strength 2	Net 0
		Net 1
		Net 2
		Net 3

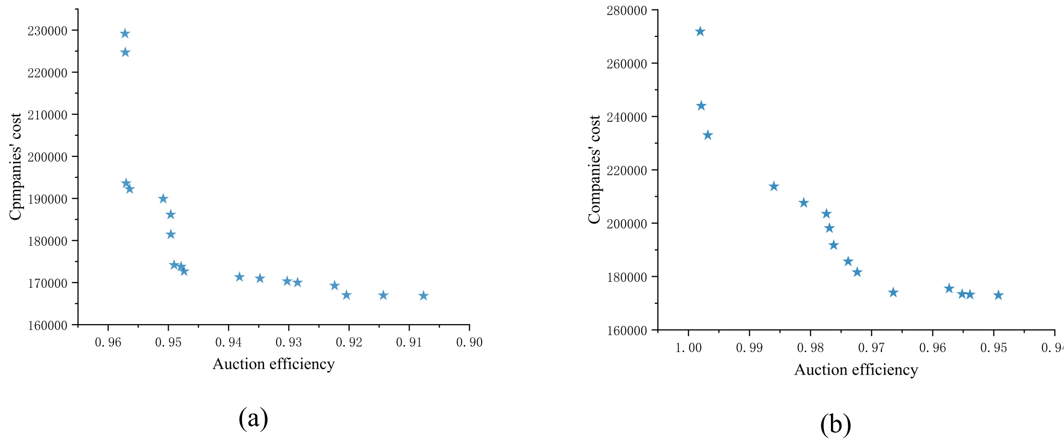

Fig. 4. The Pareto solution set.

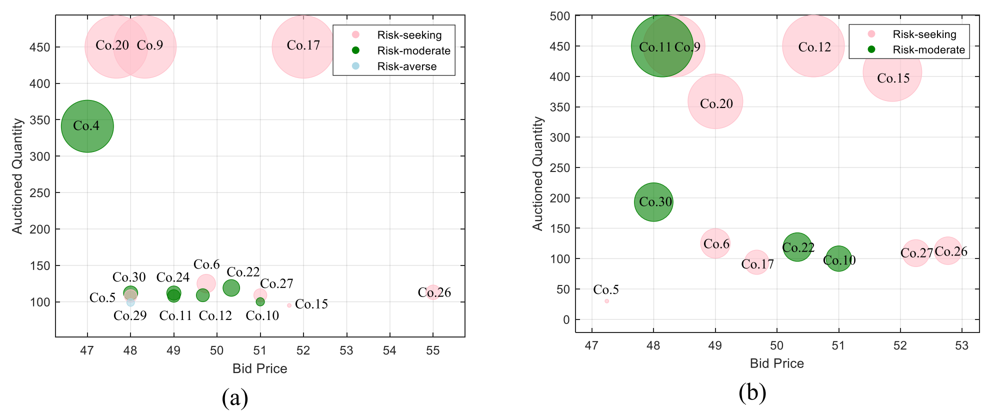

Fig. 5. The auction results.

Colors represent risk attitudes. Fig. 5(a) shows results under the uniform-price sealed-bid auction: 16 companies won, mainly risk-seeking (8) and moderate-risk (7), with only one risk-averse company. Fig. 5(b) shows the discriminatory-price auction: only 13 companies won, including 9 risk-seeking ones, and no risk-averse companies.

This suggests that bidding attitude strongly affects the outcomes. Risk-seeking companies have a clear advantage, especially under discriminatory-price format. For example, company 28, with a high valuation of 55, still failed in both auctions. Moreover, under discriminatory-price auction format, companies tend to bid a larger amount to resell in the secondary market in order to hedge costs. As more companies fail to win the allowance, they turn to buying in the secondary market or taking measures to reduce emissions, which increases total costs.

3.2.2. *Results with information feedback mechanism*

In the presence of a social network, neighbors exchange bid information. This section investigates both trusted and misinformation social networks. The networks, varying in density from sparse to dense, are defined as Net1, Net2, and Net3, as illustrated in Fig. 2.

First, the optimization results under trusted social network are analyzed. We analyze how different social networks affect auction efficiency and companies' costs under two feedback adjustment strengths. Since the shapes of the Pareto fronts are similar, we omit repetitive results under other settings. In the results, U denotes uniform-price sealed-bid auctions, D denotes discriminatory sealed-bid auctions; S1 and S2 represent adjustment strengths 1 and 2, respectively; Net refers to the different social network structures.

In Fig. 6(a), companies bid based only on limited personal information, resulting in low efficiency (0.9204). As network density increases (Net1 to Net2), companies obtain more peer bid data and adjust their strategies more effectively to improve their success rates. Auction efficiency peaks in Net2. However, in Net3, efficiency drops. Fig. 6(b) presents results under discriminatory-price sealed-bid auctions. Compared to the uniform-price setting, the auction efficiency is significantly improved in the discriminatory-price sealed auction format. This is because this format requires companies to pay as their bid, which leads to higher auction efficiency. However, efficiency still drops in Net3. We infer that overly dense networks (e.g., Net3) may lead to excessive adjustments and convergence of bids, which in turn reduces auction efficiency.

To test whether excessive adjustment based on neighbors' bids reduces auction efficiency, we ran new simulations using a weaker feedback setting (Strength 2). Fig. 6(c) shows results under uniform-price sealed-bid auctions. As social networks become denser (Net0 to Net3), auction efficiency increases steadily (0.9204, 0.9238, 0.9256, 0.9312), and companies' cost rises accordingly. Fig. 6(d) presents results for discriminatory-price auctions under the same feedback strength. Efficiency improves from 0.9573 to 0.9773 as the network becomes denser. These results support our earlier hypothesis: excessive bid adjustments based on neighbor information can cause strategy convergence and lower auction efficiency. With moderate feedback, however, social information helps improve overall performance.

Fig. 7 shows the optimization results across all scenarios. The horizontal axis represents auction efficiency, and the vertical axis indicates companies' cost. The results clearly show that, under both adjustment

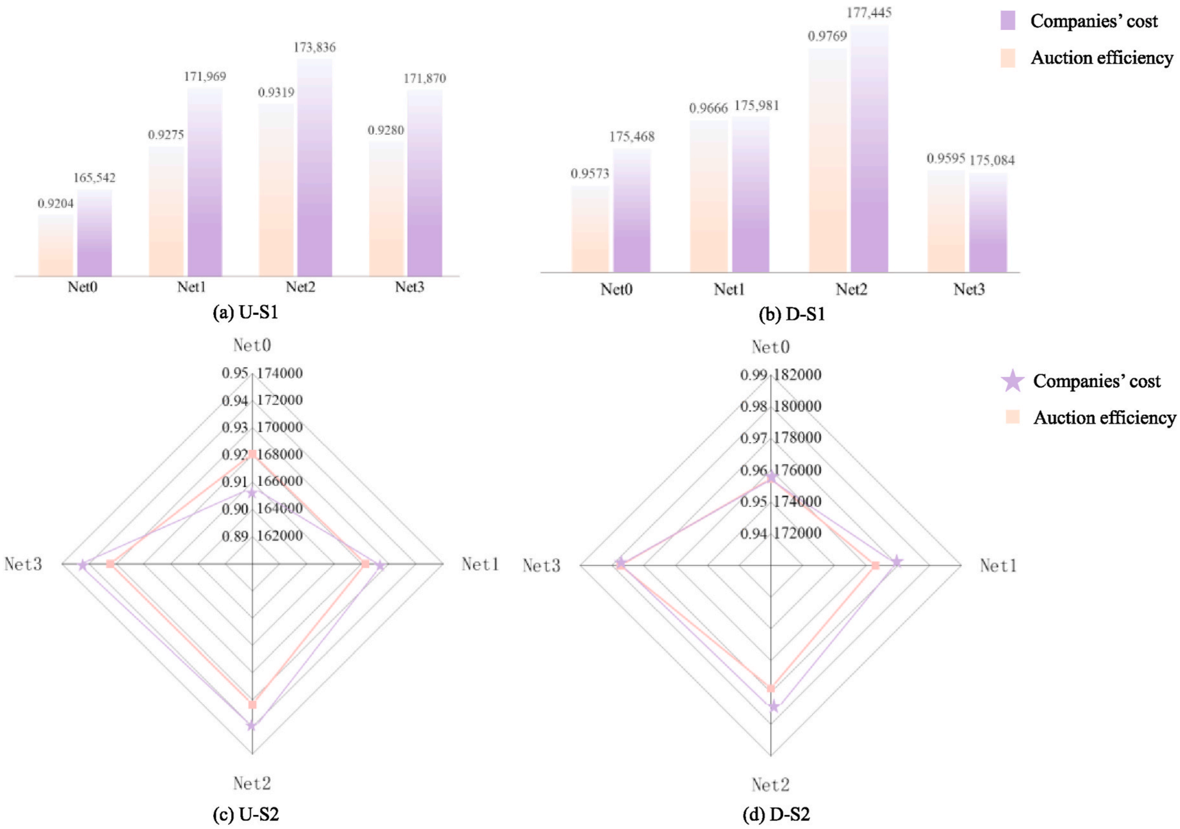

Fig. 6. Auction results on different social networks.

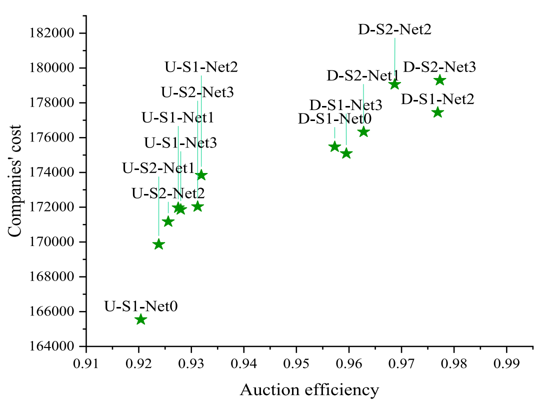

Fig. 7. Optimization results for all scenarios.

strengths, the discriminatory-price sealed-bid auction yields higher efficiency and cost than the uniform-price sealed-bid auction. When companies adjust their bids moderately, more feedback leads to higher efficiency and higher costs. However, excessive adjustments in dense networks cause bid convergence, which reduces auction efficiency.

The previous content conducted research under the assumption of trusted social networks. However, in the actual auction process, trusted social networks is an ideal state. Companies in social networks may make false reports to neighbor or adopt strategic behaviors such as collusion. However, according to existing literature(Hendricks, 1989), the existence and characteristics of collusion mechanisms are heavily dependent on the nature of the auctioned items and the specific auction rules. In addition, subsequent studies (Burtraw et al., 2009; Mougeot et al., 2011) also proved through experimental methods that in sealed bid auctions, the degree of collusion is low and difficult. Therefore, this article temporarily does not consider the collusion behavior of companies, but only considers the false reporting behavior of companies to their neighbors.

When exploring misreporting behavior among agents, some scholars have incorporated concepts related to "trust levels" into their studies. For example, Zheng et al. (2016) introduced a cognitive parameter to determine the likelihood of cooperation or betrayal between two entities. Acemoglu et al. (2010) defined a belief-updating parameter to represent the extent to which an entity trusts another entity. Referring to these approaches, we introduce a trust factor $\tau_{ij} \in [0,1]$ to represent the level of trust that agent *i* has in agent *j*, that is, the probability that agent *i* shares truthful bid information with agent *j*. This can be shown by the following equation:

$$\tau_{ij} = \begin{cases} 1, \textit{full trust} \\ < 1, \textit{partial trust} \end{cases} \tag{20}$$

The formula shows that when $\tau_{ij} = 1$, entity *i* shares the real bid with entity *j*; when $\tau_{ij} < 1$, entity *i* shares the fake bid with entity *j* with a probability of (1-τ_{ij}). To realize this behavior mechanism, referring to (Macy, 1991), this paper introduces a binary random decision method based on random numbers that obey the uniform distribution of [0,1], which is used to simulate the honest or false behavior between entities in the process of information dissemination.

Furthermore, given that in the carbon allowance auction, the main purpose of a company is to win the auction and obtain the required allowance at the lowest possible cost. Therefore, when a company makes a false offer, in order to reduce the competitiveness of other bidders, it will falsely report a low price to its neighbors instead of falsely reporting a high price to increase costs and competition. The false price is generated by subtracting the random perturbation term $\varepsilon \sim N(0, \sigma^2)$ from the true price. When company *i* shares the false offer with company

j, the bid received by company j is $(b_{pi} - |\varepsilon|)$. The randomly generated trust factor matrix is shown in supplementary material. The results are shown in Fig. 8.

The results show that: (1) When the feedback adjustment strength is high (S1), the introduction of misinformation leads to a decline in auction efficiency and total companies' cost in less dense networks (Net1–Net2). The cost reduction is particularly evident under the uniform-price sealed-bid mechanism, as firms lower their bids in response to falsely low bids from neighbors, which further drives down the clearing price and overall costs. In dense networks (Net3), however, misinformation (F) results in higher auction efficiency compared to trusted networks (T). As previously discussed, trusted networks with high feedback strength tend to induce bid convergence, whereas misinformation partially disrupts this convergence, enhancing efficiency. (2) When the feedback adjustment strength is low (S2), the impact of misinformation is relatively minor. Across Net1–Net3, auction efficiency and firm costs show slight declines compared to trusted networks, indicating that weaker feedback adjustment can mitigate the negative effects of misinformation. (3) Misinformation can significantly affect individual firms. For example, although Company 22 has a relatively high valuation and wins the auction under U–S1–T–Net1, it fails to do so under U–S1–F–Net1. This suggests that misinformation may cause firms to misjudge market competition, leading to unsuccessful bids.

3.3. Sensitivity analysis

To evaluate the performance and stability of the model we built and assess the impact of significant parameters, we conduct a sensitivity analysis on three key parameters: reserve price, secondary market transaction price, and primary market supply. The reserve price affects company participation and bidding strategy; the secondary market transaction price influences overall costs and emission reduction behavior; and supply determines market balance. The analysis is conducted under the uniform-price sealed-bid auction. To ensure comparability, other model settings remain unchanged, isolating the effects of these parameters on auction efficiency, total cost, and emission reductions.

First, the auction reserve prices are set at 43、44、45、46、47 for multi-agent simulation, as shown in Fig. 8(a). The green bars represent companies' cost, the blue bars indicate auction efficiency, and the pink line shows total emission reduction. As the reserve price increases, the clearing price also rises, leading to higher auction efficiency and total cost. A higher reserve price raises the bidding threshold, making it harder for low-valuation companies to win, prompting them to reduce emissions instead. However, when the reserve price increases from 46 to 47, five companies exit due to low valuation. The remaining companies obtain more allowances, which they can resell in the secondary market. At this time, since most companies face higher abatement costs than secondary market prices (see Section 3.1), they prefer purchasing allowances, resulting in a decrease in total emission reductions. Which means as the reserve price increases, a large number of companies are forced to withdraw from the auction due to insufficient valuation, the remaining carbon allowances in the auction market increase, and the amount available for purchase in the secondary market increases accordingly. In order to reduce costs, companies are more inclined to purchase quotas from the secondary market, resulting in a further decrease in emission reductions, affecting the emission reduction effect of carbon allowance auctions.

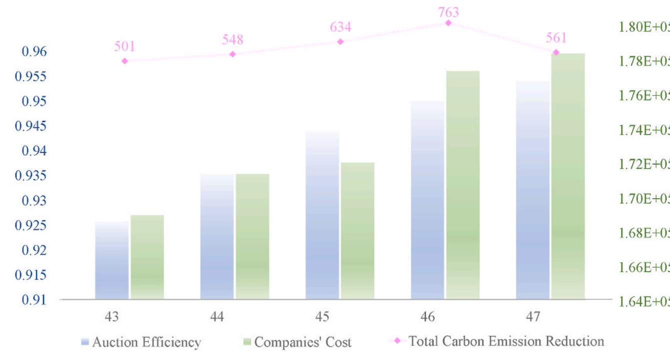

Fig. 8(a). Sensitivity analysis of reserve price.

Next, the secondary market trading prices are set at 53、54、55、

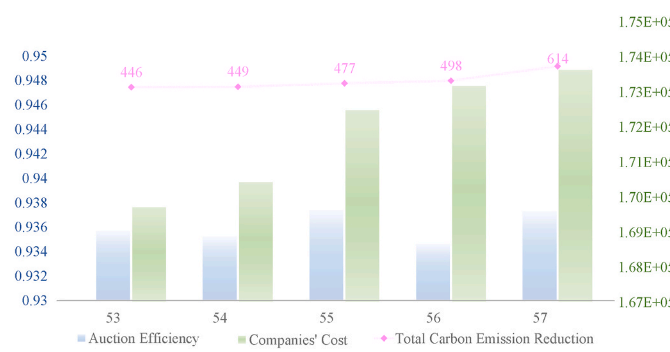

Fig. 8(b). Sensitivity analysis of secondary market transaction price.

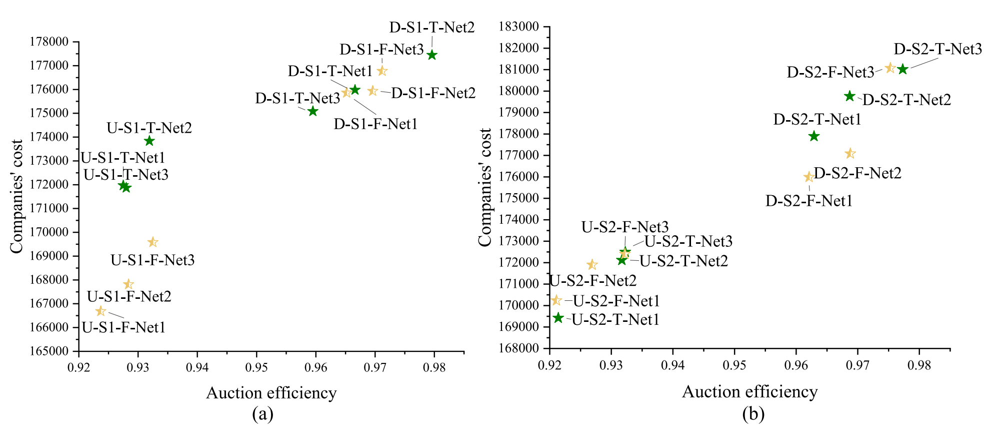

Fig. 8. Comparison of results under trusted (T) and misinformation (F) social networks.

56、57 for sensitivity analysis, with results shown in Fig. 8(b). The secondary market price has little impact on auction efficiency, which remains between 0.934 and 0.937 across all scenarios. However, as the secondary market price increases, the overall carbon compliance cost also rises. Moreover, higher secondary market prices can encourage companies to reduce emissions.

Then, the total allowance supply for the auction is set to 0.8 ts, 0.9 ts, ts, 1.1ts, 1.2ts corresponding to supply levels of 2400, 2700, 3000, 3300, and 3600, respectively. Multi-agent optimization simulations are then conducted based on these settings. The results are presented in Fig. 8(c).

First, auction efficiency shows a rise-then-fall trend. The reason is that low supply causes intense competition and low matching efficiency, while moderate increases improve allocation. When supply exceeds equilibrium demand, bidding intensity drops, leading to lower efficiency. Second, as the primary market supply grows, companies acquire allowances at lower costs, reducing their reliance on the secondary market, emission reduction measures, or penalties, thus lowering overall costs. Last but not least, companies adopt more reduction measures at lower supply, resulting in higher emission reductions. When supply increases, reduction demand falls, and in the 1.2ts case, companies almost no longer need to implement emission reduction efforts due to sufficient allowances.

In summary, increasing the total supply helps reduce companies' cost but may weaken their motivation for emission reduction. The trends under the discriminatory-price sealed-bid auction are similar and thus are not displayed. Moreover, after adjusting algorithm parameters (such as the number of iterations or learning rate), the result trends remain consistent, confirming the stability of the model.

4. Conclusion and policy implications

This study develops a carbon allowance decision optimization model with multi-agent simulation approach under a single-round sealed-bid auction format, which is commonly adopted in international carbon markets. The model jointly considers government auction efficiency and total companies' carbon compliance cost. To better reflect real-world conditions, the model incorporates key behavioral factors such as companies' risk attitudes and information feedback. Furthermore, the study explores how varying levels of social network connectivity affect auction efficiency and companies' costs. Moreover, the impact of auction design parameters, such as reserve price and allowance supply, on emission reductions and related outcomes is evaluated. The main conclusions and corresponding policy implications are summarized as follows.

(1) The uniform-price sealed-bid auction leads to lower companies' cost but also results in lower auction efficiency. As shown in the results, regardless of the type of social network or adjustment strength, the discriminatory-price sealed-bid auction achieves higher auction efficiency but incurs higher cost for companies. This matches the core conclusion of the article (Esmaeili Avval et al., 2022). Therefore, policymakers need to balance auction efficiency and company costs when designing carbon allowance auction mechanisms. If the primary goal is to support companies' adaptation during the early stage of auction implementation, the uniform-price auction is preferable. Conversely, if the government prioritizes allocation efficiency, the discriminatory-price auction is more appropriate.

(2) Companies' bidding risk attitudes have a significant impact on auction outcomes. This study finds that under both carbon allowance auction formats, bidding attitude greatly influences the likelihood of winning, with risk-seeking companies having a higher chance of success. This conclusion is consistent with the conclusion of (Cui et al., 2020) that emphasizes that risk attitude affects bidding strategies. Therefore, governments should guard against potential monopolistic behavior driven by overly aggressive bidders. Measures such as setting a cap on the maximum bidding share per company, introducing an allowance reserve mechanism to maintain market diversity and fairness.

(3) In trusted social networks, Information feedback can enhance auction efficiency. As companies are embedded in denser social networks, they gain access to more bidding information from peers, which helps refine their bidding strategies. However, when companies adjust their bids too aggressively, increased network density may lead to overreaction and bid convergence, ultimately reducing auction efficiency. However, when misinformation is present, it leads to a decline in auction efficiency and clearing prices compared to trusted networks, thereby reducing the total companies' cost. These effects are particularly pronounced under the uniform-price sealed-bid auction mechanism. Moreover, the impact of misinformation varies depending on the strength of information feedback adjustment. From an individual perspective, false bids can significantly mislead firms in their assessment of market conditions, increasing the risk of auction failure. Compared with existing studies (Harsha et al., 2010; Zheng et al., 2019b), this paper extends the information feedback mechanism to the context of carbon allowance auctions, while explicitly distinguishing between truthful and fake bidding. This broadens the scope of research in this field. Based on the above findings, governments can improve auction design by enhancing the auction process and introducing information disclosure mechanisms. For example, publishing anonymous bid distributions during the auction to increase market transparency and enable more controlled feedback. This would provide companies with a more comprehensive market reference.

(4) The reserve price and allowance supply significantly affect market efficiency, the companies' cost and carbon reduction. A higher reserve price can enhance auction efficiency, and the increases in both reserve and secondary market prices can promote carbon reduction, but at the expense of higher compliance costs. An appropriate allowance supply improves market matching, raising auction efficiency while lowering company costs. However, an excessive supply may reduce companies' motivation to reduce emissions, as they can easily acquire allowances through auctions. As research by (IEA, 2021) has shown, a moderate increase in auction allowance can effectively reduce carbon emissions. Therefore, when implementing the auction mechanism, policymakers should set a reasonable reserve price to avoid excessively high prices that affect market participation. Secondly, the government should conduct dynamic regulation of the total supply to ensure a balance between supply and demand, improve auction efficiency, reduce corporate compliance costs, and stimulate corporate emission reduction behavior to achieve a win-win situation for market efficiency and environmental goals. At the same time, the government can guide companies to balance

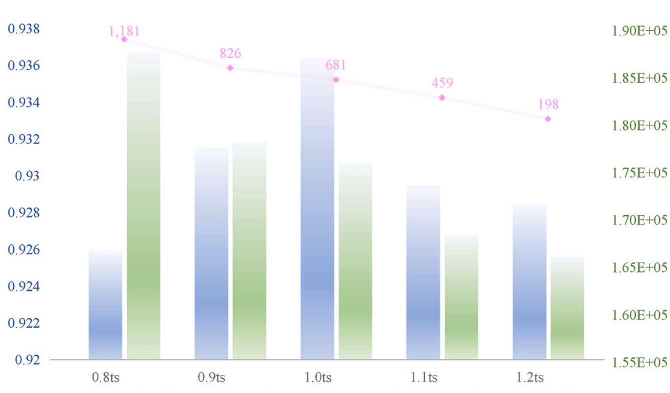

Fig. 8(c). Sensitivity analysis of auction allowance supply.

emission reduction and allowance compliance strategies by regulating the secondary market price.

CRediT authorship contribution statement

Lihui Zhang: Supervision, Funding acquisition. **Jing Luo:** Writing – original draft, Methodology, Formal analysis, Conceptualization. **Jinrong Zhu:** Validation, Supervision. **Jie Liu:** Validation, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (grant numbers 72171081). The authors are also grateful to the anonymous reviewer and editor for careful scrutiny of the details and for comments that helped improve this manuscript.

Appendix A

Table 1
Parameters of social network

Parameter	Net1	Net2	Net3
Num	30	30	30
Per	0.012	0.018	0.024
Avg_length	100	100	100

Table 2
Main symbols and definitions

Variable	Meaning
b_{pi}	Bid price of company i
b_{qi}	Bid quantity of company i
b_{pk}	Clearing price
b_{ai}	Actual payment price of company i
w_i	Allowances obtained by company i through the auction
E_i	Allowance requirement of company i
q_{2ci}	Allowances purchased by company i in the secondary market
q_{si}	Allowances achieved by company i through emission reduction measures
q_{pi}	Allowances offset by company i via penalty payment
α	Reserve price
v_i	Valuation of company i for one unit of carbon allowance
p_{2c}	Secondary market transaction price
p_{si}	Cost for company i to reduce one unit of CO_2 emissions
b_{pi}^0	Initial bid of the auction
A_{ij}	The set of companies
$N_h(i)$	Number of neighbor companies with bids higher than b_{pi}^0
$N_l(i)$	Number of neighbor companies with bids lower than b_{pi}^0
$N_t(i)$	Total number of neighbor companies
AV_h	The average price above its initial bid
AV_l	The average price below its initial bid
$P_h(i)$	The proportion of companies with bids higher than its own to the total neighbor
$P_l(i)$	The proportion of companies with bids lower than its own to the total neighbor
λ	Risk attitude coefficient
w_h	High-price weight factor
w_l	Low-price weight factor

Table 3
Parameters of MOPSO

Parameters of MOPSO	
Maximum Number of Iterations	50
Population Size	400
Repository Size	50
Inertia Weight	0.5
Intertia Weight Damping Rate	0.99
Personal Learning Coefficient	2
Global Learning Coefficient	4

(continued on next page)

Table 3 (*continued*)

Parameters of MOPSO	
Number of Grids per Dimension	7
Inflation Rate	0.1
Leader Selection Pressure	2
Deletion Selection Pressure	2
Mutation Rate	0.5

Table 4
Basic information of companies

Company ID	1	2	3	4	5	6	7	8	9	10
Risk attitude	Risk-moderate	Risk-moderate	Risk-averse	Risk-moderate	Risk-seeking	Risk-seeking	Risk-averse	Risk-averse	Risk-seeking	Risk-moderate
Value	50	46	46	48	48	51	50	48	50	54
Allowance requirement	171	135	114	136	108	125	126	100	128	100
Unit abatement cost	60	56	73	59	60	59	51	75	62	55
Company ID	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
Risk attitude	Risk-moderate	Risk-seeking	Risk-averse	Risk-moderate	Risk-seeking	Risk-moderate	Risk-seeking	Risk-averse	Risk-averse	Risk-seeking
Value	51	52	46	47	55	47	52	49	47	49
Allowance requirement	108	109	123	113	95	119	94	125	118	98
Unit abatement cost	60	63	59	54	72	65	60	52	63	77
Company ID	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**
Risk attitude	Risk-seeking	Risk-moderate	Risk-averse	Risk-moderate	Risk-averse	Risk-seeking	Risk-seeking	Risk-averse	Risk-averse	Risk-moderate
Value	46	53	46	51	50	55	54	55	54	54
Allowance requirement	109	119	108	112	118	113	109	98	99	112
Unit abatement cost	71	72	70	76	64	76	55	76	77	77

Appendix B

Zhan and Bai (2014)'s study shows that the buyer's next-period bid floor is linked to the sequence of competitors' previous transaction prices, as shown in the following formula:

$$B_i(t+1) = \min\{\lambda \cdot \min[P(t)] + (1-\lambda) \cdot \max[P(t)], V_i\} \tag{B-1}$$

where $P(t)$ represents the historical transaction price sequence up to time t, $min[P(t)]$ and $max[P(t)]$ are the historical minimum and maximum prices, respectively. $\lambda(t)$ is a dynamically adjusted optimism coefficient $(0 \leq \lambda \leq 1)$. Vi is buyer $i's$ highest valuation. However, this bidding adjustment formula relies heavily on extreme values, it may lead to over-adjustment.

In Wang (2017)'s study, the buyer's bidding adjustment formula is shown below:

$$\mathrm{P}P_{i+1} = \mathrm{PEP}_i \left(1 - \frac{\sum_{j=1}^{n} PPR_j}{\mathrm{n}} \right) \tag{B-2}$$

where n represents the cell space, $\mathrm{P}P_{i+1}$ represents the bid of the buyer in round $i+1$, PEP represents the maximum valuation of the buyer, and PPR_j represents the profit rate of the neighbor. According to this model, if the average profit rate of the neighbor is low, the buyer believes that the neighbor has obtained high profits by selling at a low price, so there is a chance of a low-price transaction, so the buyer will imitate the neighbor's strategy and lower his own bid, and vice versa.

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2025.126699.

Data availability

Data will be made available on request.

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