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Auction design for the allocation of carbon emission allowances to supply chains via multi-agent-based model and Q-learning

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Abstract
To increase competition, control price, and decrease inefficiency in the carbon allowance auction market, limitations on bidding price and volume can be set. With limitations, participants have the same cap bidding price and volume. While without the limitations, participants have different values per unit of carbon allowance; therefore, some participants may be strong and the other week. Due to the impact of these limitations on the auction, this paper tries to compare the uniform and discriminatory pricing in a carbon allowance auction with and without the limitations utilizing a multi-agent-based model consisting of the government and supply chains. The government determines the supply chains' initial allowances. The supply chains compete in the carbon auction market and determine their bidding strategies based on the Q-learning algorithm. Then they optimize their tactical and operational decisions. They can also trade their carbon allowances in a carbon trading market in which price is free determined according to carbon supply and demand. Results show that without the limitations, the carbon price in the uniform pricing is less than or equal to the discriminatory pricing method. At the same time, there are no differences between them in the case with limitations. Overall, the auction reduces the profit of the supply chains. This negative effect is less in uniform than discriminatory pricing in the case without the limitations. Nevertheless, the strong supply chains make huge profits from the auction when mitigation rate is high.

Keywords Supply chain management · Multi-agent-based model · Carbon auction market · Pricing methods · Price and volume limitations · Q-learning algorithm

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1 Introduction

Carbon emission has been a great challenge in recent years. The governments have developed some environmental policies to reduce carbon emissions, including carbon cap, carbon emission tax, carbon offset, and cap-and-trade (Mohammed et al., 2017; Moradinasab et al., 2018; Xu et al., 2018). A significant carbon emissions source is supply chains activities. Since the early 1990s, manufacturers have been forced to consider environmental issues in their supply chains (Haw-Jan and Dunn, 1995). The studies conducted by Dehghanian and Mansour (2008), Hua et al. (2011), Benjaafar et al. (2012), Palak et al. (2014), and Du et al. (2016) show the importance of developing quantitative models and decision support systems that consider issues related to reducing carbon emissions in the supply chain. Most studies in this field indicate that among the existing policies, the cap-and-trade is one of the most effective regulations that has been implemented in many countries (Wu et al., 2016; Xu et al., 2016). Under the cap-and-trade scheme, the firms are allocated a limited tradable carbon allowances quota (cap) from the government. The firms that generate emissions more than their cap should either reduce their emissions using greener technology or buy their required allowances from the carbon trading market, and those that have surplus carbon allowances can sell them on the same market (Matsumoto, 2008; Hua et al., 2011; Xu et al., 2017; Zakeri et al., 2015).

There are generally two approaches for allocating the initial carbon allowances, i.e., free allocation (history-based methods like grandfathering and benchmarking approaches) and auctioning (Khezr and MacKenzie, 2018). Between these two approaches, auctioning is preferred. Because it is more flexible in the distribution of costs, it decreases tax distortions and windfall and encourages using green technology (Cramton and Kerr, 2002). Two large emission trading systems, California and Europe, have engaged in auctioning (Haita, 2014). It is predicted that the proportion for the auction will be 90% by 2021–2030 (Jiang et al., 2016).

There are several types of auctions that are mainly divided into two groups: static (sealed) and dynamic (clock) (Tang et al., 2017). Many studies have represented the superiority of static auction over dynamic auction in terms of revenue, efficiency, and transaction cost (Cramton, 1998; Klemperer, 2002; Mandell, 2005; Burtraw et al., 2009; Goeree et al., 2013). However, the answer to which auction method is more appropriate between static methods, i.e., the uniform and discriminatory pricing, is still one of the challenges of the carbon auction market.

A carbon allowance auction may involve heterogeneous bidders; therefore, some bidders will be stronger than others. Those bidders for which allowances are more valuable are strong, and the rest are weak (Güth et al., 2005). The strong bidders may outbid the weak bidders, gain a significant fraction of carbon allowances in the auction, and cause inefficiency (Maskin and Riley, 2000). To maximize competition between bidders, the government can limit the maximum volume and price each participant can bid (Cramton, 2008). A similar volume limitation can be extended to the carbon allowance auction market based on the United Kingdom bond auction rule, allowing bidders to bid up to 25% of the total supply (Klingenfeld, 2007). The government can also set a cap for the bidding prices to prevent the carbon allowance price from rising by strong bidders. Price control has been used on other auctions like stock markets to decrease inflation or deflation. The question then arises: what is the effect of the bid limitation on bidders' behavior in the auction?

Another challenge with carbon auction is determining the carbon price in the carbon trading market. Authors such as Chang et al. (2015), Jin et al. (2014), and Sabzevar et al. (2017) have emphasized that carbon trading price has a significant impact on maximizing firms' profit. Zhang and Xu (2013) have highlighted that carbon trading price can change the supply chain's network design. The next question is how the carbon trading price should be determined?

Various techniques have been used to analyze bidders' behavior in the carbon auction market, and the most famous of them are optimization models, experimental methods, and simulation methods. Optimization models require deriving and simplifying assumptions. There is some hurdle in experimental techniques, like time limit, to avoid boredom and budget constraints (Tesfatsion, 2002). Among simulation approaches, the multi-agent-based model is a kind of computational modeling that can simulate individuals or objects and their interactions in terms of agents (Wilensky and Rand, 2015). The lack of data on carbon auctioning, on the one hand, and the nature of its gameplay, on the other, have made the auction system a complex system (Cong and Wei, 2012). Using the multi-agent-based model, we can simulate complex systems and better understand system elements' interactions (Wilensky and Rand, 2015).

Motivated by the above facts, this paper proposes a multi-agent-based model to design a cap-and-trade auction market and compare the performance of the auction and the agents' behavior under the uniform pricing and discriminatory pricing with and without price and volume cap limitations. The multi-agent-based model comprises two main agents, i.e., the government as auctioneer and supply chains as bidders. The government allocates initial carbon allowances using the auction and sets limitations on price and volume. According to limitations, supply chains determine their volume (their required carbon allowances) and bid prices (the price they want to pay for an allowance unit). In reality, supply chains are the firms that have production facilities and warehouses and deliver manufactured products to customers. They optimize their operational and tactical decisions based on their carbon allowances and trade them with each other in the carbon trading market. The supply chains have two methods for production and transportation, namely green and regular. The green methods produce fewer emissions but cost more than regular ones. Therefore, supply chains can change their methods and affect their costs and emissions. Without government intervention, the carbon trading price is freely determined based on supply and demand.

In the proposed multi-agent-based model, the Q-learning algorithm develops the agents' bidding behaviors. This algorithm is a reinforcement learning offered by Watkins (Andrew, 1999) for the Markovian decision problems with incomplete information. The existing studies in the field of multi-agent-based carbon auction, like Cong and Wei (2010) and Tang et al. (2017), used the Roth-Erev reinforcement learning algorithm. This algorithm determines the bidding strategy by information obtained from the previous period. If agents can anticipate their current bidding strategy's long-term consequences rather than optimizing their immediate rewards, they will improve their profitability (Tesauro and Kephart, 2002). The Q-learning algorithm tackles this problem because an agent can predict the long-term consequences of its actions and other agents' actions. Therefore, it can correctly model the other agents and achieve the optimal bidding strategy (Tesauro and Kephart, 2002). The Q-learning algorithm has been widely used in the electricity auction market (Xiong et al., 2002, 2004; Rahimiyan and Rajabi Mashhadi, 2008; Rahimiyan and Mashhadi, 2010).

2 Literature review

An increasing body of literature has examined the cap-and-trade scheme on different supply chains. Those related to this work can be divided into four categories: (1) the cap-and-trade scheme in supply chains; (2) comparing the pricing methods in the static auction; (3) limitation on bidding volume and price; (4) techniques for analyzing bidders' behavior in the auction market.

2.1 The cap-and-trade scheme in supply chains

As carbon cap-and-trade regulation has received increasing attention in supply chain management, there is extensive research on designing efficient supply chains under cap-and trade regulation. For example, Abdallah et al. (2012) presented a model to design a supply chain network for a company that assembles and distributes personal computers under the cap-and-trade scheme. Giarola et al. (2012) developed an ethanol supply chain considering the cap-and-trade scheme. Furthermore, Zakeri et al. (2015), Mohammed et al. (2017), and Rezaee et al. (2017) proposed optimization models to design different supply chain networks under the cap-and-trade scheme. In these types of researches, initial carbon allowances are allocated by free methods, and the auction is not considered. Furthermore, determining the carbon trading price is a significant challenge in the cap-and-trade scheme which has been ignored in these researches. Some studies, like Du et al. (2015), Sabzevar et al. (2017), and Hong et al. (2017), tried to determine the optimal carbon trading price. However, they do not consider auction methods for allocating carbon allowances.

2.2 Comparing the pricing methods in the static auction

In the carbon auction market, Cong and Wei (2010) indicated that when carbon allowances are nearly low, the discriminatory pricing method is more efficient than the uniform pricing, while small participants benefit more than the other method. Nanduri and Otieno (2011) demonstrated that uniform pricing favors small generators in electricity and cap-and-trade markets. Cong and Wei (2012) showed that when the number of bidders is relatively low in the carbon allowance auction market, and there is communication between them, discriminatory pricing is better than uniform pricing and prevents collusion. Tang et al. (2017) demonstrated that uniform pricing has a smaller effect on economic damage and emission reduction than discriminatory pricing. Esmaeili Avval et al. (2021) showed that the bidders behave differently under different amounts of carbon allowances. In other markets, Back and Zender (1993) compared the uniform and discriminatory pricing in treasury auctions. They showed that the auctioneer's revenue in the former method is lower than that in the other method. Hudson (2000) showed that high benefits could be earned under the uniform pricing in an electricity market in the presence of market power. Bower and Bunn (2001) indicated that the discriminatory pricing results in a greater market-clearing price than the uniform pricing in England and Wales electricity market. Rassenti et al. (2003) showed that the discriminatory pricing method results in higher prices than the uniform pricing in the absence of market power. Xiong et al. (2004) compared uniform and discriminatory pricing in an electricity market. Their findings demonstrated that discriminatory pricing results in a lower market-clearing price. Goldreich (2007) compared two methods in U.S treasury auction and found that in the uniform pricing, the treasury receives the average price less than the discriminatory pricing. Schwalbe (2008) demonstrated that uniform pricing smooths the way for collusion more than discriminatory pricing. Brenner et al. (2009) found that most countries use discriminatory pricing in auctioning financial assets of governments. Hortaçsu and McAdams (2010) investigated switching from discriminatory pricing to uniform pricing, or Vickrey auction, would not significantly increase revenue for an auctioneer in a Turkish Treasury auction market. Damianov and Becker (2010) demonstrated that uniform pricing generates higher revenue for an auctioneer, in an auction with variable supply. Duke et al. (2017) compared two pricing methods in purchasing ecosystem services under different information structures. They showed that information affects auction efficiency. Hattori and Takahashi (2020) compared two methods in the Japanese government bonds market and showed discriminatory pricing lowered borrowing costs. Sugiyarto (2020) examined the performance of two pricing methods in the Indonesian treasuries market and demonstrated that discriminatory pricing improved auction revenue and efficiency. Matthäus (2020) showed that the choice of pricing method does not play a significant role in designing effective renewable energy auctions. There are many studies that compared these two pricing methods in different areas, but their results are not consistent. However, studies that have compared these methods in the carbon auction market are rare in which they did not consider the effect of bid limitation on the carbon auction market. These studies are limited to decisions related to the bidding strategy and the production plan, and decisions on issues such as the use of green technology, transportation plan, inventory, etc., have been ignored. In the real world, these decisions are essential factors in supply chains planning that can affect the cost, emissions, and consequently, their strategies in the carbon auction market.

2.3 Limitation on bidding volume and price

Isaac and Plott (1981) investigated the effect of the price limitation in the auction market and demonstrated the prices converge to cap price. Ausubel and Schwartz (1999) compared the uniform price auction and a multi-period auction considering volume limitation and showed that the former could do better than the latter. Chakraborty (2002) and Forster et al. (2013) studied the impact of limit price on a sealed and dynamic auction, respectively. Gode and Sunder (2004) and Smith and Williams (2008) examined the effect of limit price on a double auction. They showed that it could limit the strategy of bidders. Talman and Yang (2008) examined the effect of limit price and volume in a dynamic auction. Vossler et al. (2009) investigated the effect of a price cap in an electricity market under uniform pricing. Olivares et al. (2012) presented an auction for a procurement school meal. Their findings showed that limitation on bidding volume could promote competition in the long run. However, they did not investigate these limitations in the carbon allowance auction.

2.4 Techniques for analyzing bidders' behavior in the auction market

As mentioned earlier, the most critical tools for studying bidders' behavior in the auction market are optimization models, experimental methods, and simulation methods. As for optimization models in the carbon auction market, Haita (2014) investigated market power's effect on carbon auction and the carbon trading market by an optimization model based on game theory with complete information. Jiang et al. (2016) presented an optimization model based on game theory to investigate market power manipulating carbon prices in the carbon auction market. For the experimental methods, Cong and Wei (2012) compared three types of carbon auction methods, i.e., uniform price auction, discriminatory price auction, and English auction, in terms of the carbon price, auction efficiency, demand withholding, and fluctuations in power supplies. Dormady (2014) provided experiments to investigate a carbon and energy market simultaneously under real-world market characteristics. For the simulation methods, Li et al. (2018) explored the impact of the cap-and-trade scheme on China's electricity industry using a dynamic computable general equilibrium (CGE) model. Li et al. (2019) also evaluated the effect of different scenarios of allocating auction revenues on economic growth, mitigation, and welfare improvement by this method. Cong and Wei (2010) used a multi-agent-based model to compare uniform pricing and discriminatory pricing auction. They considered the government as the auctioneer and two agents as the bidders (gas-fired power plants and coal-fired power). Tang et al. (2017) proposed a multi-agent-based model for carbon allowance auction. They considered two agents, i.e., the government as the regulator of emission trading scheme, and different firms in all parts of China. Yu et al. (2020) utilized a multi-agent-based model to simulate the emission trading market based on the auction. Esmaeili Avval et al. (2021) also used a multi-agent-based model for comparing uniform and discriminatory pricing methods. In other markets, for optimization models, Sofia and Edward (2020) presented an auction in cognitive radio networks. Kang et al. (2007) and Liu et al. (2010) modeled an electricity auction market. Na et al. (2010) modeled the carbon trading market as a double auction. For experimental methods, Eliaz et al. (2008) studied an auction for selling products using these methods. Sturm (2008) investigated the effect of market power in a double auction using experimental methods. Also, Rassenti et al. (2003) compared uniform and discriminatory pricing based on experimental methods. Xiong et al. (2004), Liu et al. (2012), Jaghargh and Mashhadi (2020), Poursalimi Jaghargh and Mashhadi (2021), Rahimiyan and Mashhadi (2010), and Rahimiyan and Rajabi Mashhadi (2008) used a multi-agent-based model in an electricity market.

Table 1 summarizes the abovementioned studies and compares this paper's features with them. This table reveals that a study that designs a carbon allowance auction market consisting of government and supply chains and compares the uniform pricing and discriminatory pricing under price and volume cap limitations does not exist. This paper seeks to fill this gap. Furthermore, in this paper, for the first time, supply chains are considered bidders in the carbon auction market to trace the carbon footprint better. The findings of this study provide some managerial insights for policymakers to design a more efficient carbon auction market.

3 The multi-agent-based model

In this section, a carbon auction market consisting of the government and supply chains is designed utilizing multi-agent-based modeling. The government, as auctioneer, determines the initial carbon allowances and maximum price and volume each supply chain can bid. According to limitations, the supply chains as bidders simultaneously submit their bid price and volume (the quantity they are willing to buy at that price). Then the government builds the aggregate demand curve by adding the supply chains' demand curves. The point at which the demand and supply curves intersect each other is called the clearing price. According to the clearing price, the government specifies the carbon allowances allocated to each supply chain and the actual price it has to pay. The demands above the clearing price will be fulfilled. The ones at the clearing price will be rationed, and those below the clearing price will be rejected. The supply chains adapt their operational and tactical decisions by optimizing a mixed-integer linear programming model to comply with the carbon allowances allocated by the government in carbon auction. The carbon allowances are tradable among supply chains, and the carbon trading price is obtained based on the demand and supply in a carbon trading

Table 1 A summary of the literature review

Author (year)	Allowance allocation in supply chain		Carbon trading price	Comparing pricing methods		Limitation on auction				Techniques		
	Free	Auction		Carbon auction market	Other auction markets	Carbon auction market		Other auction markets		Optimization	Experimental	Simulation
						Bidding volume	Bidding price	Bidding volume	Bidding price			
Isaac and Plott (1981)									✓			
Back and Zender (1993)					✓							
Ausubel and Schwartz (1999)								✓				
Hudson (2000)					✓							
Bower and Bunn (2001)					✓							
Chakraborty (2002)									✓			
Rassenti et al. (2003)					✓						✓	

Table 1 (continued)

Author (year)	Allowance allocation in supply chain		Carbon trading price	Comparing pricing methods		Limitation on auction				Techniques		
						Carbon auction market		Other auction markets				
	Free	Auction		Carbon auction market	Other auction markets	Bidding volume	Bidding price	Bidding volume	Bidding price	Optimization	Experimental	Simulation
Gode and Sunder (2004)									✓			
Xiong et al. (2004)					✓							✓
Goldreich (2007)					✓							
Kang et al. (2007)										✓		
Eliaz et al. (2008)											✓	

Table 1 (continued)

Author (year)	Allowance allocation in supply chain		Carbon trading price	Comparing pricing methods		Limitation on auction				Techniques		
						Carbon auction market		Other auction markets				
	Free	Auction		Carbon auction market	Other auction markets	Bidding volume	Bidding price	Bidding volume	Bidding price	Optimization	Experimental	Simulation
Rahimiyan and Rajabi Mashhadi (2008)												✓
Schwalbe (2008)					✓							
Smith and Williams (2008)									✓			
Sturm (2008)											✓	
Talman and Yang (2008)								✓	✓			

Table 1 (continued)

Author (year)	Allowance allocation in supply chain		Carbon trading price	Comparing pricing methods		Limitation on auction				Techniques		
	Free	Auction		Carbon auction market	Other auction markets	Carbon auction market		Other auction markets		Optimization	Experimental	Simulation
						Bidding volume	Bidding price	Bidding volume	Bidding price			
Brenner et al. (2009)					✓							
Vossler et al. (2009)									✓			
Hortaçsu and McAdams (2010)					✓							
Damianov and Becker (2010)					✓							
Liu et al. (2010)										✓		

Table 1 (continued)

Author (year)	Allowance allocation in supply chain		Carbon trading price	Comparing pricing methods		Limitation on auction				Techniques		
	Free	Auction		Carbon auction market	Other auction markets	Carbon auction market		Other auction markets		Optimization	Experimental	Simulation
						Bidding volume	Bidding price	Bidding volume	Bidding price			
Cong and Wei (2010)												✓
Na et al. (2010)										✓		
Rahimiyan and Mashhadi (2010)												✓
Nanduri and Otieno (2011)				✓	✓							
Abdallah et al. (2012)	✓											

Table 1 (continued)

Author (year)	Allowance allocation in supply chain		Carbon trading price	Comparing pricing methods		Limitation on auction				Techniques		
						Carbon auction market		Other auction markets				
	Free	Auction		Carbon auction market	Other auction markets	Bidding volume	Bidding price	Bidding volume	Bidding price	Optimization	Experimental	Simulation
Cong and Wei (2012)				✓							✓	
Giarola et al. (2012)	✓											
Liu et al. (2012)												✓
Olivares et al. (2012)								✓				
Forster et al. (2013)									✓			
Dormady (2014)											✓	

Table 1 (continued)

Author (year)	Allowance allocation in supply chain		Carbon trading price	Comparing pricing methods		Limitation on auction				Techniques		
	Free	Auction		Carbon auction market	Other auction markets	Carbon auction market		Other auction markets		Optimization	Experimental	Simulation
						Bidding volume	Bidding price	Bidding volume	Bidding price			
Haita (2014)										✓		
Du et al. (2015)	✓		✓									
Zakeri et al. (2015)	✓											
Jiang et al. (2016)										✓		
Duke et al. (2017)					✓							
Hong et al. (2017)	✓		✓									

Table 1 (continued)

Author (year)	Allowance allocation in supply chain		Carbon trading price	Comparing pricing methods		Limitation on auction				Techniques		
						Carbon auction market		Other auction markets				
	Free	Auction		Carbon auction market	Other auction markets	Bidding volume	Bidding price	Bidding volume	Bidding price	Optimization	Experimental	Simulation
Mohammed et al. (2017)	✓											
Rezaee et al. (2017)	✓											
Sabzevar et al. (2017)	✓		✓									
Tang et al. (2017)				✓								✓
Li et al. (2018)												✓

Table 1 (continued)

Author (year)	Allowance allocation in supply chain		Carbon trading price	Comparing pricing methods		Limitation on auction				Techniques		
						Carbon auction market		Other auction markets				
	Free	Auction		Carbon auction market	Other auction markets	Bidding volume	Bidding price	Bidding volume	Bidding price	Optimization	Experimental	Simulation
Li et al. (2019)												✓
Hattori and Takahashi (2020)					✓							
Jaghargh and Mashhadi, (2020)												✓
Matthäus (2020)					✓							
Sofia and Edward (2020)												✓

Table 1 (continued)

Author (year)	Allowance allocation in supply chain		Carbon trading price	Comparing pricing methods		Limitation on auction				Techniques		
						Carbon auction market		Other auction markets				
	Free	Auction		Carbon auction market	Other auction markets	Bidding volume	Bidding price	Bidding volume	Bidding price	Optimization	Experimental	Simulation
Sugiyarto (2020)					✓							
Yu et al. (2020)												✓
Esmaeili Avval et al. (2021)				✓								✓
Poursalimi Jaghargh and Mashhadi (2021)												✓
Present work		✓	✓	✓		✓	✓					✓

market. It should be noted that this paper assumes that all carbon allowances are allocated through the auction, and free allocation is not considered.

This model compares the uniform and discriminatory pricing methods in different settings. The model simulates the carbon allowance auction in the presence and absence of price and volume cap limitations and explores how these limitations affect the auction and supply chains' decisions. We make different policies about the initial carbon allowances and compare two pricing methods under these policies and the presence and absence of limitations. The results help to know which pricing method is proper in carbon allowance auction under different situations.

3.1 Government agent

As auctioneer, the government administrates carbon auction and determines the initial carbon allowances $Tot\_Allowance$. Assume $Totalemission$ shows the total carbon allowances required to cover the total emissions of the supply chains when there is no carbon regulation. To decrease the total emissions, the government considers a mitigation rate λ. Therefore $Tot\_Allowance$ is calculated based on Eq. (1):

$$\mathrm{Tot\_Allowance} = \mathrm{Totalemission} * (1 - \lambda) \tag{1}$$

3.2 Supply chains agents

As bidders, the supply chains decide about bidding strategy (price and bidding volume). They determine production and transportation planning to maximize their profits according to the carbon allowances obtained through the auction and trade their allowances in the carbon trading market.

3.2.1 Supply chains' decisions

Each supply chain s participating in the auction is the single firm that produces i types of products in m manufacturing centers on j sets of machines in T periods. The products are shipped to c customer zones through w warehouses by v transportation modes. There are two types of machines and transportation modes: green and regular. The green type generates fewer emissions but costs more than the regular one. Each supply chain attempts to balance its costs and emissions by applying the right technology for production and transportation. The following assumptions are considered for each supply chain's mathematical model.

- The number, location, and capacity of manufacturing centers and warehouses are known.
- The number, location, and demand of each customer zone are known.
- The demand for each product should be satisfied during each period.
- The capacity hours of each machine, the capacity of total raw material, the inventory holding capacity of warehouses and manufacturing centers, and transportation capacities are known.
- The carbon emission is considered for production, transportation, and inventory holding.
- A unit of raw material is required to produce a unit of the final product.

Definitions of parameters, sets, variables, and mathematical modeling of each chain are provided in appendix A.

3.2.2 Supply chains' bidding strategy

The amount of carbon allowances that each supply chain s requires to support its production plan (without carbon regulation) is equal to TEC_s at the cost of C_TEC_s. If the selling price per unit product i, in supply chain s is Sp_{si}, then its total sales revenue over the entire planning horizon $Sale_s$ will be $\sum_i \sum_c \sum_t de_{sict} Sp_{si}$. de_{sict} show the forecasted demand for product i in customer zone c in period t in supply chain s Therefore, the value of an allowance to supply chain s can be calculated as Eq. (2):

$$v_s = \frac{Sale_s - C\_TEC_s}{TEC_s} \tag{2}$$

v_s is the private value, i.e., the maximum price that each supply chain tends to pay for an allowance unit. The price and volume that each supply chain can offer vary according to price and volume cap limitations.

3.2.3 The bidding behavior without price and volume cap limitations

The supply chains' bidding price bp_s is between reserve price rp (the price floor that the government considers for a unit of allowance) and v_s, i.e., $bp_s \in [rp, v_s]$. The bidding volume for each supply chainbv_s is equal to or greater than TEC_s, i.e., $bv_s \in [TEC_s, \infty]$. Given that the supply chains' private values are not the same; therefore, some supply chains may be stronger than others. Those supply chains for which allowances are more valuable are strong bidders, and the rest are weak.

3.2.4 The bidding behavior with price and volume limitations

In this case, the government presents a price cap $\overline{BP}$ and a volume cap $\overline{BV}$ for all supply chains. Therefore, the supply chains' bidding prices are between rp and $\overline{BP}$, i.e., $bp_s \in \left[rp, \overline{BP}\right]$. The supply chains' bidding volumes are between TEC_s and $\overline{BV}$, i.e., $bv_s \in \left[TEC_s, \overline{BV}\right]$. Because the price and volume cap is the same for all supply chains; therefore, there are no strong or weak supply chains, and the competition between supply chains will increase.

After the supply chains submitted their bidding, the government ranks supply chains in descending order in terms of their bidding prices to form the aggregate demand curve. The equilibrium price is equal to the bidding price generated by supply chain k that satisfies the following inequalities:

$$\sum_{s=1}^{k-1} bv_s < Tot\_Allowance \tag{3}$$

$$\sum_{s=1}^{k} bv_s \geq Tot\_Allowance \tag{4}$$

Therefore the equilibrium price ep is equal to bp_k, i.e., $ep = bp_k$. The carbon allowances gained by supply chain s (gv_s) in the carbon auction market for two pricing methods is calculated according to Eq. (5):

$$gv_s = \begin{cases} bv_s bp_s > bp_k \\ \frac{bv_s\left(Tot\_Allowance - \sum_{s=1}^{j-1} bv_s\right)}{\sum_{s=j}^{k} bv_s} bp_j = \ldots bp_s = \cdots = bp_k, \, j \le s \le k \\ 0 bp_s < bp_k \end{cases} \tag{5}$$

In the uniform pricing method, every winner pays the market-clearing price cp that is equal to the equilibrium price ep. Therefore, the actual carbon price ap_s (the price that supply chain s must pay) in the uniform pricing method is calculated according to Eq. (6):

$$ap_s = \begin{cases} cp s \le k \\ \infty s > k \end{cases} \tag{6}$$

In the discriminatory pricing method, the winners pay their bidding price. So, the actual carbon price ap_s in the discriminatory pricing rule is calculated according to Eq. (7):

$$ap_s = \begin{cases} bp_s s \le k \\ \infty s > k \end{cases} \tag{7}$$

3.2.5 Determining the carbon trading price

The amount of carbon allowances allocated to each supply chain is determined when the auction process is completed. Then, supply chains make their tactical and operational decisions to minimize their costs. If supply chains have surplus carbon allowance, they can sell them, and if they have insufficient carbon allowances, they have to buy them in the carbon trading market. In this market, the carbon price is assumed to be freely determined based on supply (surplus carbon allowance) and demand (insufficient carbon allowances) without government intervention. Supply chains determine which technology (green or regular) to utilize based on carbon allowances gained at auction and carbon price in the carbon trading market. If the carbon trading price is high, the supply chains increase the usage of green technology to increase their surplus allowances and obtain more profit in the carbon trading market. With the increase in the surplus carbon allowances, the carbon trading price decreases, so the supply chains' profitability with green technology decreases. As a result, they reduce the utilization of green technology. Consequently, the surplus carbon allowances drop along with the increase in the carbon trading price. This process continues until the carbon trading price reaches the equilibrium point. In this market, the equilibrium price is achieved when supply and demand are equal (Greaves, 1982). Therefore in this market, when the amount of total emissions (TEP) is equal to the total initial allowances ($Tot\_Allowance$), the equilibrium carbon trading price is obtained.

4 Solution methodology

This section proposes a hybrid algorithm including the Q-learning algorithm, bisection, and CPLEX solver. The first two methods have been used for determining optimal bidding strategy and optimal carbon trading price (ψ^*). CPLEX is one of the most advanced and accepted optimization solvers commercialized by IBM ILOG (Anand et al., 2017). It can solve linear programming, mixed integer programming, quadratic programming, and mixed-integer quadratic constrained programming with millions of constraints and variables (Anand et al., 2017; Shinano and Fujie, 2007; Zakaria et al., 2015). It uses techniques like a branch and bound and benders' decomposition (Anand et al., 2017). For use, the problem, including the objective function and constraints, should be written in a specific standard format to CPLEX solver (ILOG, 1987). After determining the carbon trading price, the optimal supply chains' tactical and operational decisions (Eq. 13 subjected to constraints 15–31 in appendix A) are solved by CPLEX.

4.1 Q-learning algorithm

Suppose an agent that can select activities $A = \{a_1, a_2, \ldots, a_m\}$, is interacted with its environment that can take the states $S = \{s_1, s_2, \ldots, s_n\}$ at discrete time steps, $t = \{0, 1, 2, \ldots\}$. At each time step t, the agent selects the action $a_t = a \in A$ with observing the present state of the environment $s_t = s \in S$. Consequently, the agent achieves an immediate reward r_{t+1} and the environment alters its state to a new state $s_{t+1} = s^{'} \in S$.

In the Q-Learning algorithm, there is a lookup table containing Q-value for each permissible pair(s, a). That shows a discounted long-term expected reward for choosing action a in state s and is initialized with arbitrary values. Then, Q-values are updated in each iteration of the algorithm, followed by updating rules and data,s_t,a_t, s_{t+1} and r_{t+1}:

$$Q_{t+1}(s_t, a_t) = Q_t(s_t, a_t) + \alpha \Delta Q_t(s_t, a_t) \tag{8}$$

$$\Delta Q_t(s_t, a_t) = \left\{ r_{t+1} + \gamma \underset{a^{'}}{max} [Q_t(s_{t+1}, a^{'})] \right\} - Q_t(s_t, a_t) \tag{9}$$

$\gamma (0 \le \gamma \le 1)$ is the discounted factor, and α $(0 < \alpha < 1)$ is the learning rate that represents the degree of new data impact on Q-values. If each admissible pair (s, a) is visited infinitely and α decreases appropriately, the Q-values converge to their optimal values with probability 1 (Watkins, 1989). The algorithm's convergence conditions are a stationary and Markovian environment, but they do not hold with increasing the number of agents to more than one. As well as the environment, in multi-agents, the behavior of each agent depends on the behavior of other agents. Therefore, the new environment is not stationary and Markovian, and convergence is not guaranteed. However, this algorithm has been used in many studies for learning because of its simple application and low computation cost and efficiency (Huynh et al., 2021; Rahimiyan and Mashhadi, 2010).

4.2 Bidding strategy based on Q-learning

This section intends to use the Q-learning algorithm to determine the optimal bidding strategy. As mentioned before, the Q-learning algorithm requires data related to the state, action, and reward to calculate Q values.

The equilibrium price is considered as the state of the environment s_t and can change between reserve price rp and the maximum price that the supply chains can pay per unit of allowance. The action for an agent is bidding price and bidding volume that is determined according to Sect. 3.2.3 and 3.2.4. The reward of each supply chain is calculated as Eq. (10).

$$Profit_s = Sale_s - Cost\_EC_s - ap_s * gv_s \tag{10}$$

$Cost\_EC_s$ indicates total costs of supply chain s in the cap-and-trade system.

4.3 Q-learning implementation

The steps of the supply chains' bidding based on the Q-learning algorithm are as follows. These steps also are presented in Fig. 1.

1. *Initialization:* the parameters of the algorithm and lookup tables for each agent are initialized. Small random numbers or zero are assigned to all Q values in lookup tables. Suppose the maximum iteration, i.e., $Maxiter$ is the termination condition. Therefore, the steps below are repeated $Maxiter$ times:
2. *State identification:* the previous iteration's equilibrium price (ep) is utilized as the environment's current state. In the first step, the reserve price (rp) is considered as the state of the environment.
3. *Action selection:* after identifying the environment's state, the agents select their action based on Q-values and using ϵ-greedy method to balance exploitation and exploration. In this method, the agent selects the actions with a maximum Q-value in the state s with a high probability $1 - \epsilon$ and a random action from all admissible actions with a small probability ϵ.
4. *Q-value update*: After the equilibrium price and the dedicated carbon allowances of all supply chains are notified, the supply chains determine their tactical and operational decisions using CPLEX. The optimal value of carbon trading price, i.e., ψ^* is calculated by the bisection method (Sect. 4.4). Finally, supply chains compute their rewards according to Eq. (10) and then update their Q values based on Eqs. (8) and (9).

4.4 Determining the optimal carbon trading price and supply chain decisions

The green technology costs more than the regular technology; therefore, with a decrease in the carbon trading price, the total emissions either increase or do not change; since the carbon trading price is a continuous variable, the bisection method is applied to obtain an ε-approximate optimal solution. Therefore, after determining the amount of carbon allowances allocated to each supply chain in each iteration of the Q-learning algorithm (see Fig. 1), the carbon trading price is determined using the bisection method. For each carbon trading price (ψ), the optimal tactical and operational decisions of supply chains are obtained using CPLEX solver.

The steps of the bisection method are as follows. These steps also are illustrated in Fig. 2.

Step 1: initialize the lower and upper bounds of $\psi : (\psi_{LB}, \psi_{UB})$.

Step 2: compare the gap between ψ_{LB} and ψ_{UB} with ε, a given small value, if the gap is less than ε, the interval containing the optimal carbon trading price is small, then go to step 6. Else, go to the next step.

Step 3: calculate the mean value of the interval (ψ_{LB}, ψ_{UB}),ψ_{mid}, then obtain the emission of each supply chain (EC_s) based on ψ_{mid} by optimizing $Cost\_EC_s$ for each supply chain using CPLEX. According to EC_s, compute the total carbon emission produced by all supply chains (TEP).

Step 4: compare TEP to the total initial allowances ($Tot\_Allowance$). If they are equal, the second termination condition is satisfied, then go to step 6, otherwise go to step 5.

Step 5: update the lower and upper bounds of $\psi : (\psi_{LB}, \psi_{UB})$ (as shown in Fig. 2). Then go back to step 2.

Step 6: calculate the optimal carbon trading price $\psi^* = (\psi_{UB} + \psi_{LB})/2$.

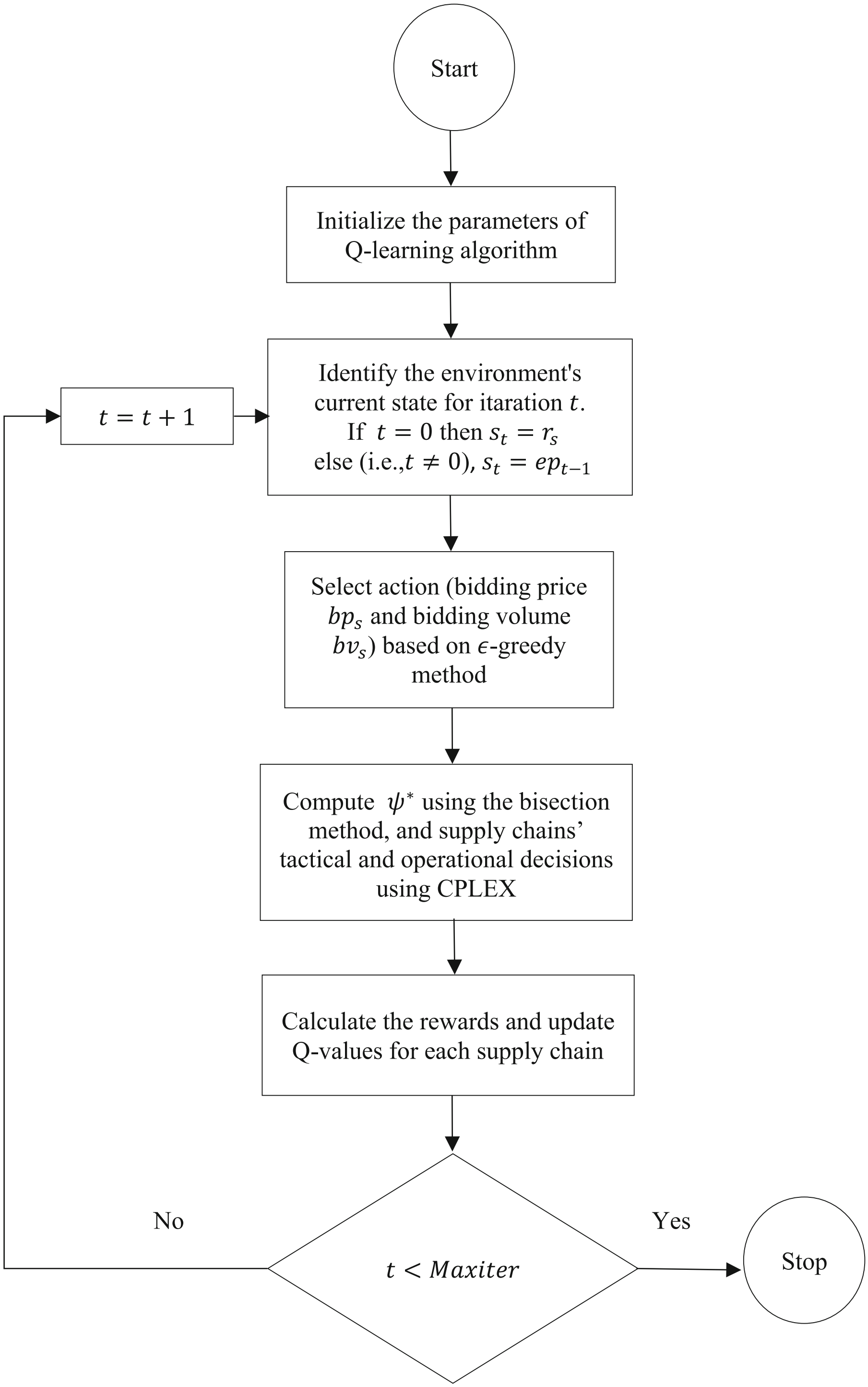

Fig. 1 Flowchart of supply chains' bidding based on Q-learning algorithm

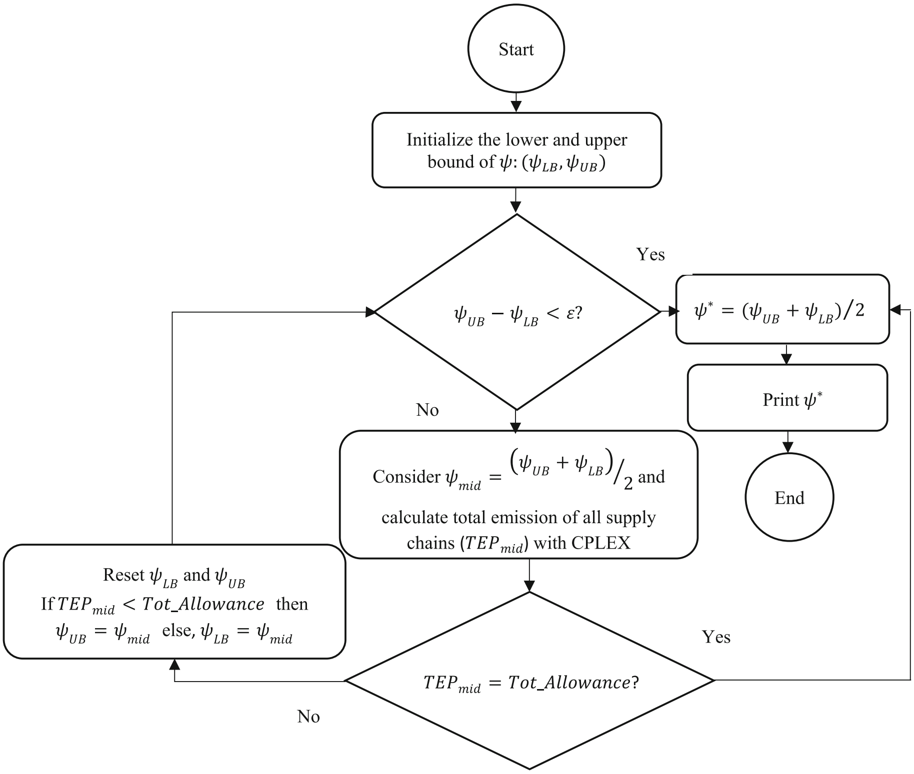

Fig. 2 Procedure for obtaining the carbon trading price

5 Computational results

In this section, some instances are presented to test the performance of the proposed algorithm. All the algorithms are coded in C + + , and the tactical and operational decisions of supply chains are obtained using ILOG CPLEX 12.3. All experiments have been done on a 64-bit computer benefits from a 2.30 GHz processor and 4 GB of RAM.

5.1 Data description

To analyze the solution methodology, two sets of problems are generated, details of which are given in Table 2. To simulate an approximate actual situation, we take our data from Zakeri et al. (2015) and generate similar supply chains around their data set. The details are presented in Appendix B. To ensure the convergence of the algorithm and not have an unlimited number of actions for each supply chain, it is assumed that the maximum bidding volume for each supply chain will be ten percent more than TEC_s. The value of the mitigation rate for all problems is 85%. It should be noted that rp, ψ_{UB}, and ψ_{LB} in all of the problem are set to 100, 0, and 10,000, respectively.

Table 2 Specifications of the problem sets

Problem set	Number of production centers	Number of warehouses	Number of Customer zones	Number of periods
s_1	2	3	4	6
s_2	2	4	5	6

Table 3 The parameters of the Q-learning algorithm

Iteration	1–600,000	600,000–800,000	800,000–1,000,000
α	0.9	0.8	0.7
γ	0.3	0.2	0.1
ϵ	0.5	0.005	0.0005

5.2 Q-learning algorithm setting

The parameters of the Q-learning algorithm, i.e., α, γ, and ϵ, are set according to Table 3. These parameters are determined based on the previous studies conducted in this context (Poursalimi Jaghargh and Mashhadi, 2021; Sadr et al., 2016). They are reduced during iterations to balance exploitation and exploration. The value of $Maxiter$ is assumed to be the large number 1,000,000 to guarantee the convergence of the Q-learning algorithm.

To prevent the curse of dimensionality, the state space, price space, and volume space should be discretized. Therefore, we equally discretize them into 81 states, 41 prices, and 16 volumes, respectively, for all problem sets. Therefore, the action space is $41 * 16$.

5.3 Computational experiments of the solution methodology

This section analyzes the proposed algorithm's performance in terms of execution time (CPU seconds) and average profit for the supply chains (million dollars) and compares it with Roth-Erev reinforcement learning (Cong and Wei, 2010; Tang et al., 2017) which has been used in the carbon auction market to determine a bidding strategy. Given the algorithm's random nature, the numerical example is run 20 times with different random seeds. For each problem set, the number of supply chains participating in the auction varies from 3 to 7. Totally, ten instances have been generated. The results are shown in Table 4. Compared to Roth-Erev reinforcement learning, although our proposed algorithm increases the execution time by an average of 4%, it leads to more profit by an average of 60% and 76% for supply chains in uniform and discriminatory pricing, respectively. For the problem with seven supply chains, Roth-Erev reinforcement learning cannot solve the problem because it takes up more running memory than is available.

Table 4 The result of the proposed algorithm for different instances

Problem set	Instance number	Number of supply chains	Our proposed algorithm				Roth-Erev				Gap (%)			
			Uniform pricing		Discriminatory pricing		Uniform pricing		Discriminatory pricing		Uniform pricing		Discriminatory pricing	
			Average profit	Time (s)	Average profit	Time (s)	Average profit	Time (s)	Average profit	Time (s)	Average profit	Time (s)	Average profit	Time (s)
s_1	1	3	504,453	227	480,522	227	242,209	215	237,115	215	108	6	103	6
	2	4	638,768	385	611,926	385	382,911	368	340,541	368	67	5	80	5
	3	5	637,273	909	636,717	909	427,714	888	368,967	888	49	2	73	2
	4	6	637,934	537	637,934	537	387,482	512	347,379	512	65	5	84	5
	5	7	573,542	585	572,811	585	–	–	–	–	–	–	–	–
s_2	6	3	655,099	1,487	655,099	1,485	479,855	1,474	408,754	1,474	37	1	60	1
	7	4	670,745	720	669,417	719	469,245	701	385,144	701	43	3	74	3
	8	5	747,148	617	747,148	616	465,214	595	424,015	595	61	4	76	4
	9	6	647,959	700	605,546	698	422,585	672	371,534	672	53	4	63	4
	10	7	590,636	1,129	517,918	1,127	–	–	–	–	–	–	–	–
Average											60	4	76	4

Table 5 Parameters related to bidding price and volume in case 1

Supply chains	1	2	3	4	5
TEC_s	2511	2774	2111	2705	2572
Maximum bidding volume	2761	3052	2322	2976	2830
Private value v_s	140	150	225	160	220

6 Auction simulation in the presence and absence of limitations

This section compares the uniform and discriminatory pricing with and without price and volume cap limitations for the different carbon policies for appropriate auction design. First, different policies are set in Sect. 6.1. Second, the results are described in detail in Sect. 6.2.

6.1 Scenario setting

We present different carbon auction policies to compare the uniform and discriminatory pricing in the two cases. In case 1, there are no limitations on bidding price and volume while in case 2 the government set limitations on bidding price and volume. For designing different policies, five mitigation rates are considered, i.e., $\lambda = 0\%, 10\%, 20\%, 30\%, 40\%$. According to Eq. (1), when λ is small, the carbon supply quantity is high and vice versa. Five supply chains are supposed to compete in the carbon auction market and trade their allowances in the carbon trading market. Each supply chain includes two manufacturing centers, three warehouses, four customer zones, and produces three product types. The details are similar to Sect. 5.1. According to the generated data, the values of TEC_s, private value v_s are according to Table 5, for case 1. According to the private values, supply chains 3, 4, and 5 are stronger than supply chains 1 and 2.

In case 2, the price and volume cap limitations are set as $\overline{BV} = 3,000$ and $\overline{BP} = 140$.

6.2 Simulation results

The results are presented based on the market share for each supply chain, the bidding price, the price that the supply chains have to pay at the auction, the carbon trading price, and the average profit of the supply chains.

6.2.1 The market share of supply chains in carbon allowance auction

In this section, the market share of each supply chain is calculated in the carbon auction market for different policies in two cases. The results are presented in Table 6, 7, 8 and 9. In these tables, bidding volume (bv_i), the carbon allowances gained (gv_i), and the market share of each supply chain in the carbon auction market are presented for uniform and discriminatory pricing in two cases.

Table 6 and Table 7 show that when there are strong supply chains, the supply chains bid their maximum bidding volumes, but the market share for strong supply chains, i.e., supply chains 3,4, and 5, is larger than the others for $\lambda = 30\%$ and 40%. As the mitigation rate decreases, the market shares of weak bidders increase, and they are equal or greater in the uniform pricing than the ones in the discriminatory pricing method. Because in the

Table 6 The market share of each supply chain for the uniform pricing method in case 1

λ Supply chains		0%	10%	20%	30%	40%
1	bv_1	2511	2637	2761	2762	2761
	gv_1	2511	873	0	0	0
	Market share	20	8	0	0	0
2	bv_2	2774	2887	2915	3,052	3,052
	gv_2	2774	2887	2061	744	0
	Market share	22	25	20	8	0
3	bv_3	2111	2179	2312	2322	2322
	gv_3	2111	2179	2312	2322	2322
	Market share	17	19	23	26	31
4	bv_4	2705	2801		2976	2975
	gv_4	2705	2801	2957	2976	2452
	Market share	21	25	29	34	32
5	bv_5	2572	2661	2809	2829	2830
	gv_5	2572	2661	2809	2829	2830
	Market share	20	23	28	32	37

Table 7 The market share of each supply chain for the discriminatory pricing method in case 1

λ Supply chains		0%	10%	20%	30%	40%
1	bv_1	2511	2642	2761	2762	2761
	gv_1	2511	542	0	0	0
	Market share	20	5	0	0	0
2	bv_2	2774	2947	3051	3052	3052
	gv_2	2774	2947	2013	744	0
	Market share	22	26	20	8	0
3	bv_3	2111	2279	2321	2322	2322
	gv_3	2111	2279	2321	2322	2322
	Market share	17	20	23	26	31
4	bv_4	2705	2883	2975	2976	2975
	gv_4	2705	2883	2975	2976	2452
	Market share	21	25	29	34	32
5	bv_5	2572	2755	2829	2829	2830
	gv_5	2572	2755	2829	2829	2830
	Market share	20	24	28	32	37

Table 8 The market share of each supply chain for the uniform pricing method in case 2

λ Supply chains		0%	10%	20%	30%	40%
1	bv_1	2511	3000	3000	3000	3000
	gv_1	2511	2281	2028	1774	1521
	Market share	20	20	20	20	20
2	bv_2	2774	3000	3000	3000	3000
	gv_2	2774	2281	2028	1774	1521
	Market share	22	20	20	20	20
3	bv_3	2111	3000	3000	3000	3000
	gv_3	2111	2281	2028	1774	1521
	Market share	17	20	20	20	20
4	bv_4	2705	3000	3000	3000	3000
	gv_4	2705	2281	2028	1774	1521
	Market share	21	20	20	20	20
5	bv_5	2572	3000	3000	3000	3000
	gv_5	2572	2281	2028	1774	1521
	Market share	20	20	20	20	20

Table 9 The market share of each supply chain for the discriminatory pricing method in case 2

λ Supply chains		0%	10%	20%	30%	40%
1	bv_1	2511	3000	3000	3000	3000
	gv_1	2511	2281	2028	1774	1521
	Market share	20	20	20	20	20
2	bv_2	2774	3000	3000	3000	3000
	gv_2	2774	2281	2028	1774	1521
	Market share	22	20	20	20	20
3	bv_3	2111	3000	3000	3000	3000
	gv_3	2111	2281	2028	1774	1521
	Market share	17	20	20	20	20
4	bv_4	2705	3000	3000	3000	3000
	gv_4	2705	2281	2028	1774	1521
	Market share	21	20	20	20	20
5	bv_5	2572	3000	3000	3000	3000
	gv_5	2572	2281	2028	1774	1521
	Market share	20	20	20	20	20

uniform pricing, supply chains shade their bidding volume further than the discriminatory pricing ones. When the government provides the carbon allowances that supply chains need to support their productions, i.e., $\lambda = 0\%$, the supply chains bid their minimum volume, i.e., TEC_s and the amount of carbon allowance gained by all supply chains is equal to the volume they bid in two pricing methods.

Table 8 and Table 9 show that when there are no strong supply chains, they bid the volume cap $\overline{BV}$ for $\lambda = 10\%$, 20%,30%, and 40%, and they win the same share from the carbon auction market. However, for $\lambda = 0\%$, the supply chains bid TEC_s and win TEC_s, like case 1.

6.2.2 The bidding prices

The bidding prices in two pricing methods under different mitigation rates are shown for two cases in Fig. 3. Two important conclusions can be drawn from this figure. First, in case 1, the strong bidders do not bid their private values or maximum bidding prices because they try to manipulate the auction's carbon price and reduce it in two pricing methods. Nevertheless, in case 2, when $\lambda = 10\%$, 20%, 30%, and 40%, the bidding prices are the same and equal to

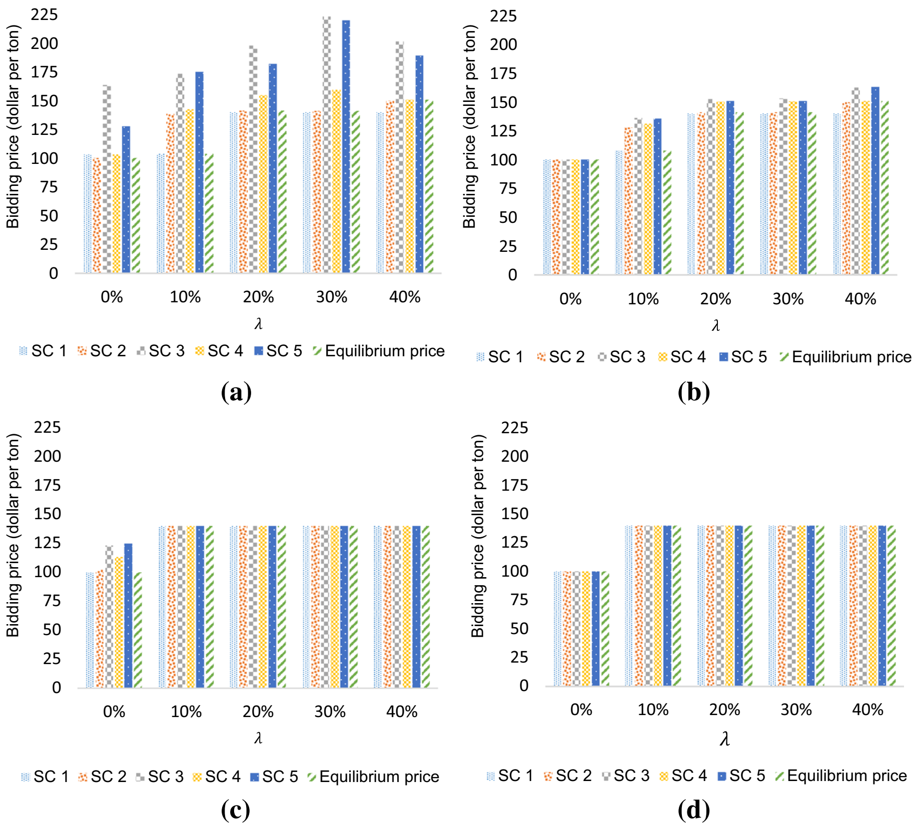

Fig. 3 The bidding prices of the supply chains (SC) under different policies (a) uniform pricing-case 1, (b) discriminatory pricing-case 1, (c) uniform pricing-case 2, and (d) discriminatory pricing-case 2

the price cap $\overline{BP}$ for two methods. As previously concluded, supply chains bid volume cap in this case (see Table 8 and Table 9). Therefore, when there are no strong supply chains, increasing the mitigation rate intensifies competition. With the decrease in the mitigation rate, the competition decreases. They can reduce the carbon allowance prices in the carbon auction so that when $\lambda = 0\%$, the equilibrium price falls to 100, i.e., the reserve price under two methods for two cases. Second, generally, the uniform method's bidding prices are higher than those in the discriminatory pricing, and they have higher dispersion. This fact is because, in discriminatory pricing, bidders pay their bidding prices; therefore, they try to predict the equilibrium price and bid close to it. Nevertheless, in the other method, every winner pays the equilibrium price; therefore, forecasting the equilibrium is less critical (Cramton and Kerr, 2002).

6.2.3 The carbon price in the carbon auction and carbon trading market

Figure 4 illustrates that for $\lambda = 10\%$ to 40%, the average paid prices in the discriminatory pricing are larger than the ones in the uniform pricing for case 1 because, in the former, the supply chains pay their bidding prices while in the latter method, they pay the equilibrium price. However, in case 2, they pay the same price, i.e., $\overline{BP}$ in two pricing methods and win the same share of the auction market (see Table 8 and Table 9). Because for these values of λ the carbon trading price are greater than $\overline{BP}$, therefore supply chains bid and pay the price cap to gain the maximum market share.

With the increase in mitigation rate, the carbon trading price rises too. For example, when λ is 40%, in case 1, strong supply chains try to buy a significant fraction of carbon allowances to make scarcity in the carbon market (see Table 6 and Table 7). Strong supply chains then sell them at a high price to losers, weak supply chains in the carbon trading market. Therefore with the decrease in carbon supply, the carbon prices increase in the carbon auction market. For high carbon allowance supply quantity, for example, when λ is 0%, the carbon trading price is zero. Therefore, supply chains should bid as much as they require. Otherwise, they have to sell their surplus allowances at zero price in the carbon trading market in two cases.

Fig. 4 The average price paid by supply chains and carbon trading price (CTP) under different policies for two cases

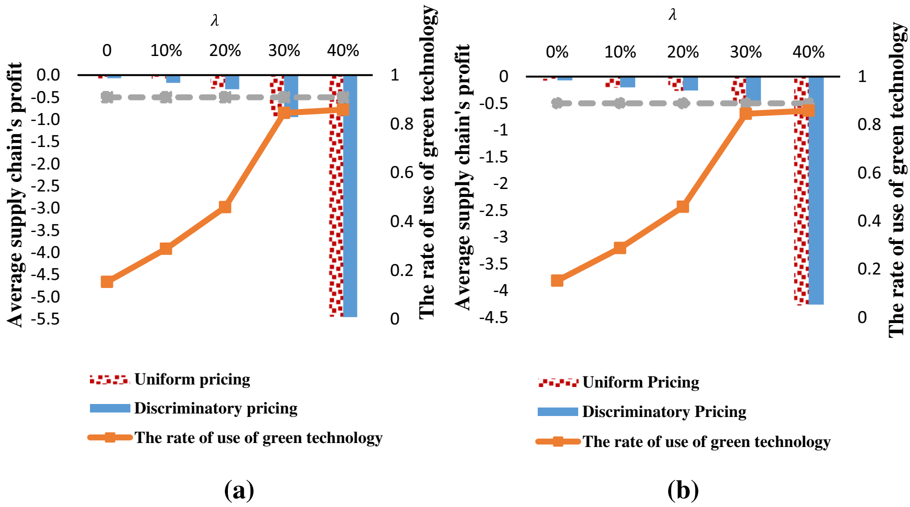

Fig. 5 The average profit of supply chains under different policies relative to the case without the policy in (a) case 1 and (b) case 2

6.2.4 The supply chains' profit

In this section, the average profits of the supply chains (ave_profpw_{policy}) are compared in the presence and absence of auction policies under the uniform and discriminatory pricing for the two cases. These values are calculated using the following equations:

$$profpw_{spolicy} = \frac{profp_{spolicy} - profw_s}{profw_s} \quad \forall s, policy \tag{11}$$

$$ave\_profw_{policy} = \frac{\sum_s profpw_{spolicy}}{S} \quad \forall policy \tag{12}$$

$profp_{spolicy}$ and $profw_s$ represent the profit of supply chain s for each policy and the profit of supply chain s without policies, respectively. Figure 5 shows that the carbon allowances auction hurts the average profit of supply chains for all policies in two cases. In case 1, the reduction in the average profit of supply chains in the uniform pricing is almost less than the discriminatory pricing because, in the former method, supply chains pay less for a unit of carbon allowances while they are equal in case 2 because the supply chains pay the same price in two pricing methods (see Fig. 4). With the increase in the mitigation rate, although the carbon emission decreases, the costs of supply chains increase sharply. For example, For $\lambda = 40\%$, the emission is reduced by 40%, but the average profit of supply chains is reduced by 543% in case 1 and 426% in case 2. This is because, firstly, by increasing the mitigation rate, as shown in Fig. 5, the use of green technology increases. Secondly, as the mitigation rate increases, the price of carbon in the carbon trading market increases. Suppose the government wants to support supply chains and not allow their average profit to reduce more than half, and the most considerable reduction in emissions occurs. In that case, the mitigation rate must be 20% in case 1 and 30% in case 2.

To examine the policy with $\lambda = 40\%$ in detail, the supply chains' profits are compared in two cases. Figure 6a illustrates that profits for strong bidders (supply chains 3, 4, and 5) are positive and negative for weak bidders (supply chains 1 and 2). Strong bidders can buy

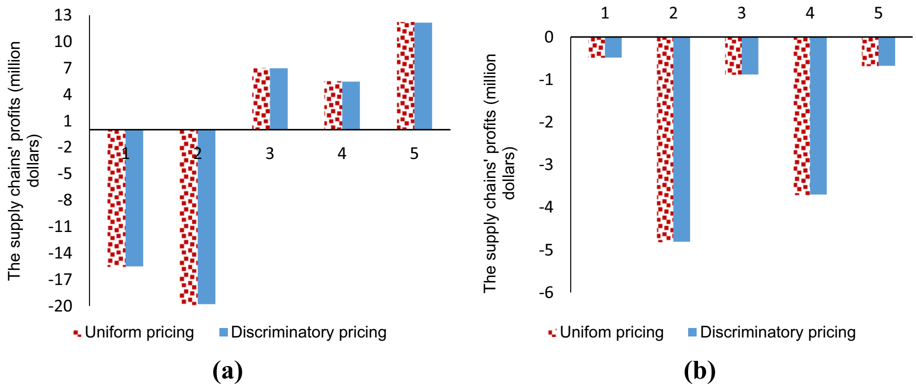

Fig. 6 The supply chains' profits for λ = 40% for (a) case 1 and (b) case 2

a large share of allowances, make scarcity in the carbon market, and then sell their surplus allowances at a high price in the carbon trading market (see Sect. 6.2.3). Nevertheless, small bidders lose the carbon auction and have to buy their required allowances at a high price in the carbon trading market. However, as shown in Fig. 6b, the profits of all supply chains are negative, unlike case 1. This is because there are no strong supply chains; therefore, all supply chains are hurt by this policy.

7 Conclusions and future research

In this paper, we studied the uniform and discriminatory pricing in the carbon allowance auction in two cases. In case 1, there are no limitations on bidding price and volume while in case 2 the government set limitations on bidding price and volume. When there are no limitations on price and volume, the carbon allowance will be more valuable for some supply chains; therefore, some supply chains will be strong in the market, and others will be weak. Whereas, if there are limitations on price and volume, supply chains have the same condition in the market. We simulated the carbon auction market, including the government and supply chains, utilizing multi-agent-based modeling. The government allocates the initial carbon allowances via auction, and the supply chains as participants in the auction determine their bidding so that their profits are maximized. They can trade their allowances with each other in the carbon trading market. The Q-learning algorithm, the bisection, and CPLEX solver were used to analyze and develop bidding strategies, determine the equilibrium price in the carbon trading market, and optimal supply chain's decision, respectively.

The simulation results demonstrated that supply chains' behavior in two cases depends on mitigation rate and type of pricing method. When the mitigation rate is high or initial carbon allowances are low, the supply chains attempt to gain more market share. In case 1, strong supply chains obtain the carbon allowance more than other supply chains. They try to reduce the auction's carbon price; therefore, they bid less than their private value. However, in case 2, because there are no strong supply chains, they bid the price cap and gain the same market shares. Otherwise, if all the carbon allowances required by the supply chains are auctioned off, the supply chain bid the lowest possible price, i.e., the reserve price.

In general, the supply chains in the uniform pricing method pay less than or equal to the discriminatory pricing in two cases. The carbon auction lessens supply chains' profits, and the higher the mitigation rate, the greater the negative effect. Between the two pricing methods, uniform pricing has a less negative impact than the other in case 1. In case 2, both pricing methods have the same impact on the supply chain's profit. But on average, supply chain's profits are reduced less in the presence of limitations. Therefore, if the government is looking for a method that has the maximum profit for the supply chains, uniform pricing is more appropriate in case 1, but in case 2, two pricing methods are the same in this respect. Furthermore, the government should determine a reasonable mitigation rate so that the supply chains' profits are not harmed, and at the same time emissions are decreased. If the mitigation rate is very high, emissions will be significantly reduced, but strong bidders will take advantage of this situation and make much profits in case 1. On the other hand, weak bidders' profits will be seriously reduced. Therefore, the government should balance economic and environmental goals by selecting an appropriate mitigation rate.

In this paper, we focused on uniform and discriminatory pricing methods for analyzing the carbon auction market. For a future research, the performance of supply chains can be investigated under the other carbon auction methods. Furthermore, the government can consider green subsidy for using green technologies to aid supply chains.

Appendices

Appendix A

The following indices are applied for each supply chain's mathematical modeling:

Supply chain index	$s = \{1, 2, \ldots, S\}$
Product index	$i = \{1, 2, \ldots, I\}$
Machine index	$j = \{1, 2, \ldots, J\}$
Manufacturing center index	$m = \{1, 2, \ldots, M\}$
Warehouse index	$w = \{1, 2, \ldots, W\}$
Customer zone index	$c = \{1, 2, \ldots, C\}$
Transportation mode index	$v = \{1, 2, \ldots, V\}$
Period index	$t = \{1, 2, \ldots, T\}$

The input parameters include the followings:

de_{sict}	Forecasted demand for product i in customer zone c in period t in supply chain s
Fc_{sm}	Fixed costs for manufacturing center m to operate in each period in supply chain s
Fc'_{sw}	Fixed costs for warehouse w to operate in each period in supply chain s
Uc_{sim}	Unit holding cost per period for product i in manufacturing center m in supply chain s
Uc'_{siw}	Unit holding cost per period for product i in warehouse w in supply chain s
Hc_{sm}	Holding capacity in manufacturing center m in each period in supply chain s
Hc'_{sw}	Holding capacity in warehouse w in each period in supply chain s

Vo_i	The volume of product i
P_{sij}	Processing time (hours) to produce a unit of product i on machine j in supply chain s
L_{sij}	Labor/hour cost to produce a unit of product i on machine j in supply chain s
Cm_{si}	Cost of raw material for producing a unit of product i in supply chain s
Oc_{sim}	Variable overhead cost for producing a unit of product i in manufacturing center m in supply chain s
Cp_{sjm}	Capacity hours for the production in manufacturing center m on machine j in each period in supply chain s
Cr_{sim}	Capacity units of raw material supply for product i in manufacturing center m in each period in supply chain s
tc_{simwv}	Unit transportation cost of product i from manufacturing center m to warehouse w through mode v in supply chain s
tc'_{siwcv}	Unit transportation cost of product i from warehouse w to customer zone c through mode v in supply chain s
$t1^{max}_{smwv}$	Maximum transportation capacity from manufacturing center m to warehouse w through mode v in each period in supply chain s
$t2^{max}_{swcv}$	Maximum transportation capacity from warehouse w to customer zone c through mode v in each period in supply chain s
$I1_{sim}$	Inventory level of product i in manufacturing center m at the start of the planning horizon
$I'1_{sim}$	Inventory level of product i in manufacturing center m at the end of the planning horizon
$I2_{siw}$	Inventory level of product i in warehouse w at the start of the planning horizon
$I'2_{siw}$	Inventory level of product i in warehouse w at the end of the planning horizon
ep_{sij}	Estimated carbon emissions to produce a unit of product i on machine j in any period per unit time in supply chain s
et_{simwv}	Estimated carbon emissions for the shipment a unit of product i from manufacturing center m to warehouse w through mode v in supply chain s
et'_{siwcv}	Estimated carbon emissions for the shipment a unit of product i from warehouse w to customer zone c through mode v in supply chain s
eh_{sim}	Estimated carbon emissions for holding a unit of product i in manufacturing center m in each period in supply chain s
eh'_{siw}	Estimated carbon emissions for holding a unit of product i in warehouse w in each period in supply chain s
G	A large number

The decision variables include the followings:

Qp_{sijmt}	Quantity of product i produced in manufacturing center m on machine j at period t in supply chain s
X_{simwvt}	Quantity of product i shipped from manufacturing center m to warehouse w through mode v at period t in supply chain s
X'_{siwcvt}	Quantity of product i shipped from warehouse w to customer zone c through mode v at period t in supply chain s
Y_{simt}	Inventory amount of product i in manufacturing center m at the end of period t in the supply chain s

Y'_{siwt}	Inventory amount of product i in warehouse w at the end of period t in the supply chain s
$F_{smt} = \begin{cases} 1, \\ 0, \end{cases}$	If the manufacturing center m operates in period t in the supply chain s Otherwise
$F'_{swt} = \begin{cases} 1, \\ 0, \end{cases}$	If warehouse w operates in period t in the supply chain s Otherwise
$Cost\_EC_s$	Total costs of supply chain s in the cap-and-trade system
EC_s	Total carbon emission produced in supply chain s
Cap_s	Carbon allocated to supply chain s in the auction
TEP	Total carbon emission produced in all supply chains
ψ	Carbon trading price

According to these parameters and variables, each supply chain's objective function is formulated using mixed-integer linear programming based on a given carbon trading price. Each supply chain aims to minimize its objective function (Eq. 13). It includes fixed costs for operating and opening manufacturing centers, and warehouses, production cost, inventory holding costs in manufacturing centers and warehouses, transportation costs for the shipment of products from manufacturing centers to warehouses and warehouses to customer zones, and the revenue (cost) of selling (buying) carbon allowances, respectively:

$$\begin{aligned} Cost\_EC_s = Min \sum_m \sum_t Fc_{sm} F_{smt} + \sum_w \sum_t Fc'_{sw} F'_{swt} \\ + \sum_i \sum_j \sum_m \sum_t Qp_{sijmt}(P_{sij} L_{sij} + Cm_{si} + Oc_{sim}) + \sum_i \sum_m \sum_t Uc_{sim} Y_{simt} \\ + \sum_i \sum_w \sum_t Uc'_{siw} Y'_{siwt} + \sum_i \sum_m \sum_w \sum_v \sum_t tc_{simwv} X_{simwvt} \\ + \sum_i \sum_w \sum_c \sum_v \sum_t tc'_{siwcv} X'_{siwcvt} + \psi(EC_s - Cap_s) \end{aligned} \tag{13}$$

The carbon emission generated by each supply chain s is calculated according to Eq. (14). It includes carbon emissions generated in manufacturing centers, shipment of products from manufacturing centers to warehouses and warehouses to customer zones, and inventory holding in manufacturing centers and warehouses.

$$\begin{aligned} EC_s = \sum_i \sum_j \sum_m \sum_t P_{sij} ep_{sij} Qp_{sijmt} + \sum_i \sum_m \sum_w \sum_v \sum_t et_{simwvt} X_{simwvt} \\ + \sum_i \sum_w \sum_c \sum_v \sum_t et'_{siwcvt} X'_{siwcvt} \\ + \sum_i \sum_m \sum_t eh_{sim} Y_{simt} + \sum_i \sum_w \sum_t eh'_{siw} Y'_{siwt} \end{aligned} \tag{14}$$

The objective function in Eq. (13) is subject to the following constraints:

Limitation on raw material supply:

$$\sum_j Qp_{sijmt} \leq Cr_{sim} \quad \forall s, i, m, t \tag{15}$$

Restriction on the total available working hours for each machine:

$$\sum_i Qp_{sijmt} P_{sij} \le Cp_{sjm} \quad \forall s, j, m, t \tag{16}$$

Storage capacity restriction in manufacturing centers and warehouses:

$$\sum_i Vo_i Y_{simt} \le Hc_{sm} \quad \forall s, m, t \tag{17}$$

$$\sum_i Vo_i Y'_{siwt} \le Hc'_{sw} \quad \forall s, w, t \tag{18}$$

Limitations on transportation capacity for shipment of products from the manufacturing centers to the warehouses and the warehouses to the customer zones:

$$\sum_i (Vo_i X_{simwvt}) \le t_1 {}^{max}_{smwv} \quad \forall s, m, w, v, t \tag{19}$$

$$\sum_i (Vo_i X'_{siwcvt}) \le t_2 {}^{max}_{swcv} \quad \forall s, w, c, v, t \tag{20}$$

The inventory balance in manufacturing centers, warehouses, and customer zones:

$$Y_{simt} - Y_{sim(t-1)} = \sum_j Qp_{sijmt} - \sum_w \sum_v X_{simwvt} \quad \forall s, i, m, t \tag{21}$$

$$Y'_{siwt} - Y'_{siw(t-1)} = \sum_m \sum_v X_{simwvt} - \sum_c \sum_v X'_{siwcvt} \quad \forall s, i, w, t \tag{22}$$

$$\sum_j \sum_m \sum_t Qp_{sijmt} = \sum_c \sum_t de_{sict} + \sum_m I'_{1_{sim}} - \sum_m I_{1_{sim}} + \sum_w I'_{2_{siw}} - \sum_w I_{2_{siw}} \quad \forall i, s \tag{23}$$

Restriction on satisfying demand:

$$\sum_w \sum_v X'_{siwcvt} = de_{sict} \quad \forall s, i, c, t \tag{24}$$

Inventory levels at the start and end of the planning horizon in manufacturing centers and warehouses:

$$Y_{sim0} = I_{1_{sim}} \& Y_{simT} = I'_{1_{sim}} \quad \forall s, i, m \tag{25}$$

$$Y'_{siw0} = I_{2_{siw}} \& Y_{siwT} = I'_{2_{siw}} \quad \forall s, i, w \tag{26}$$

Limitation on decision variables:

$$0 \le Qp_{sijmt} \le GF_{smt} \quad \forall s, i, m, t \tag{27}$$

$$0 \le X_{simwvt} \le GF_{smt} \& 0 \le X_{simwvt} \le GF'_{swt} \quad \forall s, i, m, w, v, t \tag{28}$$

$$0 \le X'_{siwcvt} \le GF'_{swt} \quad \forall s, i, w, c, v, t \tag{29}$$

$$0 \le Y_{simt} \quad \forall s, i, m, t \tag{30}$$

$$0 \le Y'_{siwt} \quad \forall s, i, w, t \tag{31}$$

Appendix B

The centers of each supply chain are dispersed randomly in a square area with a size of 10×10 units of distance. Euclidean distance is considered between the two centers. The distance between manufacturing center m and warehouse w and between warehouse w and customer zone c are represented by dis_{mw} and dis_{wc}, respectively. These distances are used for the following parameters that their values are dependent on distance. They are calculated according to the following formulas (the brackets indicate the generation of a random number from a uniform distribution in the interval):

$$tc_{simwv} = Vo_i[2,4] * dis_{mw} * ts_v \tag{32}$$

$$tc'_{siwcv} = Vo_i[2,4] * dis_{wc} * ts_v \tag{33}$$

$$et_{simwv} = Vo_i[2,4] * dis_{mw} * cts_v \tag{34}$$

$$et'_{siwcv} = Vo_i[2,4] * dis_{wc} * cts_v \tag{35}$$

The parameters ts_v and cts_v indicate the cost and carbon emissions for shipping a unit of product in a distance unit through mode v, respectively. These two parameters are generated according to Table 10:

The inventory level for all products at the start and the end of the planning horizon in the manufacturing centers and warehouses are zero. The parameters regarding the manufacturing machine are calculated based on Table 11. The others are generated according to the details given in Table 12.

Table 10 Specifications of transportation mode-dependent parameters

The parameter	Mode	Value
ts_v	1	$[1, 2]$
	2	$[2, 3]$
cts_v	1	$[16 * 10^{-3}, 20 * 10^{-3}]$
	2	$[12 * 10^{-3}, 16 * 10^{-3}]$

Table 11 Specifications of the machine-dependent parameters

The parameter	The type of machine	Value
L_{sij}	1	$[15, 20]$
	2	$1.1 * [15, 20]$
ep_{sij}	1	$1.25 * [40, 45] * 10^{-3}$
	2	$[40, 45] * 10^{-3}$

Table 12 Specifications of the generated examples

Parameters	Value
de_{sict}	[30,200]
Fc_{sm}	[40000, 60000]
Fc'_{sw}	[30000, 40000]
Uc_{sim}	$u[15, 40]$
Uc'_{siw}	$u[30, 70]$
Hc_{sm}	$\left(\frac{\sum_i \sum_c \sum_t de_{sict}}{T}\right) * \max\{Vo_i\}$
Hc'_{sw}	$\left(\frac{\sum_i \sum_c \sum_t de_{sict}}{T}\right) * \max\{Vo_i\}$
P_{sij}	$u[0.5, 2]$
cm_{si}	$u[55, 85]$
Oc_{sim}	$u[15, 30]$
Cp_{sjm}	$(max\{P_{sij}\} * \sum_i \sum_c \sum_t de_{sict})/M$
Cr_{sim}	$(\sum_j (Cp_{sjm}/\sum_i P_{sij}))/I$
$t1^{max}_{smwv}$	$u[300, 600]$
$t2^{max}_{swcv}$	$u[300, 600]$
eh_{sim}	$u[3, 4] * 10^{-3}$
eh'_{siw}	$u[2, 4] * 10^{-3}$

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