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Modeling the emission trading scheme from an agent-based perspective: System dynamics emerging from firms' coordination among abatement options

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ABSTRACT

Though sharing a similar practice form, the emission trading scheme is distinguished from traditional financial markets: firms coordinate three abatement options at the micro level, including allowance trading, output adjustment, and low-carbon technology adoption. Then, at the macro level, this leads to dynamic interactions among allowance market, output market, and low-carbon technology diffusion. This is the fundamental characteristic of the emission trading scheme, and modeling the dynamics behind is a major difficulty for relevant studies, especially when following complexities are considered: (1) different planning horizons of the three abatement options, (2) heterogeneity among sectors and firms, and (3) details of firms' production and optional low-carbon technologies. Aiming at this difficulty, we establish an agent-based model for the emission trading scheme, and within a novel multi-level time frame, the fundamental characteristic is reflected and the complexities are considered. Firms' production and low-carbon technologies are discretely modeled at a process level from a bottom-up perspective, and based on European data, our model is calibrated to cover 5 industrial sectors, 11 emission-intensive products, 25 production processes, and 52 low-carbon technologies. With this model, the emergence properties and uncertainty of the system are captured, and the non-linear impact of the abatement target is reflected and discussed. We find that, after a certain level, higher target leads to lower allowance price uncertainty but stronger output impact, which is a trade-off for setting the abatement target.

1. Introduction

Against the background of global climate change, the emission trading scheme (ETS) is regarded as a key policy instrument for controlling greenhouse gas (GHG) emission and promoting the diffusion of low-carbon technologies, due to its cost-effectiveness, comprehensiveness, and flexibility (Newell, Pizer, & Raimi, 2014). Using this mechanism, the government sets a target level of emissions over a specified abatement phase, and allocates the right to emit – that is, allowances – among covered firms. Then, the firms trade with one another based on their allowance holding and abatement cost. The primary intention of the ETS is to form price signals through allowance trading, to guide firms' emission abatement behaviors, especially to promote their adoption of low-carbon technologies, and ultimately to achieve an abatement target at lowest cost within the entire society.

Though sharing a similar practice form, the ETS is fundamentally different from traditional financial markets, because apart from trading allowance with one another, firms can also adjust their output or adopt low-carbon technologies for carbon dioxide (CO_2) abatement, and these two decisions directly influence the demand and supply in the allowance market. Then, at the macro level, firms' coordination among the three options emerge into dynamic interactions among the allowance market, output markets, and low-carbon technology diffusion.

This is the fundamental characteristic of the ETS, and has been reflected in literature, but the modeling of the emerging process from micro to macro level, and heterogeneity among sectors and firms, are still remaining difficulties. Specifically, complexity is further added due to the fact that the three abatement options correspond to different planning horizons, short-term for allowance

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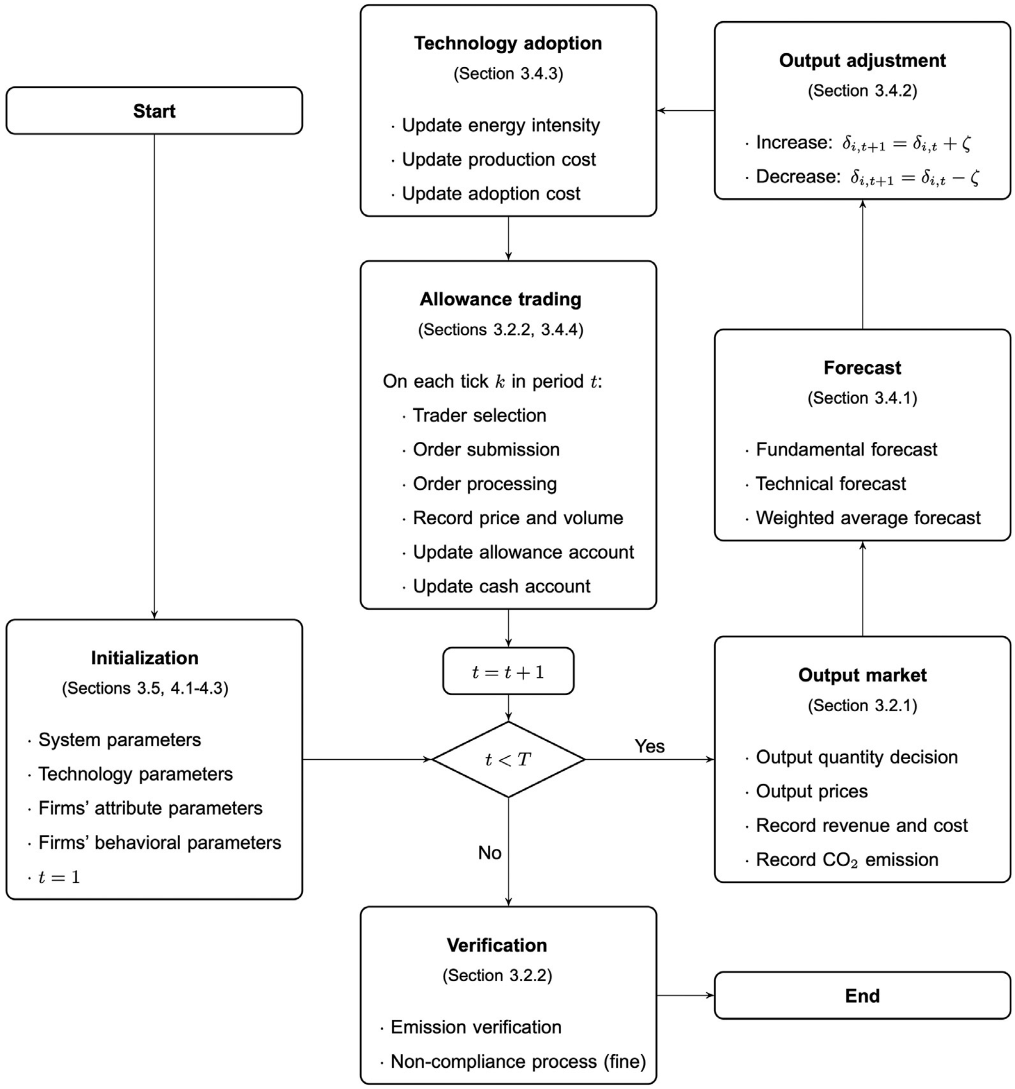


Fig. 1. Flowchart of the model.

trading, short- to medium-term for output adjustment, and long-term for low-carbon technology adoption, respectively. Aiming at this, we establish the AMETS (Agent-based Model for Emission Trading Scheme) model.

- Firstly, in order to reflect the different planning horizons of firms' three abatement options, AMETS is established within a novel multi-level time frame, ranging from "second" to "year", which helps capturing the emergence properties and uncertainty of the system. The time frame of the AMETS is as shown in Figs. 1 and 2.
- Secondly, firms' heterogeneity with respect to multiple aspects are considered in AMETS: (1) scale and productivity, which has been elaborated in empirical studies (Cabral & Mata, 2003; Eaton, Kortum, & Kramarz, 2011); (2) abatement cost and potential of low-carbon technologies, which fundamentally influences the cost efficiency and liquidity of the ETS; (3) risk preference in long-term investment and decision-making behaviors. Consideration of firms' heterogeneity helps us answering two questions: (1) how does the existence of firms' heterogeneity influence the ETS? (2) What are the heterogeneous impacts of the ETS on heterogeneous firms?
- Thirdly, to detailedly model and calibrate firms' marginal abatement cost curve (MACC), production is modeled at a process level in AMETS, following the FORECAST model[1] (Fleiter et al., 2018). Low-carbon technologies are assigned to each process, and discretely modeled from a bottom-up perspective, as parameters of cost and saving effect of multiple energy carriers. This helps enhancing the calibration of the model, trackability of technology diffusion, and identification of key low-carbon technologies under different scenarios.

This paper is structured as follows. In Section 2, we review current equilibrium- and agent-based models for the ETS, and summarize their limitations and deficiencies. Next, AMETS is introduced in detail in Section 3. Section 4 deals with the calibration and setting for simulation. Then, the results are provided and discussed in Section 5. Finally, we conclude in Section 6.

[1] FORECAST is developed by Fraunhofer Institute for System and Innovation Research. It is based on a bottom-up modeling approach, and aims to develop long-term scenarios for future energy demand of individual countries and world regions until 2050. The FORECAST model includes a broad range of mitigation options combined with a high level of technological detail.

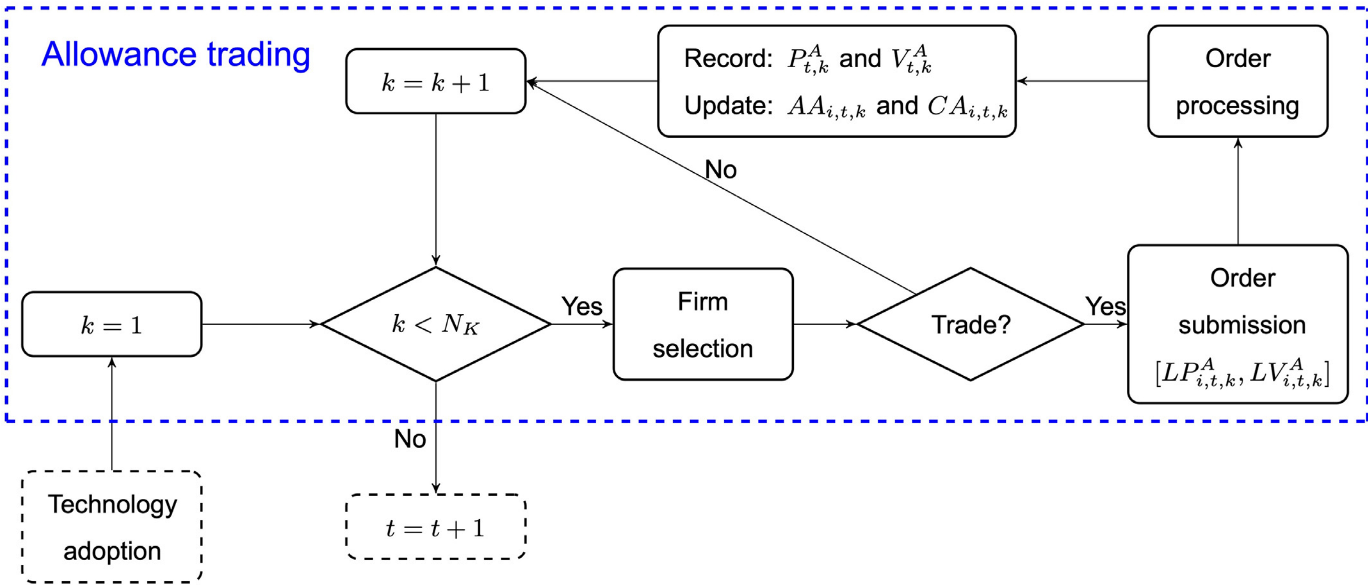


Fig. 2. Time frame of the allowance trading process.

2. Literature review

2.1. Equilibrium-based models for the ETS

Corresponding to the fundamental characteristic of the ETS, the first strand of literature establishes partial equilibrium models from the perspective of a representative firm or sector (Anouliès, 2017; Demailly & Quirion, 2006; 2008; Downing & White, 1986), to analyze firms' incentive for low-carbon technology adoption, and impact of the ETS on firms' competitiveness. Then, in order to analyze macro impact of the ETS, or its interaction with the fiscal system, another strand of literature establishes general equilibrium models for the ETS (Fischer & Fox, 2007; Goulder, 2013; Goulder, Hafstead, & Dworsky, 2010; Wu, Fan, Xia et al., 2016). Both of these two strands are equilibrium-based models, which usually presume a series of simplifying assumptions, including the representative agent, market equilibrium condition, perfect rationality, and complete information.

However, with these assumptions, the analysis of the ETS is constrained in three aspects. Firstly, given the different planning horizons of firms' abatement options, the assumption of market equilibrium weakens the capture of emergence properties and uncertainty of the system, especially when firms' bounded rationality and incomplete information are taken into consideration. Secondly, the assumption of representative firm or sector limits the model to consider the heterogeneity among firms, and further limits the analysis of intra-industry impact of the ETS. Thirdly, in most equilibrium-based models, the optional low-carbon technologies of a firm are modeled as a continuous MACC (Baker, Clarke, & Shittu, 2008; Bauman, Lee, & Seeley, 2008), which is a function of the CO_2 abatement rate or quantity. However, this continuous depiction ignores the impact of technologies on firms' productivity (production cost or energy intensity), and it also limits the full use of technology data for calibration, and the trackability of technology diffusion.

2.2. Agent-based models for the ETS

In order to supplement equilibrium-based models, scholars have also proposed agent-based models for the ETS. Agent-based models are regarded as important tools for the modeling and analysis of complex systems for its four distinct perspectives: agents' interaction, heterogeneity, bounded rationality (including incomplete information), and learning. For social economic complex systems, ABMs characterize them as dynamic interactions among agents from a bottom-up perspective (Tesfatsion, 2006), and they are applied in the fields of financial markets (Mandes & Winker, 2017), macro economy (Dawid, Gemkow, Harting, & Sander, 2013), transportation system (Bazzan & Klügl, 2014; Zhao & Ma, 2016), supply network (Nair & Vidal, 2011), electricity market (Ringler, Keles, & Fichtner, 2016), technology innovation and diffusion (Kiesling, Günther, Stummer, & Wakolbinger, 2012; Ma & Nakamori, 2005), marketing (Negahban & Smith, 2017). From the four distinct perspectives, ABMs provide supplementary insights for the dynamics of these systems.

The ABMs for the ETS mainly fall into two categories depending on the scale of the simulated market. The first are ABMs for an international ETS, in which the agents represent countries or regions (Mizuta, Kato, & Tai, 2008; Mutlu & Fescioglu-Unver, 2011; Zhu, Duan, Wu, & Wang, 2016). The second are ABMs for a regional ETS, in which the agents represent firms. Within a bottom-up agent-based framework, these models provide new insights for the analysis of the ETS. However, regarding to this second group, into which the AMETS falls, three aspects of current models can be improved:

- First is the modeling of the fundamental characteristic of the ETS.
  Concerning firms' three abatement options, some models ignore the output adjustment option (Bakam & Matthews, 2009; Huang & Ma, 2016; Zhang, Zhang, & Bi, 2011; Zhang, Cao, & Zhang, 2016) or the low-carbon technology adoption option (Tang, Wu, Yu, & Bao, 2017; Wang, Koritarov, & Kim, 2009), or both of them (Posada, Hernández, & López-Paredes, 2005). In Tang, Wu, Yu, and Bao (2015), the authors modeled all firms' three options, but the output adjustment decision is not related to firms' abatement consideration.
  Besides, in some studies, the different planning horizons of firms' abatement options are ignored (Bakam & Matthews, 2009; Huang & Ma, 2016; Tang et al., 2015; 2017; Zhang et al., 2016), which weakens the capture of emergence properties and uncertainty of the system, as well as the

Table 1
Design of AMETS at a module level.

Perspective	Introduction
(A) Agents interaction	
· Output market	These markets are organized based on the clearing price mechanism (Palmer, Arthur, Holland, LeBaron, & Tayler, 1994).
· Allowance market	This market is organized based on the continuous double auction mechanism (Chiarella et al., 2002).
(B) Heterogeneity	
· Attributes	Firms are heterogeneous with respect to 7 attributes (Chen, Chang, & Du, 2012), as shown in Table 2.
· Behaviors	Firms make decisions following the same set of behavioral functions, but with heterogeneous behavioral parameters. Based on an endogenous mechanism, firms learn and discover new strategies on their own.
(C) Bounded rationality	Following the "Observe - Forecast - Decision" mode (Arthur, Holland, Lebaron, Palmer, & Tayler, 1997; Beltratti, Margarita, & Terna, 1996; LeBaron, 2001), firms first observe the environment and form their forecast of allowance price based on incomplete information, then follow a set of "fast and frugal heuristics" (Gigerenzer, 2004) and make decisions for three abatement options.
(D) Learning	At the beginning, each firm is randomly initialized with a strategy pool, which contains N_S strategies. During the learning stage, firms try the strategies one by one, and individually update their strategy pools based on the Multiple-population Genetic Algorithm (Chen & Yeh, 2001).

interactions among allowance market, output market, and low-carbon technology diffusion.

- Second is the modeling of firms' trading behavior and the price formation mechanism.
  In the ETS system, firms' trading behaviors are influenced by multiple factors, which endogenously vary along with their decisions, including allowance holding, abatement cost, forecast of allowance price, and current allowance price. However, they are not reflected in the studies reviewed above. Some models characterize firms' allowance trading decisions in an exogenous way, which is based on an exogeneously set and fixed roles of buyers and sellers (Bakam & Matthews, 2009; Huang & Ma, 2016), or reservation price and marginal abatement cost (Posada et al., 2005).
  Concerning the price formation mechanism in the allowance market, the choice of market maker mechanism (Tang et al., 2015; 2017), clearing price mechanism (Bakam & Matthews, 2009; Wang et al., 2009; Zhang et al., 2016), or the floor trading mechanism (Huang & Ma, 2016) deviate from the reality of the ETSs, in which trading is organized based on the continuous double auction mechanism. This also weakens the capture of emergence properties and uncertainty of the system.
- Third is the modeling of the low-carbon technologies.
  For the modeling of low-carbon technologies, some studies ignore it (Posada et al., 2005; Tang et al., 2017; Wang et al., 2009), and some model them as a function of abatement ratio (Zhang et al., 2016), or a parameter of cost (Huang & Ma, 2016; Tang et al., 2015; Zhang et al., 2011). In these models, it is difficult to take fully advantage of the data for calibration, or trace the diffusion of technologies.

To improve the deficiencies among previous equilibrium- and agent-based models, AMETS is established within a multi-level time frame. Firms' coordination among the three abatement options with different planning horizons at the micro level is modeled, from which there emerges the system dynamics at the macro level. As a result, the emergence properties and uncertainly of the system are captured, the heterogeneous and non-linear impact of the ETS are reflected, and the diffusion of low-carbon technologies is presented at a higher resolution.

3. Model

Following the four distinct perspectives of ABMs, the design of AMETS is broken into modules and briefly introduced in Table 1, and detailed introductions for each module are provided in this section.

3.1. Model frame

AMETS simulates an abatement phase of the ETS that lasts for T periods in which each period is denoted by t. For understanding and calibration simplicity, we assume that corresponding to the real world, the abatement phase is as long as one "year", and each period represents one "day". The system covers multiple sectors and products. Firms selling different products compete with others in different output markets, while all the firms trade allowances in a common allowance market. With the abatement pressure, firms maximize their total profit by coordinating three abatement options: output adjustment, low-carbon technology adoption, and allowance trading. For clarification, AMETS is introduced from the perspective of a representative "firm i" in this section, so the subscripts for its sector and product are omitted.

Compared with the existing ABMs for the ETS, we introduce a multi-level time frame in AMETS, to reflect the different planning horizons of the three abatement options. As Fig. 1 shows, AMETS runs as follows.

1. AMETS starts by exogenously initializing four groups of parameters, including system parameters, technology parameters, firms' attribute parameters, and firms' behavioral parameters. The calibration and setting of the first three aspects are introduced in Sections 4.1–4.3, and firms' behavioral parameters are initialized based on a learning stage, which is introduced in Section 3.5.
2. At the beginning of period t, each firm competes with others in the output market by choosing an output quantity. The equilibrium prices in the output markets are calculated, and firms' output, revenue, production cost, and emission are recorded, as introduced in Section 3.2.1.
3. In order to coordinate the three options, firms first form their forecasts of the allowance price based on incomplete information. This process is introduced in Section 3.4.1.
4. Based on the forecasts and several relevant factors, in each period t, firm i makes its output adjustment decision, represented by an increase or decrease of its output coefficient ($\delta_{i,t}$). This is introduced in Section 3.4.2.
5. Then, firms make their low-carbon technology adoption decisions. In each period t, firm i considers whether to adopt its current cheapest low-carbon technology. Influences of several factors are synthesized by a probabilistic behavioral function, including the average abatement cost and absolute abatement potential of the technology, firm i's forecast of allowance price, and its expected net allowance at hand. This is introduced in Section 3.4.3.
6. In accordance with reality, we introduce the continuous double auction mechanism to organize firms' trading in the allowance market. Each period in the abatement phase is

further divided into N_K ticks. On each tick, a firm is randomly selected to make a trading decision. After the matching process, firms' allowance and cash accounts are updated. This process is introduced in Section 3.2.2, and firms' decision-making process is introduced in Section 3.4.4.

7. By the end of the abatement phase, firms' total emissions are verified, and those who emit more than their holdings must pay a fine for its excess emissions.

3.2. Agents interaction: output and allowance markets

Concerning the interaction among firms, they compete with others in different output markets, which are organized based on the clearing price mechanism, and they also compete in a common allowance market, which is organized based on the continuous double auction mechanism.

3.2.1. Output market

At the beginning of each period t, in the output market, each firm i competes with others by choosing an output quantity ($q_{i,t}$), which is modeled as the product of a benchmark output quantity ($q_{i,L}$, average daily output of firm i in the last year) and an output coefficient ($\delta_{i,t}$), as calculated by using Eq. (3.1). Then, the price of the product (PO_t) is calculated by using Eq. (3.2) based on a constant elasticity daily demand. Q_t is firms' total production. M is a parameter of the demand function, and ε is the elasticity of market demand.

$$q_{i,t} = q_{i,L} \cdot \delta_{i,t} = \frac{Q_{i,L}}{T} \cdot \delta_{i,t} \tag{3.1}$$

$$Q_t = M \cdot {PO_t}^{-\varepsilon} \tag{3.2}$$

The unit output cost of each firm i ($C^O_{i,t}$) is modeled as three parts. The first is non-energy cost (CNE^O_i), which is constant in the whole abatement phase. The second is operation and maintenance cost ($COM^O_{i,t}$), which comes from the adopted low-carbon technologies and varies with firm's technology adoption decisions. Following the FORECAST model (Fleiter et al., 2018), firm's production is modeled at a process level, and the third part, energy cost ($CE^O_{i,t}$), is the sum of energy consumption of all production processes. For each process p, consumption of four energy carriers are considered, including coal ($EC_{i,p,t}$), gas ($EG_{i,p,t}$), oil ($EO_{i,p,t}$), and electricity ($EE_{i,p,t}$). Firms' low-carbon technologies are assigned to each process, as shown in Table C.3 in Appendix C. When a technology is adopted, firm's energy consumption in the corresponding process is changed accordingly. As a result, firm i's unit cost of output in period t is calculated by using Eqs. (3.3) and (3.4). PC, PG, PO, and PE are prices of the four energy carriers. By the end of period t, firms' revenue, production cost, and total emissions are calculated and recorded.

$$C^O_{i,t} = CNE^O_i + COM^O_{i,t} + CE^O_{i,t} \tag{3.3}$$

$$CE^O_{i,t} = \sum\nolimits_p (PC \cdot EC_{i,p,t} + PG \cdot EG_{i,p,t} + PO \cdot EO_{i,p,t} + PE \cdot EE_{i,p,t}) \tag{3.4}$$

3.2.2. Allowance market

At the beginning of the abatement phase, the total allowance of emission (TA) is set as a share of the total emission in the last phase (TE_L) based on an abatement target (τ, $0 \le \tau \le 1$), as calculated by using Eq. (3.5). Taking the Grandfathering Allocation rule as example in this paper, the allocation for each firm i (A_i) is based on its share of total emissions in the last phase ($E_{i,L}$), as calculated by using Eq. (3.6).

$$TA = TE_L \cdot (1 - \tau) \tag{3.5}$$

$$A_i = TA \cdot \frac{E_{i,L}}{TE_L} \tag{3.6}$$

In the allowance trading process, each period is further divided into N_K ticks, corresponding to "seconds" in the real world. On each tick, several steps are modeled to follow in succession, as shown in Fig. 2, which is a zoom-in graph for the "Allowance trading" module in Fig. 1.

As Fig. 2 shows, when it goes into the "Allowance trading" process (from "Technology adoption" process), on each tick k, a firm is randomly selected to enter the market. It will decide whether to trade or not. If the firm decides to trade, it will submit an order to the market, which is a combination of price and volume ($[LP^A_{i,t,k}, LV^A_{i,t,k}]$), meaning to sell (or buy) $LV^A_{i,t,k}$ allowances at a price no lower (or higher) than $LP^A_{i,t,k}$.

With the tick going on, all the orders are processed based on the continuous double auction mechanism (Chiarella, Iori et al., 2002). Under this mechanism, the orders which have not been executed are stored in an order book. On one side, bid orders are arranged in a list from lower to higher, and highest price of the order to buy is called best bid; On the other side, ask orders are arranged in a list also from lower to higher, and lowest price of the order to sell is called best ask. Then, when a new bid order enters the order book, if its price is higher than the best ask, trade will be executed, and if its price is lower than the best ask, it will be stored in the order book. The process is similar when a new ask order enters the order book.

For each tick, the trading price ($P^A_{t,k}$) and volume ($V^A_{t,k}$) are recorded, and relevant firms' allowance ($AA_{i,t,k}$) and cash ($CA_{i,t,k}$) accounts are updated. If the selected firm decides not to trade, it will leave the market directly, and the model will run to the next tick $k+1$. When the allowance trading process in period t ends ($k = N_K$), the model will run to the next period $t+1$. At last, by the end of the whole abatement phase ($t = T$), firms' total emission will be verified. For any firm with excess emissions, it will pay a fine for each ton of over-exceeded emissions.

3.3. Heterogeneity: attributes and behaviors

As introduced in Table 1, the heterogeneity among firms in AMETS includes two aspects: firms' attributes and behaviors. Concerning the first aspect, the heterogeneity among firms can be depicted by different values of 7 attribute parameters, which are listed in Table 2. Concerning the second aspect, the parameters in firms' behavioral rules are heterogeneous, which is introduced in detail in Sections 3.4 and 3.5.

3.4. Bounded rationality: decisions coordination

As introduced above, with the abatement pressure, firms maximize their profit by coordinating three decisions, including output adjustment, low-carbon technology adoption, and allowance trading. In AMETS, firms are boundedly rational and follow a set of "fast and frugal heuristics" (Gigerenzer, 2004) in the decision-making processes as follows.

- Firstly, firm i forecasts the allowance price based on incomplete information. It serves as a "benchmark" for firm i's coordination among three abatement options. This process is introduced in Section 3.4.1.
- Secondly, firm i first calculates the "abatement costs" of three abatement options. Then, by comparing them with the benchmark and taking consideration of other influencing factors, firm i makes the three decisions. These processes are introduced in Sections 3.4.2–3.4.4.

Table 2
Attribute parameters of firms.

Variable	Explanation
$Q_{i,L}$	Total output of firm i in the last year.
NTA_i	Number of initial technology adoption of firm i at the beginning of the abatement phase.
CNE_i^O	Non-energy cost for unit production of firm i.
ER_i	Expected rate of return of firm i, representing its attitude towards risk.
TW_i	Weight for the technical information of firm i, when it forms forecast.
ML_i	Memory length firm i.
EYE_i	Number of other firms that can be observed by firm i for forecasting the allowance price.

3.4.1. Allowance price forecast based on incomplete information

In each period t, firm i alters its forecast of the allowance price based on incomplete information, which is is depicted by two aspects in AMETS.

- The first aspect is firm i's accessibility of information, which is depicted by the number of other firms it can observe when forming its forecast of the allowance price, denoted by EYE_i. By observing these firms, firm i collects the information about their output, available low-carbon technology options, holdings of allowance, etc. This information is referred to as "fundamental information", based on which firm i forms its "fundamental forecast" of the allowance price ($FFP_{i,t}^A$).
- The second aspect is that, firm i takes the public allowance price information into consideration, referred to as "technical information". Firm i calculates the moving average of the allowance price within its memory length (ML_i), and regard it as its "technical forecast" of the allowance price ($TFP_{i,t}^A$).

The formation of these two forecasts are introduced in detail in Appendix A. At last, based on $FFP_{i,t}^A$ and $TFP_{i,t}^A$, firm i will take a weighted average of these two, compare it with the fine for unit excess emission ($Fine$), and form its forecast of the allowance price ($FP_{i,t}^A$), as calculated by using Eq. (3.7). TW_i is firm i's weight for technical forecast.

$$FP_{i,t}^A = min\{(1-TW_i)\cdot FFP_{i,t}^A + TW_i \cdot TFP_{i,t}^A, Fine\} \tag{3.7}$$

3.4.2. Output adjustment

As introduced in Section 3.2.1, firm i's output quantity ($q_{i,t}$) is modeled as the product of a benchmark output quantity ($q_{i,L}$) and an output coefficient ($\delta_{i,t}$). $q_{i,L}$ is the average daily output of firm i in the last year, and we assume $\delta_{i,1}=1$, which is also firm i's production capacity, i.e. the uplimit for its daily output. Then, in each period t, firm i considers whether to adjust its output in the next period $t+1$, i.e. to increase or decrease its current output coefficient ($\delta_{i,t}$) by an exogenously set quantity (ζ), which is equal for all the firms.

Three factors are related to this decision: (1) profit from unit emission in the output market ($PUE_{i,t}^O$), (2) expected net allowance ($ENA_{i,t}$), and (3) forecast of the allowance price ($FP_{i,t}^A$). We assume that the higher $PUE_{i,t}^O$ and $ENA_{i,t}$ and the lower $FP_{i,t}^A$, the stronger propensity for firm i to increase its output, and vice versa.

In order to synthesize the three factors above, each firm i is modeled to first calculate a threshold price of allowance for output adjustment decision ($TP_{i,t}^O$), which increases with the decrease of $ENA_{i,t}$ and the increase of $FP_{i,t}^A$, as shown in Eq. (3.8).

$$TP_{i,t}^O = FP_{i,t}^A \cdot \left\{1+\alpha_{i,1}\left[\left(\frac{1}{1+\alpha_{i,2}{}^{ENA_{i,t}}}\right)^{\alpha_{i,3}} - 0.5\right]\right\} \tag{3.8}$$

Then, firm i will compare $PUE_{i,t}^O$ with $TP_{i,t}^O$. If $PUE_{i,t}^O$ is higher than $TP_{i,t}^O$, firm i will increase its output coefficient – $\delta_{i,t+1}=\delta_{i,t}+\zeta$ – with a probability of $\Phi_{i,t}^1$, as calculated by using Eq. (3.9). Otherwise, firm i will decrease its output coefficient – $\delta_{i,t+1}=\delta_{i,t}-\zeta$ – with a probability of $\Phi_{i,t}^2$, as calculated by using Eq. (3.10).

$$\Phi_{i,t}^1 = \left(\frac{PUE_{i,t}^O}{TP_{i,t}^O} - 1\right)^{\alpha_{i,4}} \tag{3.9}$$

$$\Phi_{i,t}^2 = \left(\frac{TP_{i,t}^O}{PUE_{i,t}^O} - 1\right)^{\alpha_{i,5}} \tag{3.10}$$

In Eqs. (3.8)–(3.10), $\alpha_{i,l}$ $(l=1,2,\ldots,5)$ are firm i's 5 behavioral parameters. For each firm i, there are 16 behavioral parameters relating to its coordination among three abatement options. The others are $\beta_{i,m}$ $(m=1,2,\ldots,6)$ for technology adoption decision, and $\gamma_{i,n}$ $(n=1,2,\ldots,5)$ for allowance trading decision. To guarantee the monotone relations between each decision and its influencing factors, values of the 16 parameters are initialized based on a learning stage, which is introduced in Section 3.5.

3.4.3. Low-carbon technology adoption

As introduced above, firms' production is modeled at a process level in AMETS, and each process is assigned with optional low-carbon technologies. For each low-carbon technology j of process p, it is modeled as 6 parameters: (1) energy saving parameters, including coal saving ($CS_{p,j}$), gas saving ($GS_{p,j}$), oil saving ($OS_{p,j}$), and electricity saving ($ES_{p,j}$); (2) cost parameters, including investment cost ($IC_{p,j}$), operation and maintenance cost ($OMC_{p,j}$).

In each period t, we assume that firm i considers whether to adopt its current cheapest low-carbon technology j, and we assume it is related to the following four factors: (1) average abatement cost ($AC_{i,j}$), (2) absolute abatement potential ($AAP_{i,j,t}$), (3) expected net allowance ($ENA_{i,t}$), and (4) forecast of the allowance price ($FP_{i,t}^A$). $AC_{i,j}$ and $AAP_{i,j,t}$ are calculated from a bottom-up perspective, by using Eqs. (3.11)–(3.14). $ECS_{p,j}$ and $EA_{p,j}$ denote the energy cost saving and emission abatement of technology j for process p for unit production. EFC, EFG, EFO, and EFE denote emission factors of the four energy carriers. $LT_{p,j}$ denotes the lifetime of technology j, and ER_i denotes firm i's expected rate of return. By discounting the cash flow in the following $LT_{p,j}$ years, firm i makes the adoption decision for technology j from a long-term perspective, which is different from its output adjustment and allowance trading decisions.

$$ECS_{p,j} = PC\cdot CS_{p,j} + PG\cdot GS_{p,j} + PO\cdot OS_{p,j} + PE\cdot ES_{p,j} \tag{3.11}$$

$$EA_{p,j} = EFC\cdot CS_{p,j} + EFG\cdot GS_{p,j} + EFO\cdot OS_{p,j} + EFE\cdot ES_{p,j} \tag{3.12}$$

$$AC_{i,p,j} = \frac{IC_j + \sum_{y=1}^{LT_{p,j}} \frac{OMC_{p,j}-ECS_{p,j}}{(1+ER_i)^y}}{\sum_{y=1}^{LT_{p,j}} EA_{p,j}} \tag{3.13}$$

$$AAP_{i,j,t} = EOL_{i,t}\cdot EA_{p,j} \tag{3.14}$$

$ENA_{i,t}$ is calculated by subtracting expected total CO_2 emission from its allowance account ($AA_{i,t}$), by using Eqs. (3.15–3.16).

$EAC_{i,t}$ denotes firm i's accumulated emission. $EIU_{i,t}$ and EIP_i denote firm i's emission intensity of unit output for energy- and process-related[2] reasons, and $EOL_{i,t}$ denotes firm i's expected output in the remaining periods.

$$EIU_{i,t} = \sum_p (EFC \cdot EC_{i,p,t} + EFG \cdot EG_{i,p,t} + EFO \cdot EO_{i,p,t} + EFE \cdot EE_{i,p,t}) \tag{3.15}$$

$$ENA_{i,t} = AA_{i,t} - EAC_{i,t} - EOL_{i,t} \cdot (EIU_{i,t} + EIP_i) \tag{3.16}$$

At last, based on these four influencing factors, we assume that the higher $AAP_{i,j,t}$ and $FP^A_{i,t}$ and the lower $AC_{i,j}$ and $ENA_{i,t}$, the stronger propensity for firm i to adopt technology j, and vice versa. Then, a probability ($\Psi_{i,t}$) is introduced to characterize firm i's propensity, which is calculate by using Eq. (3.17). Once a low-carbon technology is adopted, it is irreversible, and according this decision in each period t, firm i's variables of relevant aspects are updated, including energy intensity, operation and maintenance cost of unit output, and adoption cost.

$$\Psi_{i,t} = \left(\frac{1}{1+{\beta_{i,1}}^{AC_{i,j}/FP^A_{i,t}}}\right)^{\beta_{i,2}} \left(\frac{1}{1+{\beta_{i,3}}^{ENA_{i,t}}}\right)^{\beta_{i,4}} \left(\frac{1}{1+{\beta_{i,5}}^{-AAP_{i,j,t}}}\right)^{\beta_{i,6}} \tag{3.17}$$

Following the idea of discrete choice model (Train, 2009), we introduce the probability $\Psi_{i,t}$ to characterize firm i's propensity for action. In order to synthesize multiple influencing factors, Eq. (3.17) is designed based on the sigmoid function, for its continuity, smoothness, monotonicity, and value range of (0,1). With this equation, the monotone impact of the four factors on the adoption probability are synthesized and maintained, and additionally, further reasonability is provided by the behavioral parameters, $\beta_{i,m}$ $(m = 1, 2, \ldots, 6)$, initialized based on a learning stage.

3.4.4. Allowance trading

As introduced in Section 3.2.2, under the CDA mechanism, on each tick k in one period t, one firm is randomly selected to make trading decisions, i.e. to submit an ask order to sell allowances, or to submit a bid order to buy allowances, or to leave the allowance market without submitting any order. Three factors are related to this decision: (1) allowance price at the current tick k ($P^A_{t,k}$), (2) expected net allowance ($ENA_{i,t}$), and (3) forecast of the allowance price ($FP^A_{i,t}$). We assume that the higher $P^A_{t,k}$ and $ENA_{i,t}$, and the lower $FP^A_{i,t}$, the stronger propensity for firm i to sell its allowance, and vice versa.

Similar with the behavioral rules for output adjustment decision, in order to synthesize the three factors above, we assume that firm i will first calculate a threshold price of allowance for allowance trading decision ($TP^A_{i,t}$), which increases with the decrease of $ENA_{i,t}$ and the increase of $FP^A_{i,t}$, as shown in Eq. (3.18).

$$TP^A_{i,t} = FP^A_{i,t} \cdot \left\{1 + \gamma_{i,1}\left[\left(\frac{1}{1+{\gamma_{i,2}}^{ENA_{i,t}}}\right)^{\gamma_{i,3}} - 0.5\right]\right\} \tag{3.18}$$

Then, firm i will compare $P^A_{t,k}$ with $TP^A_{i,t}$. If $P^A_{t,k}$ is higher than $TP^O_{i,t}$, firm i will submit an ask order to sell allowances with a probability of $\Omega^1_{i,t}$, as calculated by using Eq. (3.19). Otherwise, firm i will submit a bid order to buy allowances with a probability of $\Omega^2_{i,t}$, as calculated by using Eq. (3.20).

$$\Omega^1_{i,t,k} = \left(\frac{P^A_{t,k}}{TP^A_{i,t}} - 1\right)^{\gamma_{i,4}} \tag{3.19}$$

$$\Omega^2_{i,t,k} = \left(\frac{TP^A_{i,t}}{P^A_{t,k}} - 1\right)^{\gamma_{i,5}} \tag{3.20}$$

An ask (or bid) order is a combination of limit price ($LP^A_{i,t,k}$) and volume ($LV^A_{i,t,k}$), which means selling (or buying) $LV^A_{i,t,k}$ allowances at a price no lower (or higher) than $LP^A_{i,t,k}$. For an ask order, we assume that $LP^A_{i,t,k} = P^A_{t,k} - \eta$ and $LV^A_{i,t,k} = ENA_{i,t} \cdot \varsigma \cdot \Omega^1_{i,t,k}$. For a bid order, we assume that $LP^A_{i,t,k} = P^A_{t,k} + \eta$ and $LV^A_{i,t,k} = ENA_{i,t} \cdot \varsigma \cdot \Omega^2_{i,t,k}$. The parameters η and ς are exogenously and homogeneously set for all the firms.

By introducing this "threshold price" combined with two probabilistic behavioral functions, an endogenous mechanism for the decision of firms' trading direction is implemented. This is different from common financial ABMs using the CDA mechanism, which usually focus more on the mechanism aspect rather than the micro-behaviors of agents. For simplification, they also use zero-intelligence agents, whose trading direction is exogenously fixed, for example, at a fifty-fifty probability (Raberto & Cincotti, 2005). This common depiction properly reflects the random fluctuation of a financial asset's price when there is no fundamental change, and from a modeling perspective, the probability of 50% also guarantees that the price will not boom up or fall to zero in the simulation under the CDA mechanism. However, in the ETS, the change of demand and supply in the allowance market is directly and fundamentally decided by firms' decisions of output adjustment and technology adoption. So, corresponding to this property of the ETS, the endogenous mechanism based on "threshold price" and probabilistic behavioral functions is introduced in AMETS.

3.5. Learning: behavioral parameters initialization

As introduced in Section 3.4, firms make decisions based on the same set of behavioral functions, but with heterogeneous behavioral parameters. In order to initialize these parameters with reasonable values, a learning stage based on the Multiple-population Genetic Algorithm (MPGA)[3] is introduced. A flow chart for the implementation of MPGA in AMETS is provided in Fig. 3, and explained as follows.

1. At the beginning of the learning stage, each firm i is randomly initialized with a strategy pool (SP), which contains N_S strategies. The sth strategy in firm i's SP in the rth generation is denoted by $S_{i,r,s}$. For each strategy s, it is a 80-digit binary series, and can be translated as values for firm i's 16 behavioral parameters. A detailed introduction for the translation rule is provided in Appendix B.1.
2. In the rth generation, the abatement phase is run N_S times, during which each firm i tries its N_S strategies in the pool one by one, and record the final total profit (FTP_i) led by each strategy s, which is calculated by using Eq. (3.21). $TR^O_{i,t}$, $TC^O_{i,t}$ and $ACT_{i,t}$ denote firm i's revenue, production cost and low-carbon technology adoption cost in period t, $CA_{i,t,k}$ denotes firm i's cash account in period t on tick k, and FEE_i

[2] For the cement production, there are also CO_2 emissions from the clinker calcination process ($CaCO_3 \xrightarrow{\text{heat}} CaO + CO_2$) apart from the energy combustion.

[3] MPGA is different from the common Genetic Algorithm, i.e. Single-population Genetic Algorithm (SPGA). In MPGA, each agent is represented by a population of strategies (or chromosomes) in its mind (referred to as "strategy pool" in our model), and learning is implemented by running the Genetic Algorithm inside each agent. However, in SPGA, each agent is represented by only one strategy (or chromosome), and learning is implemented by running the Genetic Algorithm inside the whole society. So, from the perspective of the population-level of learning, with the SPGA, agents learn from others, i.e. social learning based on "imitation"; while with the MPGA, agents learn from their own experience, i.e. individual learning based on "meditation" (Chen & Yeh, 2001).

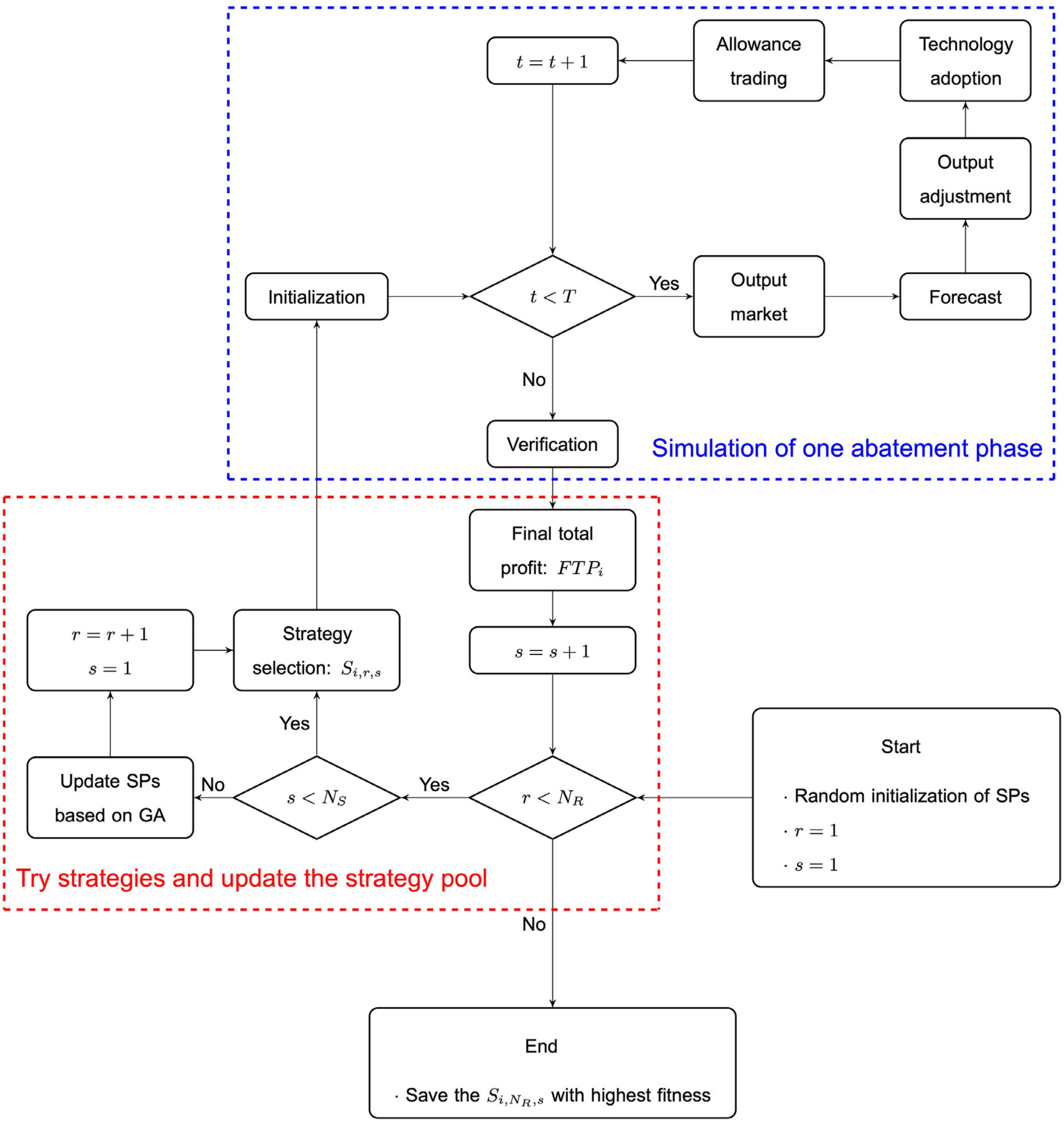


Fig. 3. Flowchart of the learning stage.

denotes firm i's fine for excess emission.

$$FTP_i = \sum_{t=1}^{T}\left(TR^{O}_{i,t} - TC^{O}_{i,t}\right) - \sum_{t=1}^{T} ACT_{i,t} + \left(CA_{i,T,N_K} - CA_{i,1,1}\right) - FEE_i \tag{3.21}$$

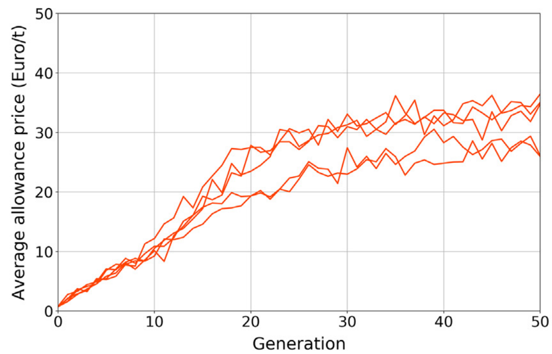
3. After trying all its N_S strategies and recording corresponding profit values, firm i updates its SP of rth generation based on GA, and gets a new SP for the $(r+1)$th generation. A detailed introduction for the implementation of GA is provided in Appendix B.2.
4. At last, after N_R generations, each firm i gets its final SP, and it will choose the strategy with highest FTP_i to initialize its strategy (behavioral parameters) for the simulation stage.

Four aggregate results are selected to show the converging process of the learning stage, including average allowance price, total allowance trading volume, total abatement rate, and firms' total profit. With the learning stage proceeding, the convergence indicates that firms are getting smarter and smarter, and the learning stage is approaching its termination. As shown in Fig. 4, with randomly generated seed strategies for all the firms, the learning stage is run for five times. In each of the five, after 50 generations, the evolution of the four aggregate results show significant convergence. Furthermore, five evolution paths follow similar pattern, which indicates the robustness of this learning algorithm.

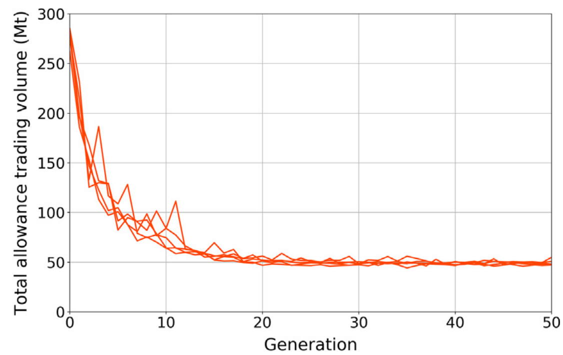
The introduction of this learning stage essentially combines the optimization and simulation methods, and, to a certain extent, it guarantees the "reasonability (not optimality)" of the simulation results. This is further reflected in a comparison between the results of two cases, in which firms' behavioral parameters are randomly initialized or based on the learning stage, as provided in Appendix B.3.

4. Model calibration and simulation setting

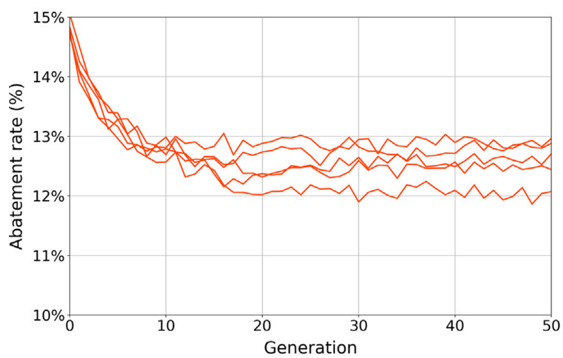
For higher resolution and reference value of the model results, AMETS is calibrated from a fundamental perspective in detail. As shown in Table 3, 11 most emission-intensive products from 5



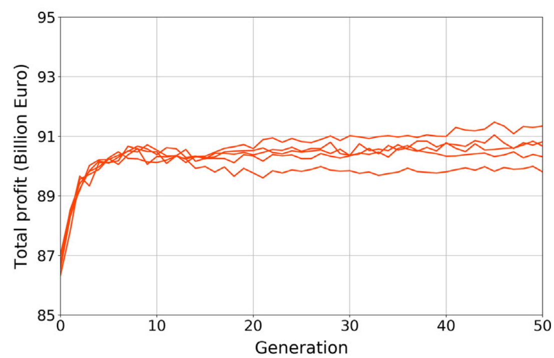
(a) Average allowance price



(b) Total allowance trading volume



(c) Total abatement rate



(d) Firms' total profit

Fig. 4. Evolution paths of aggregate results during learning stage.

Table 3
Coverage of AMETS.

Sector (5)	Product (11)	Process (25)	Number of low-carbon technologies (52)
Iron and steel	**Steel**	Sinter	1
		Coke oven	1
		Blast furnace and converter (BFC)	4
		Electric arc furnace (EAF)	3
		Rolling	1
Non-metallic minerals	**Cement**	Limestone preparation	0
		Clinker calcination	5
		Grinding	0
	Glass	Glass production (container)	6
		Glass production (flat)	1
Non-ferrous metals	**Aluminum**	Aluminum (primary)	0
		Aluminum (secondary)	1
		Further treatment	4
	Copper	Copper primary	0
		Copper secondary	5
		Further treatment	4
Paper	**Paper**	Chemical pulp	0
		Mechanical pulp	0
		Recovered fibers pulp	0
		Paper making	3
Chemistry	**Ethylene**	Ethylene	3
	Ammonia	Ammonia	3
	Carbon black	Carbon black	3
	Soda ash	Soda ash	2
	Chlorine (membrane)	Chlorine (membrane)	2

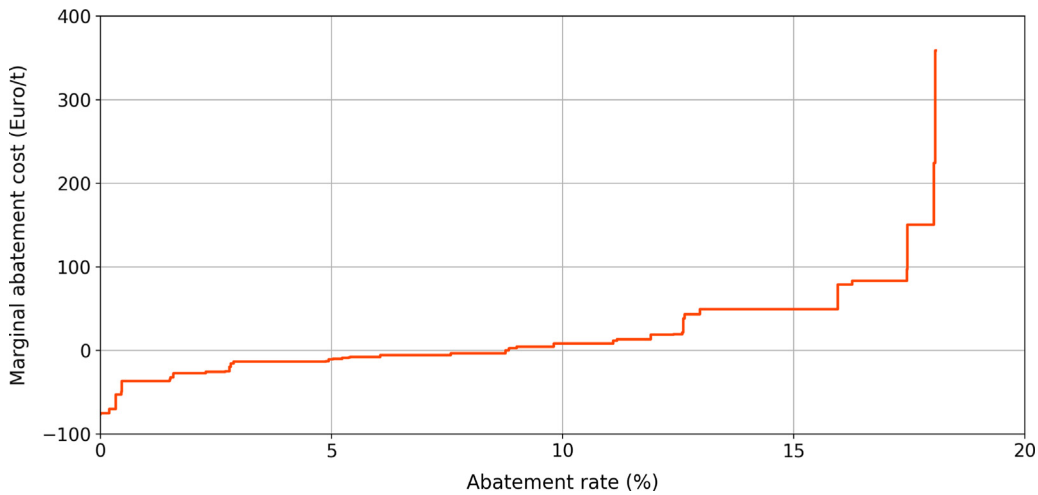


Fig. 5. Marginal abatement cost curve.

Table 4
Initialization of the system parameters.

Parameter	Value	Explanation
T	365	Number of periods in an abatement phase.
N_K	3400	Number of ticks in one period.
N_F	340	Number of firms in the system (20 for each product).
EFC	0.11	CO_2 emission factor of coal (ton CO_2/GJ).
EFG	0.06	CO_2 emission factor of gas (ton CO_2/GJ).
EFO	0.08	CO_2 emission factor of oil (ton CO_2/GJ).
EFE	0	CO_2 emission factor of electricity (ton CO_2/GJ).
PC	3.4	Coal price (Euro/GJ).
PG	9.88	Gas price (Euro/GJ).
PO	14.72	Oil price (Euro/GJ).
PE	16.36	Electricity price (Euro/GJ).
Fine	100	Fine for each ton of excess emission (Euro/ton).

sectors are selected and covered, accounting for about 70% of the CO_2 emission from the whole industry in the EU, and following the FORECAST model (Fleiter et al., 2018), 25 production processes and 52 low-carbon technologies are also included.

4.1. System parameters

The system parameters include two parts. As shown in Table 4, the first part includes length of simulation, number of firms, price and emission factor of energy carriers, and fine price. The values for energy-related parameters are from the FORECAST model, and the fine price is from the EU ETS.

The second part of system parameters are related to the output markets. We assume constant elasticity demand functions for the products, which are calibrated based on data of production quantity, price, and demand elasticity. We also collect the non-energy cost data for each product. These data are from the FORECAST model (Fleiter et al., 2018) and relevant studies (Allevi, Oggioni, Riccardi, & Rocco, 2017; Demailly & Quirion, 2008; Kannegiesser, Günther, van Beek, Grunow, & Habla, 2009; Mansikkasalo, Lundmark, & Söderholm, 2014; Stuermer, 2017), as shown in Table C.2 in Appendix C.

4.2. Process and low-carbon technology parameters

In AMETS, firms' production are modeled at a process level, and each process is assigned with optional low-carbon technologies.

Based on the data from FORECAST (Fleiter et al., 2018), relevant study (Arens, 2017) and energy statistics (Eurostata, 2018), all the processes and technologies are calibrated as provided in Table C.3 in Appendix C, and the MACC of the whole system is provided in Fig. 5.

4.3. Firms' attribute parameters

The initialization of firms' attribute parameters includes two parts. Firstly, following previous studies (Anouliès, 2017; Axtell, 2001; Cabral & Mata, 2003), firms' scale and productivity are assumed to follow a Pareto distribution. Secondly, firms' other attribute parameters are homogeneously initialized, as shown in Table 5. A full list of firms' parameters and variables is provided in Table D.4 in Appendix D.

5. Results and discussions

In this section, we first select two scenarios, with abatement targets of 2% and 18%, to compare and discuss the impact of the ETS on output markets and diffusion of low-carbon technologies. Then, based on the ability to capture uncertainty and non-linear relationships of AMETS, the trade-off between allowance price uncertainty and output impact for setting abatement target is revealed and briefly discussed.

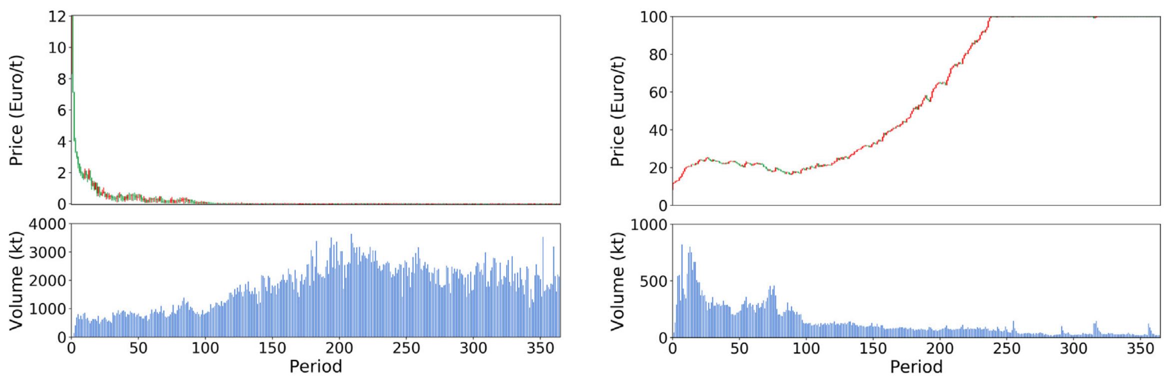
5.1. Impact of the ETS

For the abatement target of 2% and 18%, Fig. 6 shows the price and trading volume in the allowance market under the two scenarios. As the candlestick charts show, when the abatement target is low, the allowance price drops to zero with the trade proceeding, corresponding to the negative marginal abatement cost for 2% abatement target, as shown in Fig. 5. When the abatement target is as high as 18%, the allowance price stays around 20 Euro/ton in the first 100 periods, then followed by a quick increase, which finally leads to 100 Euro/ton, the fine price for each ton of excess emissions.

This quick increase comes from firms' deficit in allowances, as well as the dynamic interactions among the allowance market, output market, and low-carbon technology diffusion. As shown in Fig. 7, unlike a static MACC in most equilibrium-based models, firms face steeper and steeper MACCs with the proceeding of the abatement phase, because the abatement potential of low-carbon technologies decreases with the decrease of potential output in the

Table 5
Initialization of the firms' homogeneous attribute parameters.

Parameter	Value	Explanation
ER_i	30%	Expected rate of return of firm *i*.
EYE_i	5	Number of other firms that can be observed by firm *i* for forecasting the allowance price.
TW_i	0.3	Weight for the technical forecast of the allowance price of firm *i*.
ML_i	10	Memory length firm *i* (period).
ζ	0.1%	Firms' output adjustment parameter.
η	0.01	Firms' price adjustment parameter for order decision (Euro).
ς	0.1%	Firms' volume choice parameter for order decision.



(a) Target = 2% (b) Target = 18%

Fig. 6. Allowance market result.

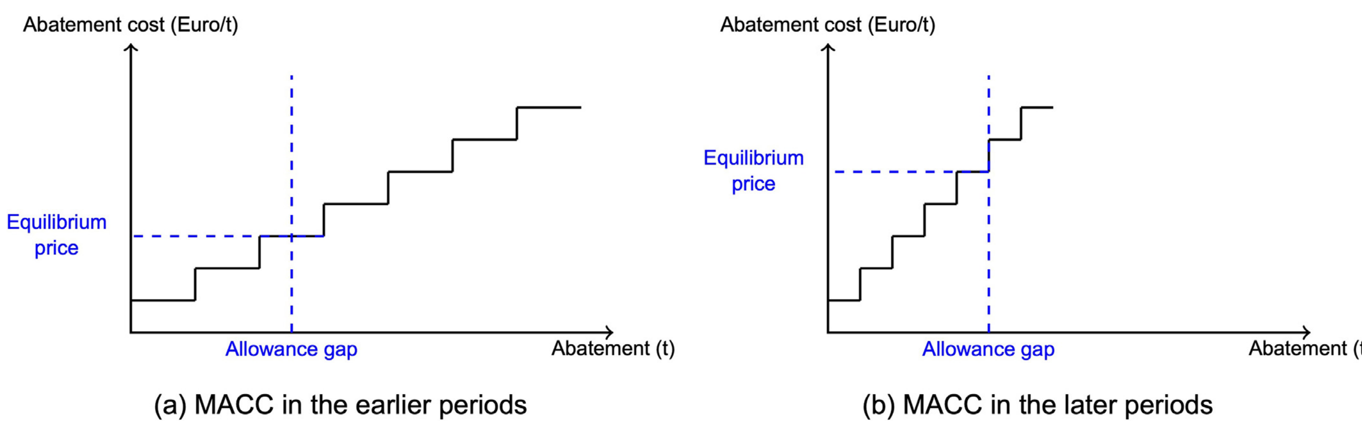


Fig. 7. Dynamic marginal abatement cost curve.

remaining periods. So, if firms do not adopt enough low-carbon technologies before a certain reversal point, the allowance price will increase quickly in the later periods.

With the consideration of heterogeneity, the allowance flow among firms are also revealed in the result. As shown in Fig. 8, the average values and standard deviation of net trading volume for the products[4] are provided for both scenarios. Firms producing steel (blast furnace) and paper are major buyers in the market, and firms producing cement and glass are major sellers, while firms of several products change their position under different abatement targets, including copper, ammonia, etc.

In the output markets, firms are also motivated to reduce their output for abatement. As shown in Fig. 9, given the low target of 2%, the ETS does not show impact on the output markets, while when the target is 18%, the impact is significant for the production of cement, soda ash, aluminum (primary), and chlorine (membrane). The cement is the most influenced, because apart from CO_2 emission from energy combustion, it also has process emission, which means higher abatement contribution of each ton of output reduction.

Concerning the diffusion of low-carbon technologies, as shown in Fig. 10, the total count of diffusion are 685 under the 2% scenario and 885 under the 18% scenario. Most of them are adopted in the earlier periods, because with adoption proceeding, the abatement potential of low-carbon technologies decreases, and the marginal cost increases.

[4] According to the different production methods, 5 products are further divided in AMETS: (1) Steel is modeled as BF- and EAF-based production; (2) glass is modeled as container and flat production; (3) aluminum is modeled as primary and secondary production; (4) copper is modeled as primary and secondary production; (5) paper is modeled as chemical-, mechanical-, and recovered-fibers-based production. As a result, there are in total 17 products in the model, as shown in Figs. 8, 9, 12, and 15.

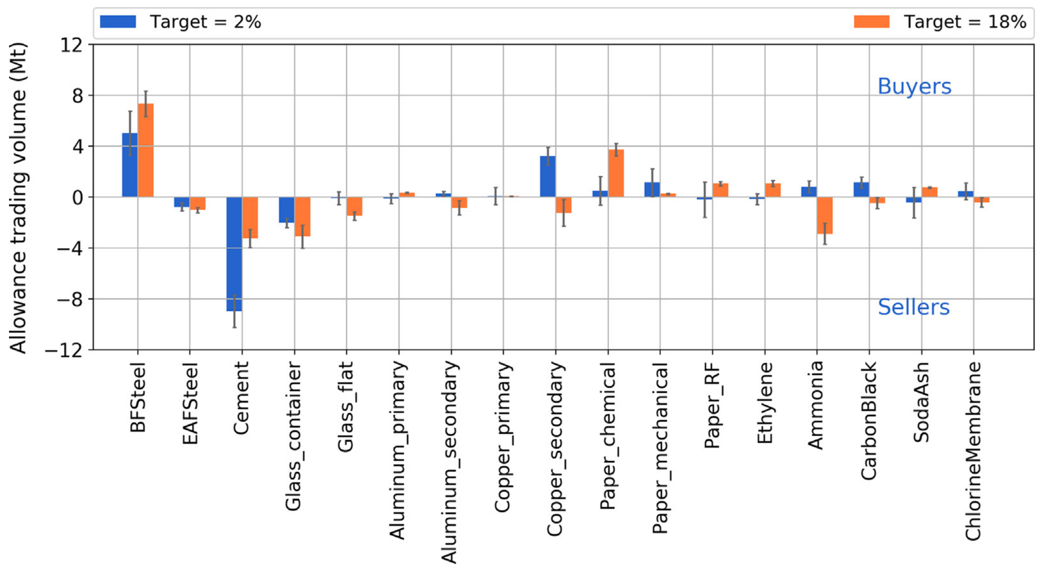
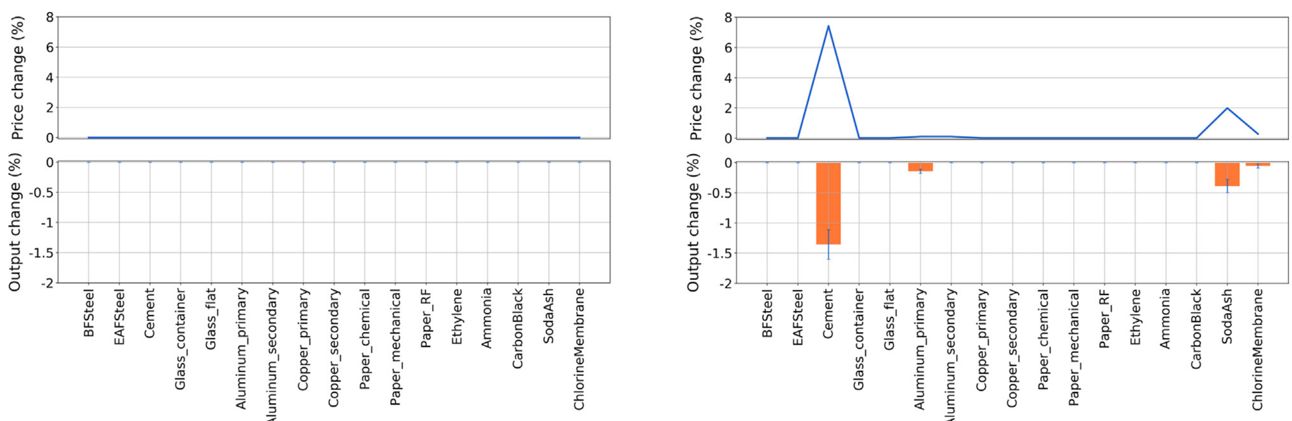


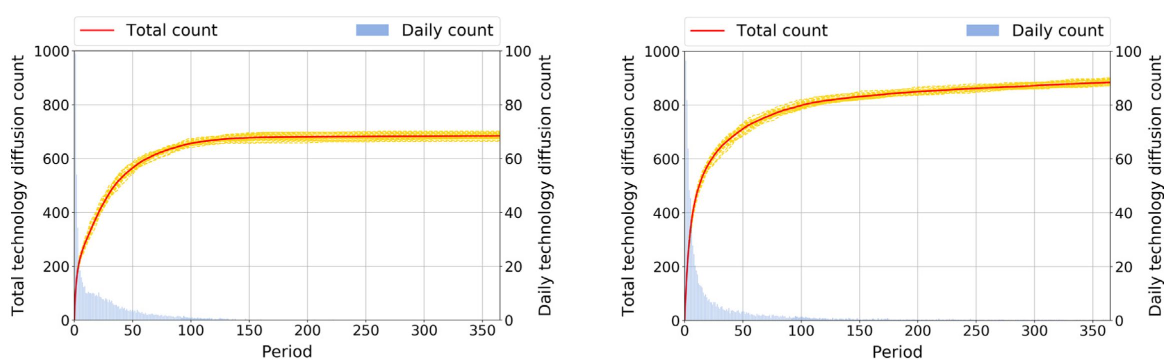
Fig. 8. Allowance trading volume flow by product.



(a) Target = 2%

(b) Target = 18%

Fig. 9. Impact on output markets.



(a) Target = 2%

(b) Target = 18%

Fig. 10. Technology diffusion count.

Furthermore, the diffusion of each low-carbon technology under the two scenarios are also provided, as shown in Fig. 11, and the key technologies contributing most to the abatement are also identified, including clinker_dry_1, clinker_dry_3, rolling_1, BFC_3, and glass_flat_1.

At last, the total abatement under the two scenarios, as well as their composition, are provided by Fig. 12. Firms producing cement, steel (blast furnace) and glass contribute most abatement.

As shown in the results above, AMETS captures the allowance price evolution processes under different scenarios, falling when

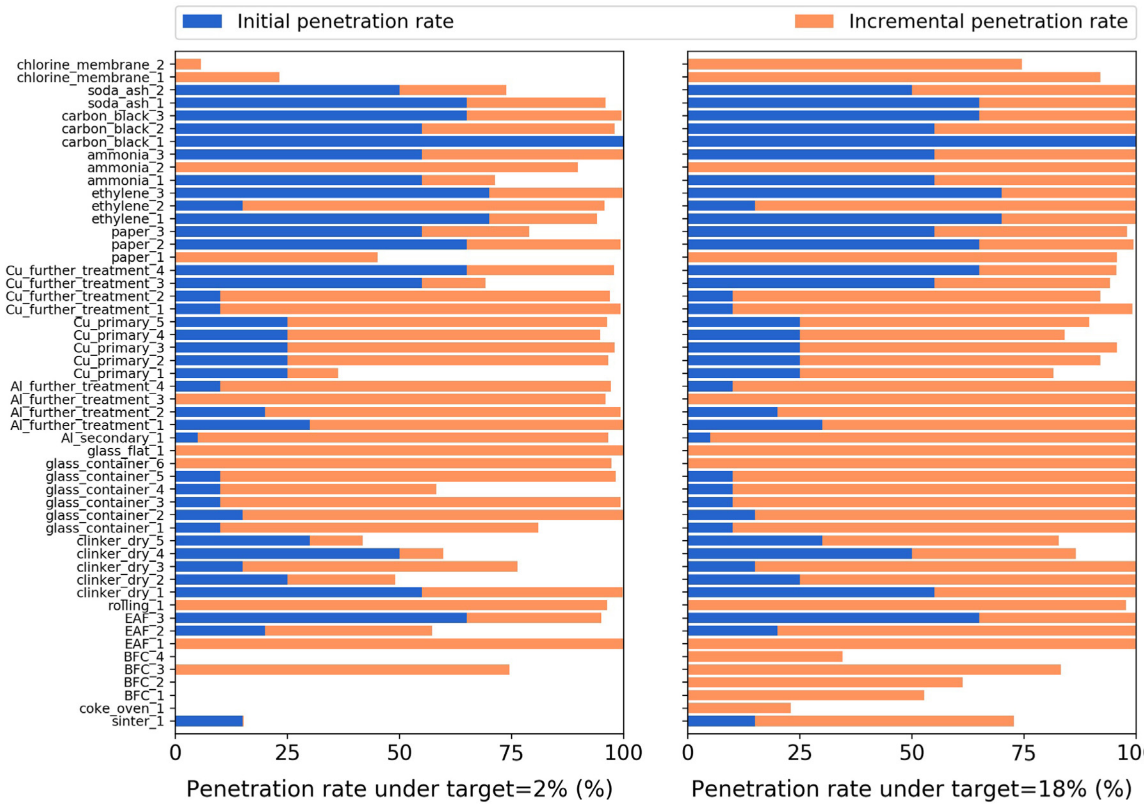
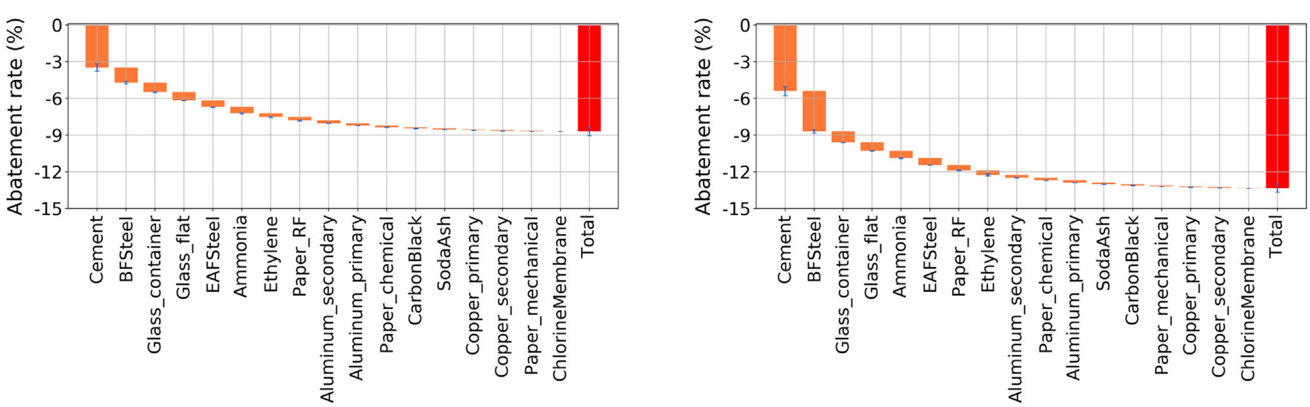


Fig. 11. Technology penetration rate.



(a) Target = 2%

(b) Target = 18%

Fig. 12. Abatement decomposition by product.

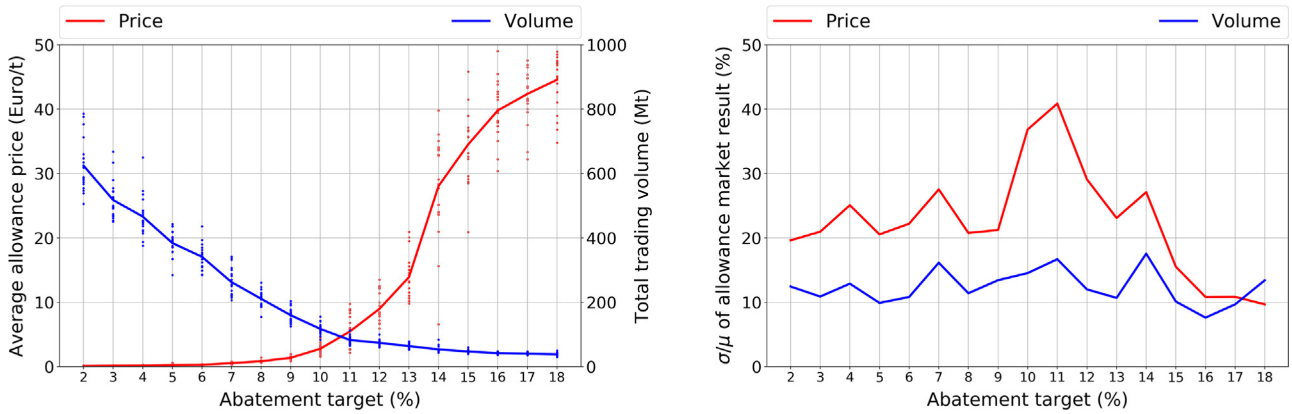
the target is low, and rising when the target is high. Both of them have been observed in the real ETS system. On the other hand, by comparing the two scenarios, it is also shown that the function of the ETS system is fundamentally decided by the shape of MACC, which determines firms' forecasts and behaviors, and at the macro level, links the allowance market and output markets. The evolution of the allowance price can be different, but the patterns of technology diffusion are similar, as well as the abatement contribution of the major players in the market.

5.2. Abatement target setting: trade-off between allowance price uncertainty and output impact

For further analysis of the impact of abatement target, the abatement phase is simulated 20 times under each of the 17 scenarios with targets ranging from 2% to 18%, and the results are as shown in Fig. 13.

As shown in Fig. 13(a), the abatement target has non-linear impact on the average allowance price, which first stays low when the abatement target is no higher than 10%, and then increases sharply. For the total trading volume, it decreases with the abatement target going up. On the other hand, as shown in Fig. 13(b), the abatement target also impacts the uncertainty of the average allowance price, which first increases, then decreases with the target going up, and the highest level appears under the scenario of 11%. Comparison based on the simulations under three scenarios is provided in Fig. 14.

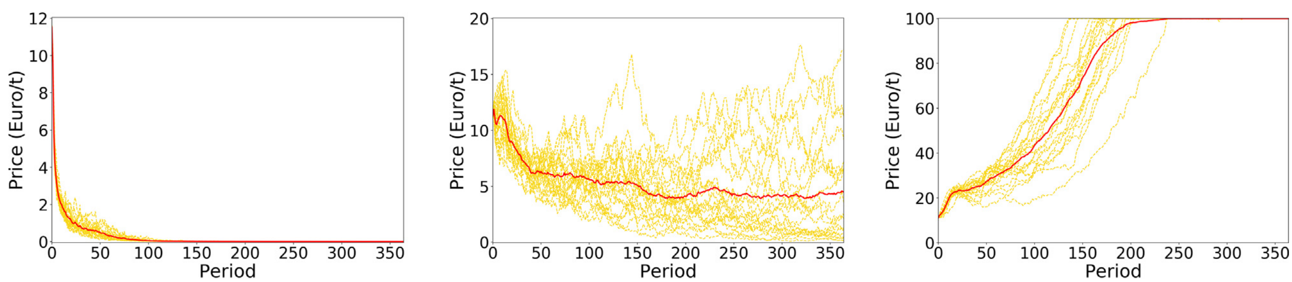
The highest average allowance price uncertainty appears when the target is 11%, because as shown in Fig. 5, it is just behind the point where the MACC crosses the 0 Euro/ton line. Facing the pos-



(a) Impact on price and trading volume

(b) Impact on uncertainty of price and trading volume

Fig. 13. Impact of abatement target on the allowance market.



(a) Target = 2%

(b) Target = 11%

(c) Target = 18%

Fig. 14. Uncertaity of allowance price.

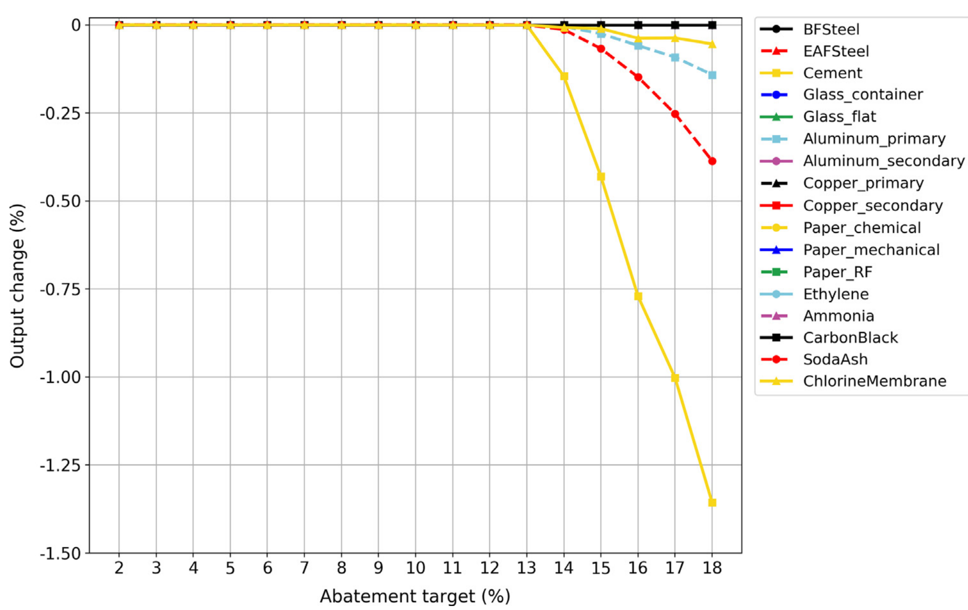


Fig. 15. Impact of abatement target on the output markets.

itive but low cost, firms are more hesitant to adopt low-carbon technologies, compared with a lower or higher target. This leads to the uncertainty: if firms hesitate less and adopt more technologies before some reversal point, they will face a less steeper MACC in the later periods; while if they do not, the allowance price can be much higher.

Non-linear impact of the abatement target also exists in the output markets, as shown in Fig. 15. When the abatement target is low, the output markets are not influenced, however, when the target is higher than 13%, firms start to reduce their output, and the production of cement, soda ash, aluminum (primary) and chlorine (membrane) are affected. This non-linear impact is also fundamentally decided by the shape of MACC: a higher target leads to higher cost for low-carbon technology adoption, when is high enough, it starts motivating firms to reduce their production for abatement. However, as long as the fine price is not too high, com-

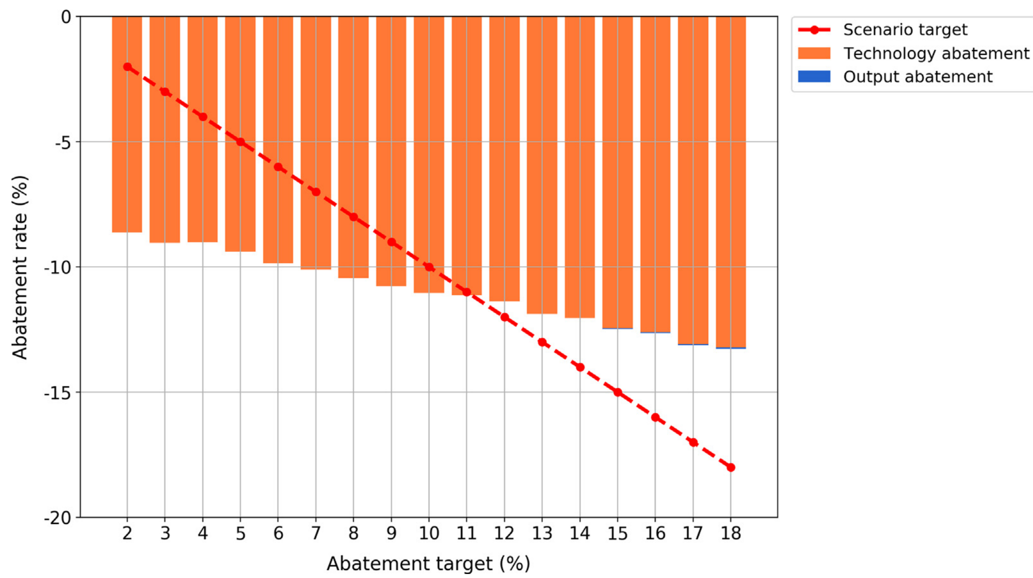


Fig. 16. Impact of abatement target on the total abatement and composition.

pared with firms profit of unit CO_2 emission in the output markets, abatement contribution from production reduction is limited, as shown in Fig. 16.

In summary, based on the ability to capture the emergence properties and uncertainty of the system, AMETS reveals the non-linear impact of the abatement target, and the trade-off for setting it: after a certain point, higher target leads to lower allowance price uncertainty but stronger output impact. Furthermore, there are three points worth pointing out: firstly, the output impact is heterogeneous for different products, and production of cement is influenced the most; secondly, given the cost of low-carbon technologies, unit CO_2 emission profit of products, and the fine price, most abatement is contributed by low-carbon technology diffusion, and the contribution from production reduction is quite limited; thirdly, when the target is low, the natural diffusion of technologies with negative cost will contribute abatement higher than the target, so the ETS is unnecessary, while when the target is high, firms will not reach the target because the abatement cost is too high, so to a certain extent, the ETS serves as an emission tax.

6. Conclusions

In this paper, model AMETS is established within an agent-based framework for the ETS, in which modules are organized within a novel multi-level time frame. Firms' coordination among three abatement options are modeled, as well as the emerging interactions among allowance market, output markets, and low-carbon technology diffusion. Furthermore, three complexities are also considered, including different planning horizons of different abatement options, heterogeneity among sectors and firms, and details of production and technologies. Based on the advantages above, AMETS can be used as a policy simulation platform for the mechanism design and impact evaluation of the ETS.

Compared with existing equilibrium- and agent-based models, AMETS provides higher resolution results for the ETS, and based on the calibration with European data, it provides supplementary insights in the following three aspects. Firstly, AMETS captures the emergence properties and uncertainty of the system, the non-linear impact of the abatement target, and reveals the trade-off between allowance price uncertainty and output impact for a higher target. Secondly, AMETS reflects the heterogeneous impact of the ETS on firms producing different products, including their allowance trading volume flow, output reduction, and CO_2 abatement. At last, AMETS provides detailed results for technology diffusion at a process level, and for different abatement scenarios, key low-carbon technologies are identified.

There are also major limitations of AMETS. Firstly, the construction time of technology adoption is ignored, as well as the barriers including imperfect information, hidden cost, and access to capital (Fleiter, Worrell, & Eichhammer, 2011; Schleich, 2009; Sorrell, O'Malley, Schleich, & Scott, 2004). These two simplifications indicate an underestimation of the allowance price, and could be improved by further calibration. Secondly, the coverage of the model can be extended to include more pollutants from industry, based on which we can analyze the trade-off between them and CO_2 emissions. At last, firms' behavior of fuel switching and upgrade of production line based on innovative technologies (e.g., hydrogen-based production line for steel making) are also worth being included, considering their importance for the reduction of CO_2 emission in the long term. In our future study, AMETS will be further developed and applied to analyze more questions about the ETS, including the allowance allocation mechanism, coverage and transaction cost, abatement target setting, etc.

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Supplementary material

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