Quantitative models in emission trading system research: A literature review

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Abstract: Diverse quantitative models have been applied to analyse emission trading system, as the top effective climate change policy. This paper is the first attempt to present a comprehensive literature review on full-scale types of quantitative models in emission trading system research. The models dominating emission trading system-related literature could be categorized as optimization models, simulation models, assessment models, statistical models, artificial intelligences and ensemble models. Using different quantification and solution tools, these models complemented and enriched each other in serving the various agents involved in emission trading system and facilitating their respective emission trading system related works: the government to design emission trading system policies, enterprises to participate in emission trading system and goods markets, third parties to regulate emission trading system and emission trading system markets involving different agents. For each agent, a systematic analysis is provided on research hotspots (the challenges to address), quantitative models (to describe the problems and find the results), main findings (the policy implications from the models) and future research (potential improvements on existing models). Some interesting conclusions are obtained. (1) Generally, China was the largest contributor to emission trading system research using quantitative models (representing 35.71% of the total articles). (2) The research hotspots were decision making by enterprises under an emission trading system (20.92%), spillovers amongst emission trading system and other markets (17.54%) and allowance allocation by the government (12.52%). (3) Popular quantitative models included various optimization models (32.00%) and simulation models (29.64%).

Highlights:

- A variety of quantitative models have been applied to ETS research.
- A comprehensive review on full-scale types of models in ETS research is presented.
- Optimization, simulation, assessment, statistical, AI & ensemble models were built.
- Models helpfully served the government, enterprises, third parties & market in ETS.
- For each agent, hotspots, models, main findings and future research are analysed.

Keywords: Carbon cap-and-trade; Carbon markets; Allowance allocation; Measuring, reporting and verification; Computable general equilibrium model; Data envelopment analysis

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Abbreviations

Abbr.	Full name	Abbr.	Full name
ABM	Agent-based models	ETS	Emission trading system
AHP	Analytic hierarchy process	EU ETS	European Union emissions trading scheme
AI	Artificial intelligence	GARCH	Generalized autoregressive conditional heteroskedastic
ANN	Artificial neural network	GDP	Gross domestic product
CER	Certified emission reduction	MRV	Measuring, reporting and verification
CGE	Computable general equilibrium	SD	System dynamic
DEA	Data envelopment analysis	SVM	Support vector machine
DT	Decision tree	TOPSIS	Technique for order preference by similarity to an ideal solution
EMD	Empirical mode decomposition	VAR	Vector autoregressive

1 Introduction

Emission trading system (ETS) has consistently been considered as the top promising instrument to mitigate global greenhouse gas emissions, due to the virtues of flexibility, cost saving and effectiveness [1,2]. However, as a market-driven policy, ETS is inherently a typical complex system and has become one of the most challenging topics in the research fields of energy and climate economics [3]. On the one hand, unlike compulsory regulations (such as emission standards) directly targeting emitting behaviours, ETS regulates the emitters in a quite roundabout way through the market mechanism, with final efficacy impacted by a variety of uncertain factors [4,5]. On the other hand, rather than price instruments (such as carbon tax and subsidy) just imposing a cost or benefit on emissions, an ETS policy otherwise entails a series of rules and designs for different agents and markets, with each largely determining the mitigation effect [1,6]. Since the European Union Emissions Trading Scheme (EU ETS) was launched in 2005, a total of 28 ETS markets or pilots with distinctive features from each other have been built throughout the world; nevertheless, no uniform agreement regarding an optimal ETS policy has yet been achieved [7].

Actually, the complexity of ETS mainly lies in the coexistence of various agents performing different ETS-related works and interacting with each other to jointly determine the final impacts of the ETS policy [4]. According to existing literature, major agents in an ETS include: the government (i.e., the ETS designer) who sets, for example, the overall framework [8,9], the levels of the carbon cap [10,11], the coverage of sectors or regions targeted by ETS [12-16] and the rules for allocating the initial credits [1,17-19] with the aims to maximize mitigating effect [20,21], minimize economic loss [19,22,23], balance equity and effectiveness [24-27], etc.; enterprises from different sectors (i.e., the ETS targets) who attempt to find optimal decisions regarding production [28-30], technology improvement [31-33], allowance transaction [13,28,34], etc., in order to maximize profits [29,35] and avoid financial costs under an ETS [34,36,37]; third parties (i.e., the ETS regulators) to conduct the measuring, reporting and verification (MRV) work for estimating the emissions and emission reductions reported by enterprises [38-40]; the ETS market (i.e., the ETS media), through which various agents interact with each other and jointly determine the final impacts and which requires careful exploration to support the coordinated, harmonious development of different competing and conflicting agents [41-45].

Due to such complexity, a variety of quantitative models have been applied to ETS research, offering specific (quantitative) implications for ETS-involved agents to work out their respective ETS-related challenges. The prevailing quantitative models dominating the ETS literature can generally fall into six categories by quantification and solution tools: optimization models, searching for the optimal solution to an ETS-related task that maximizes the fitness of the associated agents [35,46,47]; simulation models, conducting *ex-ante* analyses to estimate the potential impacts under a series of policy scenarios (corresponding to different policy candidates) and to select the most satisfactory policy through result comparison [17,22,48]; assessment models, relying on *ex-post* analyses to evaluate the impacts and efficacy of an existing ETS policy implementation and to offer policy implications for future policy making [49,50]; statistical models, using statistical analyses to investigate the profound relationships across the factors in ETS [51,52]; artificial intelligences (AIs), employing the powerful learning abilities of computers or machines to adaptively capture the underlying mechanisms of an ETS system [44,53,54]; and ensemble models, as a rising star finely combining different models to take advantage of their respective strengths to address the weaknesses [44].

A systematic literature review on full-scale types of quantitative models in existing ETS research is needed, given that each different model with different quantification and solution tools will serve an ETS agent and facilitate an ETS task from a different perspective. However, a comprehensive review on different sorts of models and agents is still lacking. In particular, the existing ETS-related reviews were somehow confined to: a certain model, such as the generalized autoregressive conditional heteroskedastic (GARCH) model [2,55,56]; a certain kind of agents, such as the government [57], enterprises [57-59] or third parties [60]; and agents in a certain market, such as the primary ETS market, the secondary ETS market [55,56,59] or goods market [57,59]. Against such a background, this paper attempts to fill in this literature gap by conducting a systematic review that encompasses full-scale types of both quantitative models and agents interacting in the ETS and goods markets.

The main aim of this paper is to present a comprehensive map of the quantitative models used in ETS research, detailing how the different types of models serve each ETS-involved agent and facilitate its ETS-related challenges. Relative to the existing reviews, the major contributions of this paper can be summarized into three aspects: (1) it is the first attempt to review the full-scale types of quantitative models used in ETS literature; (2) diverse agents involved in ETS are considered, including the government (i.e., the ETS designer), enterprises (the ETS targets), third parties (the ETS regulators) and ETS markets (i.e., the ETS platform) involving different agents; (3) for each type of agent, a systematic analysis is conducted on the research hotspots (the ETS-related challenging problems to address), quantitative models (the way to describe the problems and find the results), main findings (the policy implications suggested by the quantitative analyses) and future research (potential improvements of the existing models).

The remaining part of the paper is organized as follows. Section 2 explores the general developments in ETS research via quantitative models, based on both descriptive and scientometric statistics. Section 3 details how different types of quantitative models serve each type of agents involved in an ETS system. Section 4 concludes the review and outlines further directions to improve and extend the existing quantitative research on ETS.

2 Statistical analysis

This section employs both descriptive and scientometric statistics to capture the general research development of applying quantitative models into ETS research. In particular, Section 2.1 elaborates on the literature collection. Sections 2.2-2.5 conduct a systematic statistical analysis of the selected literature, introducing both descriptive and scientometric measures to reveal the temporal trend, spatial distribution, publication sources and research hotspots of applying quantitative models into ETS research, respectively. Section 2.6 points out the practical implications of this study.

2.1 Databases

The ETS literature using quantitative models is derived from the academic databases of the Google Scholar, Web of Science, Science Direct, Emerald Insight, SAGE Journals Online, Springer and Wiley Online Library. To obtain full-scale results, not only the keywords *emission trading scheme* and *quantitative model*, but also other words related to ETS (*emission* trading scheme* OR *carbon emission* trading* OR *cap-and-trad**, etc.) coupled with a term regarding quantitative models (*modelling* OR *quantitative analysis* OR *simulation* OR *estimation* OR *measurement* etc.) are employed, where the symbol * denotes a derivative word for a term, such as "emissions" for "emission" [61]. The time limitation for the literature retrieval was set to before the end of 2019.

The types of literature are limited to journal full-length articles written in English, excluding research notes, reports, viewpoints, short communications, book reviews and conference papers. The collected articles are carefully re-checked for the relevancy to the topic of ETS research using quantitative models [62]. Finally, a total of 1053 papers are selected in this review. For each article, not only the basic information (on author(s), title, publishing time, keywords, journal title, country/region, etc.) but also the research focuses and methods for ETS and quantitative models (e.g., market(s), agent(s), topic(s), quantitative model(s), the techniques for quantification and solution) are analysed and recorded.

2.2 Temporal trend

ETS research using quantitative models started from 2000, with a total of 1, 3, 6, 2, 4, 11, 22, 31, 37, 43, 49, 47, 62, 75, 92, 122, 118, 149 and 179 articles published annually from 2000 to 2019, respectively. Four important findings can be obtained regarding the temporal trend. First, scholars started introducing quantitative models into ETS research in 2000, 3 years after the promulgation of the ETS policy in 1997 and 5 years before the launch of the first ETS market (i.e., EU ETS) in 2005. This result further implies that quantitative models were introduced into the emerging research of ETS, even when ETS was just a theoretical concept and then made a great contribution to its realization and adjustment. Second, the annual number of published articles shows a generally growing trend from 2000 to 2018. Such increasingly large attention confirms the effectiveness and usefulness of quantitative models in analysing the complex system of ETS and then addressing ETS-related challenges. Third, there existed a clear growth point in 2016, since which the number of papers has reached over 100 per year, and finally hit a peak of 179 in 2019. The hidden reason might be the recent boom in computer science, Internet techniques and big data analysis, which brought forth powerful quantitative models (particularly the AI technologies) [62]. Fourth, the massive proliferation of quantitative models in the Chinese academic community since 2012 (the year that China launched its ETS pilots) might also be a reason for the recent increase in the number of ETS modelling papers.

2.3 Spatial distribution

Thereafter, the scientometric analyses are conducted, which can provide some interesting information that cannot be derived from traditional statistical analysis. Fig. 1 provides the contribution network of countries or regions to the body of knowledge in ETS research using quantitative models, which is a useful scientometric method to discover the leading research countries and the associated international cooperation.

As for the leading countries, there are 33 nodes (corresponding to countries or regions) in Fig. 1, with the size proportional to the research contribution of the associated country or region (i.e., the proportion of the articles generated by the scholars in the associated country or region). The top contributors to ETS research using quantitative models include China (with 335 articles, representing 37.68% of the total articles), the USA (169 articles, 19.01%), Australia (50 articles, 5.62%), Germany (44 articles, 4.95%) and England (37 articles, 4.16%). The USA is a relatively early adopter of the ETS policy (introducing the cap-and-trade system to California in 2007 [63]) and has been a leading research contributor since the beginning of the related research (i.e., in 2000). In comparison, China is a relative latecomer to ETS (launching ETS pilots in 2013 [7] and a national market for the power sector in 2017) and quantitative research (beginning in 2009 [64]); however, China has experienced a quite rapid progress, overtaking other countries in the annual number of publications in 2013 and becoming the largest research contributor since then. Interestingly, different countries or regions have their own research focuses: for example, the scholars in New Zealand prioritized the agriculture and forestry sectors in the ETS market [63,65], those in Australia preferred the pricing mechanism [66-68] and those in the EU strived to build an integrated ETS market covering the involved countries (particularly the UK, Germany, Sweden and Austria) [55,69].

In terms of international cooperation, there are 71 links (connecting countries who collaborated in writing the associated articles) in the figure, with the colours indicating the years of the collaborating publication (see the corresponding legend at the top of the figure) [70]. It can be found that the earliest inter-country collaboration occurred between the USA and Germany in 2005 (light blue links), while the cooperative relationships among the top 10 influential countries become prosperous since 2008 (light green links). Furthermore, the thickness of a link indicates the strength of the cooperation (in terms of the total number of the mutual cooperations in writing papers). The analysis results reveal strong cooperative relationships (representing 41 collaborations) between Switzerland and France, Italy and France, Spain and Italy, and Netherlands and Germany. In contrast, Denmark and Scotland had no international cooperation in this research, which, in turn, substantially refrained their research contribution (both representing 0.2%).

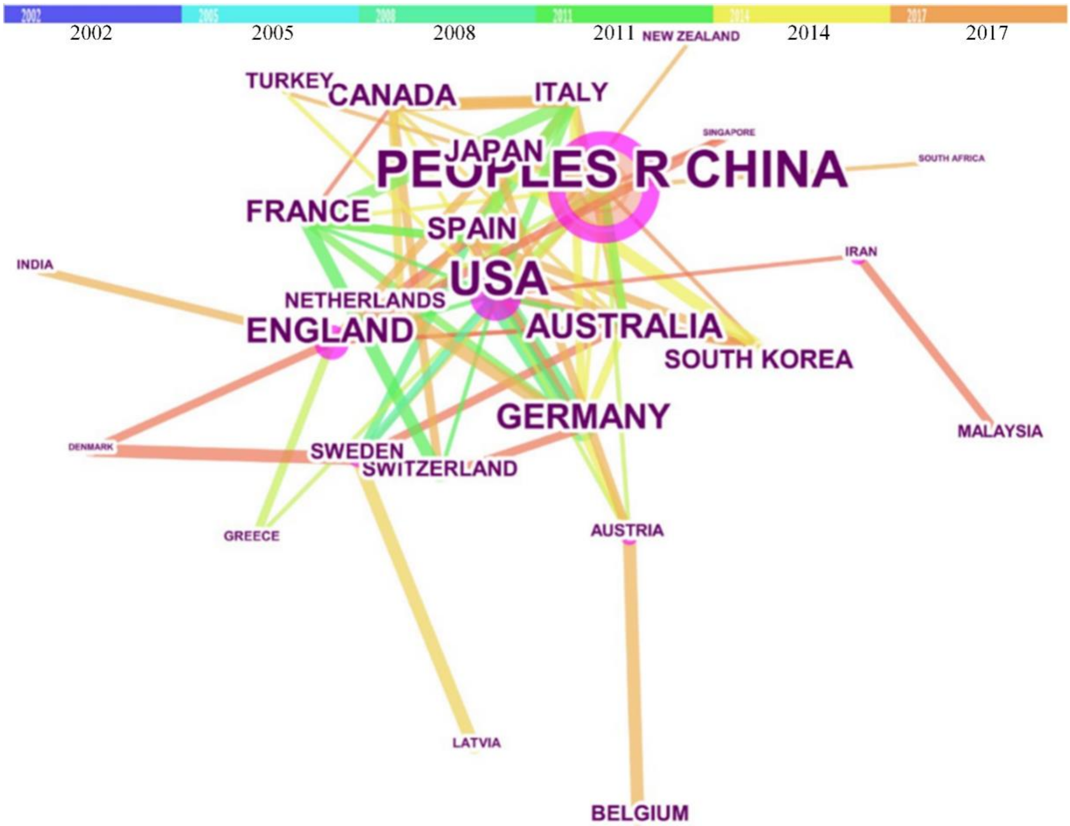

Fig. 1. Contribution network of countries or regions. The font size is proportional to the research contribution of the associated country or region (i.e., the proportion of the articles generated by their scholars) to the body of knowledge in ETS research using quantitative models. The links indicate the associated international cooperation between different countries or regions.

Fig. 2 reveals the spatial distribution of the ETS markets studied in the existing ETS-related articles using quantitative models, which is generally consistent with the above scientometric analysis on the spatial distribution of the research contribution (in Fig. 1). First, it can be obviously seen that all the 29 ETS markets throughout the world have been studied using quantitative models, while the related countries or regions hosting these ETS markets were all involved in the research contribution network (Fig. 1). Second, the ETS markets in the EU (i.e., EU ETS) and in China (i.e., the 7 provincial ETS pilots and the national market for the power sector) were research hotspots, which have been studied in 268 and 220 publications (representing 43.51% and 35.71% of the total), respectively. Associated host countries, e.g., China, Germany and England, were the top leading research contributors to ETS research via quantitative models. In contrast, some ETS markets in Greece, Canada, Turkey, etc. (all with 1 publication) have aroused the smallest attention, to which more attention can be taken in the future research [71]. Accordingly, these related countries have made a quite small contribution to the quantitative research for ETS, as shown in Fig. 1.

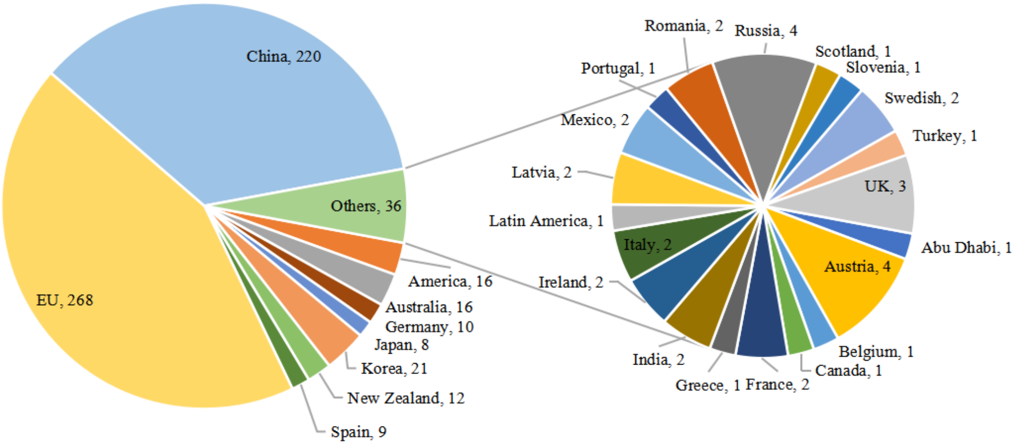

Fig. 2. Regional distribution of studied ETS markets. The numbers refer to the total number of articles using quantitative models to study ETS in the associated countries or regions.

2.4 Leading journals

A total of 391 journals have published articles applying quantitative models to analysing ETS. Fig. 3 presents a dual-map of these publications for identifying the leading journals and influential domains based on the co-citation relationships. In the figure, the colours differentiate different clusters which are grouped via the Blondel cluster algorithm [72]; the links connect the citing (i.e., the research front on the left) and cited clusters (i.e., the intellectual base on the right), and the thickness of the links indicates the z-score-scaled frequency of the citation [72].

Fig. 3 indicates that the leading journals in ETS research using quantitative models were *Energy Policy* (publishing a total of 255 articles), *Journal of Cleaner Production* (229 articles), *Applied Energy* (122 articles) and *Energy* (82 articles), jointly accounting for 86.32% of the total articles. Furthermore, these four journals are the top cited journals, having a relatively high co-citation frequency (1083 times altogether, representing 15.28% of the total citations).

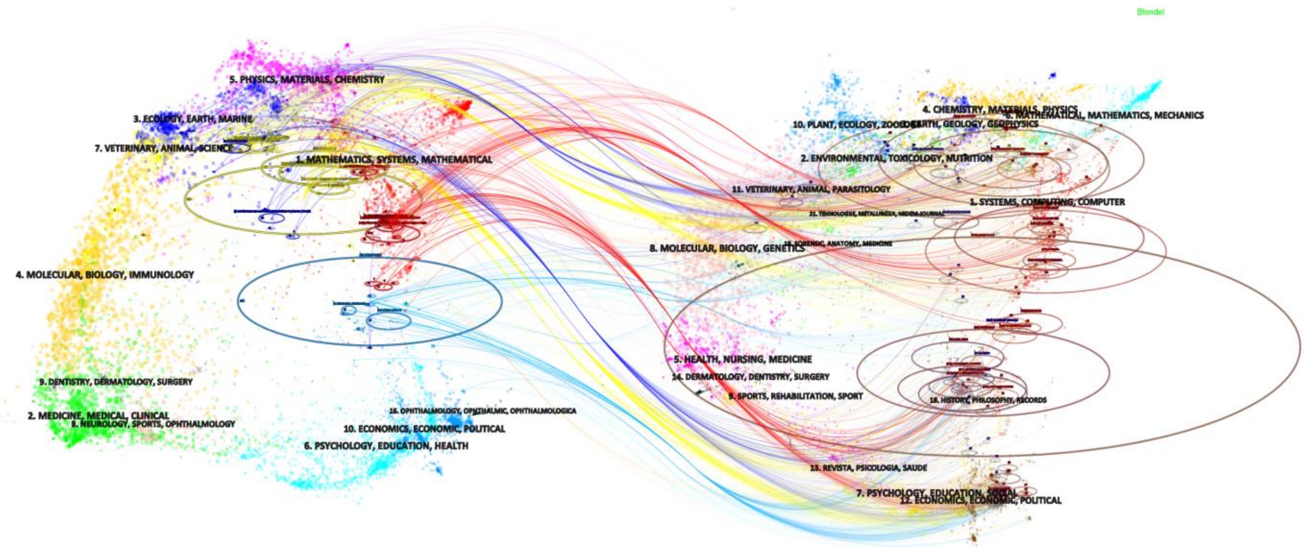

Fig. 3. Dual-map overlay of publications. The area dimension in the figure is proportional to the numbers of citing (on the left) and cited articles (on the right) in the associated journals.

Table 1. The top 10 journals in the citing and cited domains.

Rank	The citing journals (number of articles)	The cited journals (number of articles)
1	*Journal of Cleaner Production* (306)	*Energy Policy* (444)
2	*Energy Policy* (256)	*Energy Economics* (275)
3	*Applied Energy* (144)	*Applied Energy* (225)
4	*Energy* (99)	*Journal of Cleaner Production* (217)
5	*International Journal of Production Economics* (70)	*Energy* (197)
6	*Environmental Science & Technology* (52)	*Journal of Environmental Economics & Management* (196)
7	*Computers & Industrial Engineering* (47)	*European Journal of Operational Research* (196)
8	*Renewable & Sustainable Energy Reviews* (46)	*Climate Policy* (167)
9	*Energy Journal* (43)	*International Journal of Production Economics* (164)
10	*Energies* (41)	*Ecological Economics* (151)

2.5 Hot keywords

This section employs two effective scientometric measures for co-citation relationships and keyword co-occurrence analysis to capture the research hotspots in applying quantitative methods to ETS research, and finds that the terms regarding the types or features of ETS-related tasks and quantitative models have been identified as hot keyworks.

Based on the co-citation relationship, Fig. 3 also reveals that the existing ETS research using quantitative methods involves diverse research domains, and the top hotspots were ‘‘mathematics, systems, mathematical’’, which was largely influenced by the domain of ‘‘systems, computing, computer’’. These terms are all related to “models” or “quantitative analysis”, which are the searching keywords used to collect the articles. In particular, the identified keyword “systems” on both sides of the co-citation relationships implies that ETS has been consistently recognized as a typical system involving various interactive factors; “mathematics” and “mathematical” correspond to quantitative models based on mathematical theory and techniques; and “computer’’ and “computing” suggest an increasingly important role of computer science (i.e., AI techniques) in quantitative research for ETS.

Furthermore, the scientometric technique of keyword co-occurrence analysis is conducted to capture the research hotspots over time in ETS research using quantitative models [72]. Fig. 4 displays the keyword co-occurrence network, in which the keywords co-concurring above 9 times are shown and arranged by the frequency of occurrence. As for development trends, hot keywords were relatively few from 2002 to 2005 but largely increased since 2006, again implying growing interest in the quantitative analysis for ETS over time. Not surprisingly, the keywords “model” (113 times) and those pertaining to ETS (e.g., “emissions trading” (113 times), “emission trading scheme” (113 times) and “cap and trade” (97 times)) [69-73] are identified as hot keywords, given that they are the right searching keywords used to retrieve articles in this review.

The keyword co-occurrence analysis reveals the research hotspots of applying quantitative models to ETS research. As for the ETS-related tasks, the analysis results showed that quantitative methods have been popularly used to estimate the “impact” (85 times) and “performance” (43 times) of ETS policy and the associated “mitigation” (24 times) and effects on “climate change”, and to capture the complex relationships between the key factors in the ETS system, e.g., “emission” (70 times) or “carbon emission” (45 times), “reduction” (23 times), “permit” (25 times), “cost” (59 times), “demand” (25 times), “allowance” (39 times) and "supply chain" (40 times). As for quantitative analyses, the identified hot keyword of "optimization" (43 times) represents that the optimization model was a prevailing model in ETS research, and "uncertainty" (38 times) suggests that uncertainty control might be one challenge when modelling an ETS via quantitative models.

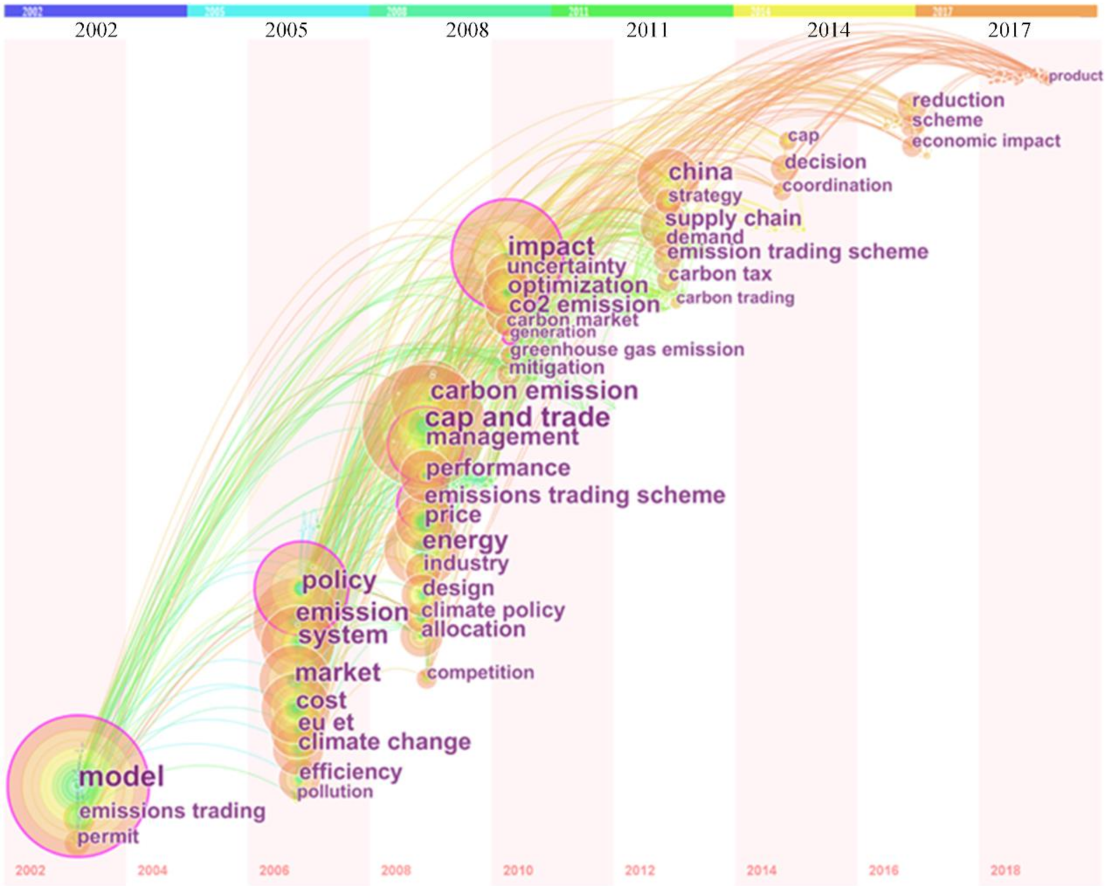

Fig. 4. A timezone view of keywords. The dimension of circles and the font size of keywords are proportional to the frequencies of keyword co-occurrences.

2.6 Practical implications of this study

With the boom in ETS, as the most effective mitigation tool, a variety of quantitative models have been employed to enrich and improve ETS research. This paper might be the first attempt to present a systematic literature review on full-scale types of quantitative models used in ETS literature. In particular, this review details what and how different quantitative models serve different agents to address their different ETS-related challenges, via a systematic analysis for each agent on (1) research hotspots, the challenges that the associated agents confronted; (2) quantitative models, the quantification tools that the associated agents can employ to solve the problems; (3) main findings, the policy implications that are recommended by existing quantitative research for the associated agents; and (4) future research, the problems that associated agents should still be concerned about in the future. Generally, major ETS-involved agents include the government (the ETS designer), enterprises (the ETS targets), third parties (the ETS regulator) and ETS markets (the ETS platform).

This review also provides insights into improving existing ETS research using quantitative models. On the one hand, the review details the special advantages of different models, which made different models dominating different ETS-related research hotspots. On the other hand, the review also points out the disadvantages of different models, which prevented them from being applied to some research hotpots, and further provides related suggestions to improve and extend the existing research.

3. Agent-specific analysis

The statistical analyses on the selected literature in Section 2 demonstrate that a variety of effective quantitative models have been and will still be introduced to help ETS-involved agents effectively carry out their respective ETS-related problems. Accordingly, this section presents a comprehensive review on the relationship across the three research attributes—agents, tasks (or hotspots) and models—as the analytical framework illustrated in Fig. 5.

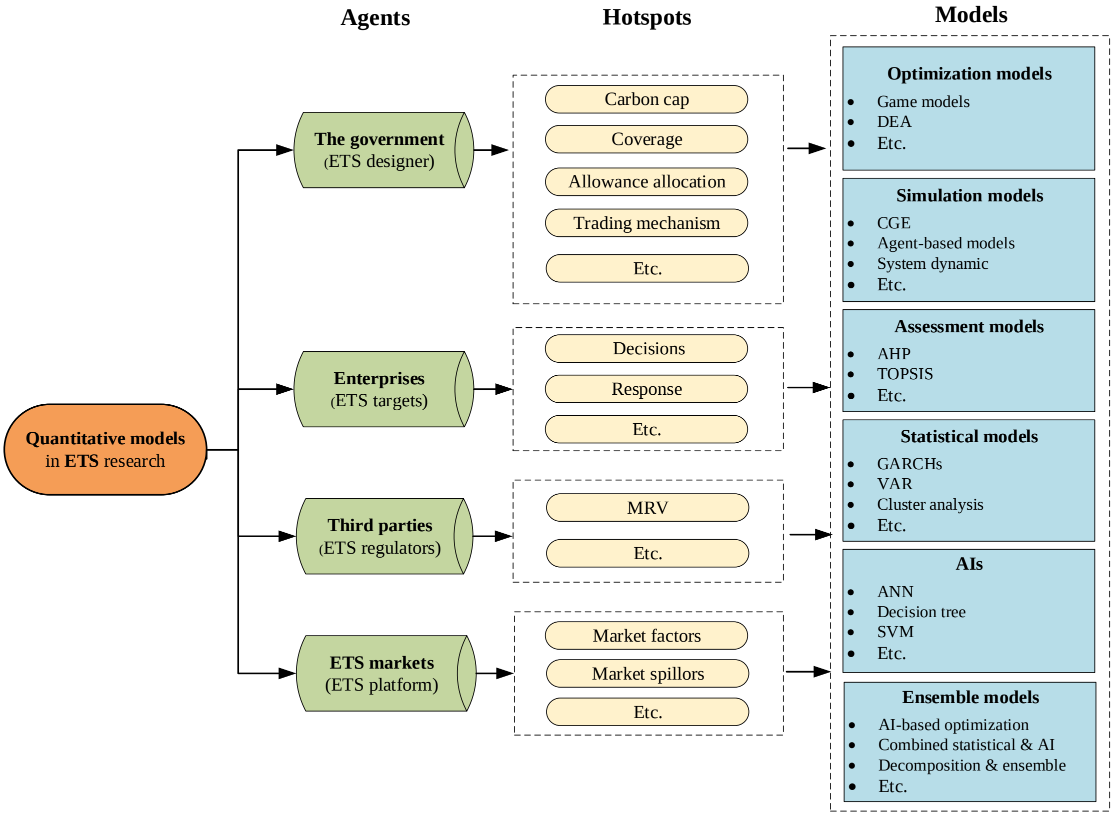

Fig. 5. General analytical framework of applying quantitative models to ETS research.

As for agents, the existing relevant literature mostly focused on four types of agents in the ETS system: the government (i.e., the ETS designer), enterprises (the ETS targets), third parties (the ETS regulators) and ETS market (the ETS platform). As for quantitative models, prevailing models for ETS research fall into six categories by quantification and solution: optimization models (game models [27,33], data envelopment analysis (DEA) [73-75], and other linear or nonlinear programming models [46,76]), simulation models (e.g., computable general equilibrium (CGE) [17-19], agent-based models (ABM) [1,5] and system dynamic (SD) models [25,48]), assessment models (e.g., analytic hierarchy process (AHP) [77-79], technique for order preference by similarity to an ideal solution (TOPSIS) method [80-82]), statistical models (e.g., difference in difference [83-85], GARCH processes [45,69], vector autoregressive (VAR) models [51,64]), AIs (e.g., artificial neural network (ANN) [54] decision tree (DT) [86-87], support vector machine (SVM) [26,44]) and ensemble models (e.g., AI-based optimization models [44,87], combined statistical and AI models [44,83] and decomposition and ensemble models [54]).

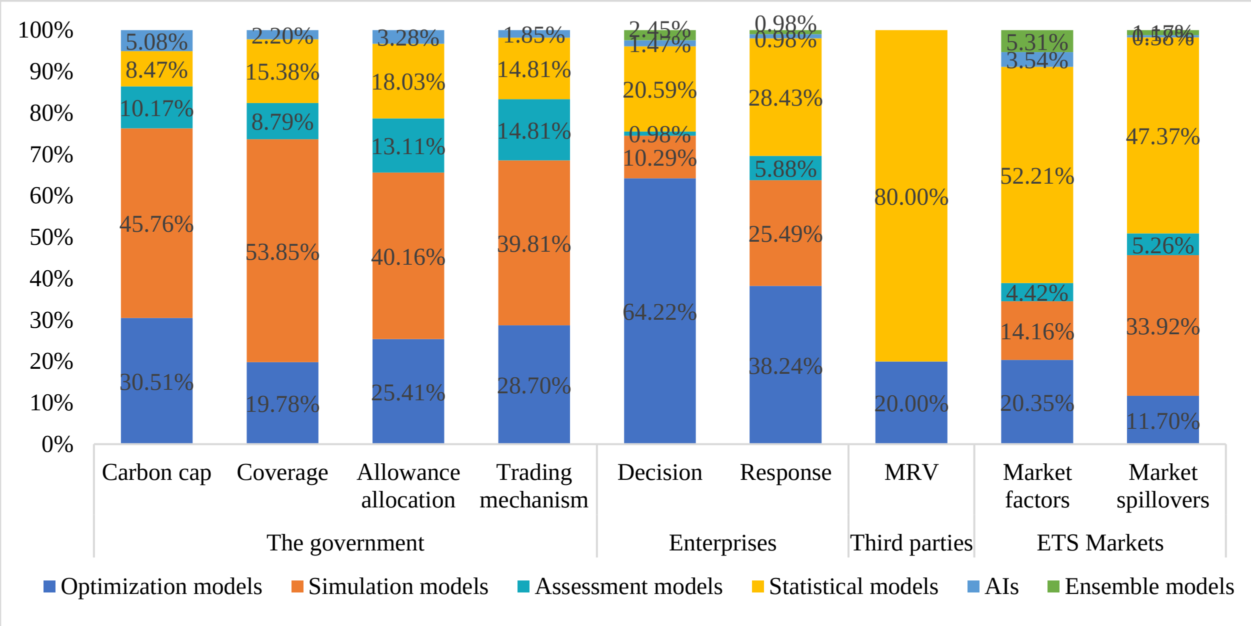

Fig. 6. Top research hotspots and the associated quantitative models for ETS-involved agents. The Y axis shows the contribution of different quantitative models used in each agent's research hotspots.

Fig. 6 further shows the top research hotspots and quantitative models for each agent. As for the government, simulation models (accounting for 44.21% of total associated studies for the government) and optimization models (25.79%) were popularly used to facilitate ETS design, with the hotspots of carbon cap for a region or firm (45.76% and 30.51%, respectively), regional or sectoral coverage (53.85% and 19.78%), allowance allocation (40.16% and 25.41%) and trading mechanism (39.81% and 28.70%). As for enterprises, optimization models (representing 55.56% of the associated articles) and statistical models (23.20%) were extensively employed to guide ETS-related decisions (64.22% and 20.59%, respectively) and the response policy to ETS (38.24% and 28.43%, respectively) for reducing the financial losses caused by ETS. As for third parties, statistical models dominate the related research (representing 80% of the associated articles), which have been employed to streamline the MRV work for accurately estimating the emission reduction and regulation costs. For ETS markets, statistical models (accounting for 49.30% of the associated articles) and simulation models (33.92%) were mostly used to capture the intrinsic relationship between the related market factors (52.21% and 14.16%, respectively), and the spillover effects between ETS and other goods markets (47.37% and 33.92%, respectively).

Accordingly, Sections 3.1-3.4 detail how different models have been used to serve the agents of the government, enterprises, third parties and ETS market, respectively. For each type of agent, a systematic analysis is conducted on research hotspots, quantitative models, main findings and future research.

3.1 The government

The government is the designer and supervisor of the ETS policy and responsible for designing and adjusting its specific rules and regulations, with each directly determining the final impacts [1]. Accordingly, a variety of quantitative models have been introduced to help the government to work out cost-effective designs for the key rules to guarantee the efficacy of ETS.

3.1.1 Research hotspots

The quantitative analyses on ETS design mostly focused on the carbon cap [10,11], coverage [12-16], allowance (or credit and permit) trading mechanism [13,28,35] and allowance allocation [1,17-19], which were consistently considered as the decisive components in the framework of an ETS policy [88-92].

(1) Carbon cap is mathematically defined as the total emissions allowed in an ETS or the total allowances supplied by the government. Existing quantitative analysis estimated its levels for different years or regions according to the targets for global warming control (e.g., those in the Paris Agreement) [93] or promises made in international conferences (e.g., organized by Intergovernmental Panel on Climate Change) [94], and then introduced these values as a constraint on the total emissions (or mitigation rates) [21] or a criterion to evaluate the performance of the ETS policy [89,90].

(2) Coverage defines an ETS system, i.e., which regions or sectors should be involved in the ETS policy. As for regional coverage, existing research has been continuously devoted to building an integrated global ETS market covering various countries [95,96], in a jurisdiction (i.e., the EU) covering the involved members [20] or in a nation (particular China [14,19,90] and the US [97]) covering different provinces or states, in which a variety of multi-region ETS models at the worldwide, international or nationwide levels, respectively, have been built [98,99]. As for sectoral coverage, existing research largely focused on energy- and emission-intensive sectors, such as the sectors of power generation [14,17,19], chemicals [17,19], nonmetal [14], construction [1,19], coal mining [1,14], metal smelting [14,17,19], and aviation [20].

(3) Allowance allocation is the crucial regulation in the primary ETS market, where initial allowances are allocated among different regions [21,89,100] and enterprises [1,17,19]. For regions, existing research attempted to explore a reasonable allocation method that well balanced fairness and efficiency, using different mathematical definitions for the two factors (based on regional information regarding emissions, production, economic development, technology progress, etc.) [21,100] and weight optimization methods (e.g., the Shapley value-based method [27]). For enterprises, existing quantitative research have extensively compared grandfathering methods (based on historical levels of emissions, emission intensity, production or technology for a firm) [22,100] versus benchmarking methods (considering the general levels for a whole sector) in allocating free allowances [17,19,22], and auction-style (e.g., using uniform or discriminative prices) versus fixed-price trading in the primary ETS markets.

(4) Trading mechanism determines the rules for enterprises to exchange allowances in the ETS market. As a research hotspot, multi-period [75] and multi-market models [95] have been built to investigate whether allowances can be traded across periods and markets, respectively, in order to enhance the flexibility of the ETS policy.

3.1.2 Quantitative models

To find optimal designs for the aforementioned issues, diverse quantitative models have been employed, as follows.

(1) Simulation models might be the dominant type of quantitative models facilitating ETS design, including CGE [14,17,19], ABM [1,100] and SD [31,48,89]. Generally, these simulation models explore effective ETS rules by following three major steps. First, macro-economic simulation models incorporated an ETS module [19,31] (or environmental policy module [14]) into economic modules (production module [19], trading module [17], consumption module [31,48] and income-expenditure module [88,89], etc.), to connect ETS factors (carbon cap [90], carbon price [14,17], free allowance quota [31,89], total allowance quota [89], allowance transaction [31,89], emission cost [17,19], etc.) to the related economic factors (carbon emissions [14,19], fossil combustion [14,19], commodity prices [31], costs [48], profits [89], etc.) for the involved sectors and regions. Second, a set of policy scenarios (with different rule candidates) were formulated and simulated fixing the related factors as exogenous variables or model parameters [1,14]. Third, the results for economic and environmental factors under different policy scenarios were comprehensively analysed and compared, to find optimal ones with effective mitigation and reasonable costs [1,90].

(2) Optimization models, e.g., DEA [20,21,75], game models [101-103] and other linear or nonlinear programming models [22,91], have been used to design different ETS rules. First, a series of DEA models have been built to allocate allowances across regions or sectors, in order to maximize desirable outputs (e.g., income [20], economic development [21] and gross domestic product (GDP) [75]) and minimize undesirable outputs (i.e., carbon emissions in an ETS [20,75]). Second, game models were used to describe the relationship between the conflicting agents of the government (the ETS supervisor attempting to reduce the emissions [101], which would increase enterprises' production costs [101]) and enterprises (the ETS targets aiming to reduce production cost [103] and increase profits [101-103]) under an ETS, to find a reasonable design for obtaining mutually satisfactory results (in terms of Nash equilibrium). Third, a variety of linear or nonlinear programming models have been built to find an optimal ETS-related rule (e.g., carbon cap [104]) to minimize the system cost [16,22] or maximize the profit [101,103], under given levels of emissions [91], technology [22], etc.

(3) Assessment models have been used to evaluate the performance of an existing ETS policy that has already been enforced, from the major perspectives of mitigation effect (with popular evaluation indicators regarding emission reduction [49,81,105], carbon intensity decline [80,81], energy technology updates [49,105], production structure improvement [50,106], etc.), cost-effectiveness (regarding emission costs [98], marginal mitigation cost [98,107], etc.), and political acceptability (regarding equity [49], flexibility [108], competitiveness [107], compliance [87,98], feasibility of implementation [80,105], etc.). Different techniques, such as the Wideband Delphi method [49,105], AHP [109] and Euclidean distance methods [80,81]), were used to determine the weights on the various evaluation indexes. The evaluation results for existing policies provide helpful insights for future policy.

(4) Statistical models, e.g., GARCHs [110] and other linear regression analyses [53,92], have been introduced to capture the relationship between the ETS rules (e.g., existence of ETS market [92], covered enterprise numbers [92] and free carbon allowances [92], as the explanatory variables) and the associated mitigating effect (emission reduction [92,111] as the

dependent variable), as well as the performance of ETS market (carbon prices [92,110] and volatility [97]). Furthermore, cluster analyses have been used to group various existing ETS markets with different policy designs into categories with similar features (e.g., GDP [54,109], carbon emissions [54,109] and carbon intensity [112]), providing policy implications for other markets based on their features.

(5) AI tools of ANNs [53] and DT [86] have been employed to forecast the future emissions for determining the carbon cap and allowance allocation for an ETS market.

3.1.3 Major findings

To select the most satisfactory designs, existing research has extensively compared different candidates in terms of their impacts on environmental or energy factors (carbon emissions [17,19,90], energy consumption [14,90], energy structure [90,100], technological improvement [17,31], etc.), economic factors (GDP [14,17,19], production outputs [14,19], welfare [14,19], employment [90], commodity prices [19], imports [14,90], exports [14], etc.) and ETS-related factors (carbon price [1,31], mitigation costs [14,100], allowance purchase [17], carbon market scale [17], etc.). Based on diverse models, existing research quantitatively confirmed the mitigating efficacy of the ETS policy and suggested constructing large-scale, compatible international or national ETS markets involving emission-intensive regions and sectors. However, there were few uniform agreements regarding a specific ETS rule. Taking allowance allocation methods as an example, Refs. [20,22] preferred benchmarking methods for free allowances due to their high mitigation effectiveness, Ref. [22] liked grandfathering methods due to their moderate financial cost, Refs. [89,100] preferred fixed-price trading in the primary ETS market due to simplicity, and Ref. [1] suggested auctions due to their flexibility.

3.1.4 Future research

Simulation models, optimization models and assessment models were the prevailing types of quantitative models for ETS design, while the emerging AI models were relatively few. However, with the boom in computer science, AI models have been shown to be effective in analysing various complex systems (e.g., energy market [113]). Therefore, introducing power AI tools to capture the nonlinear, complex relationship between different specific rules and the associated factors in an ETS system can be considered promising future research. Furthermore, different models have their own advantages and disadvantages. Taking simulation models for example, CGE and SD can effectively capture the macroscopic spillover effects across the ETS market and different commodity markets in a general equilibrium [54] and the relationship across different ETS-related factors with feedback loops [53], respectively; game models and ABM can vividly describe the microscopic activities of heterogeneous enterprises (e.g., carbon trading, technology improvement and carbon bidding) [86,113], which are the targets of an ETS policy. Therefore, a combination of different models to take advantage of their respective merits to address the weaknesses might be an interesting direction largely improving and extending the existing models for ETS.

3.2 Enterprises

Enterprises act as both direct targets by ETS and major sources of carbon emissions [28,29], with their emission reductions adding up to represent the final mitigating effect of ETS.

3.2.1 Research hotspots

Numerous models have been employed to help enterprises (1) make decisions for not only economic factors (regarding production quantity [28,114], energy consumption [115], inventory [116], commodity transaction [29,117], commodity price [29,116,117], etc.) but also ETS-related factors (allowance trading quantity [28,117], allowance bidding or selling price [28,116], technology investment for abatement [28,114], etc.), in order to minimize emissions cost (or quota) [114] or maximize economic profit [114,116]; and (2) study the potential response to ETS (with different levels of carbon allocation price [28,116], allowance allocation [28,29,112], etc.) in terms of changes in profit [28,112], intention to reduce emissions [32] and intention to adopt green technology [117], etc.

3.2.2 Quantitative models

Among various models, optimization models dominated the related research for serving enterprises in decision making, followed by statistical models for capturing the impact of ETS on individual enterprises, while AI models become a rising star in solving optimization models.

(1) Fruitful research using optimization models has been conducted to help enterprises make optimal decisions under ETS. In these optimization models, ETS-related decisions are treated as decision variables, e.g., allowance trading quantity [29,117], allowance bidding or selling price [28,116] and technology investment for abatement [28,114]. Furthermore, as a major agent in an economic system, the related economic activities (regarding production quantity [28,117], energy consumption [115], inventory [116], commodity transaction [29,117], commodity price [29,116,117], etc.) would be impacted by ETS and could also be carefully investigated as decision variables or model parameters. The optimization models were run to optimize their fitness minimizing emissions cost (or quota) [28,29,112] and maximizing profit [28,112]. Furthermore, some interesting game models have also been designed to capture the competition and conflict between different types of enterprises (e.g., manufacturers versus retailers [118] and enterprises versus banks [119-121]) when entering the new environment of ETS market. In addition, DEA has been used to help enterprises adapt to ETS and gain more expected outputs (e.g., profit [28,112] and production [29,114]) and less unexpected outputs (i.e., emissions [28,114,117]), at given levels of inputs or other attributes (e.g., employees [121], energy consumption [115], size [28,114] and costs [117]).

(2) Statistical models, particularly GARCHs [122-125] and other linear regressions, have been used to capture the relationship between different ETS-related factors (e.g., carbon allocation price [28,112] and carbon allowance quota [28,29,112]) and their financial factors (e.g., production [28,29,117,121], energy consumption [115], technology investment [117,126], profit [28,112]) and firm attributes (e.g., ownership [32,127], size [32], location [32] and age [32]). Such modelling can effectively capture the potential impacts of ETS on the firm's profit [128,129], price [129,130] and the intention of emissions reduction [129] and technology improvement [127,130].

(3) Simulation models serving enterprises under ETS mainly include CGE and input-output analysis. The CGE model introducing an ETS module (with the related factors of emissions cap [127,130], free quota [131], allowance purchase [132], carbon price [132,133], emissions cost [132,134], etc.) has been used to estimate the impacts of different ETS policies on the firm (in terms of profits [133], generation [133,134], costs [134], etc.). The input-output analyses have been used to describe the carbon footprint across sectors [134-136], to estimate total emission

costs [133,134] and to identify potential sellers and buyers in the ETS market [134].

(4) Interestingly, emerging AI optimization algorithms, e.g., particle swarm optimization [137] and genetic algorithms [138], have recently been introduced to solve the optimization models. Such an interesting idea brought about a promising type of quantitative model, i.e., AI-based optimization models, effectively searching optimal decisions using the powerful learning capability of computers and machines.

3.2.3 Major findings

Using different models, the existing quantitative analyses have provided generally similar suggestions for enterprises, even with different prioritizations or to different extents. On the one hand, existing literature strongly recommended enterprises to actively adjust themselves to ETS (in terms of voluntary emission reductions for credits [136,137], technology investment [121], clean technology adoption [5], energy structure improvement towards cleaner energy [133], etc.), as the top measure to preserve profitability in a long term, in view of the large benefit from selling excessive credits and reducing emission costs. On the other hand, different models consistently revealed a negative impact of ETS on highly energy- and emission-intensive enterprises [132-134], implying the efficacy of the ETS in improving both energy and production structures toward a cleaner economy in the future [133,134]. The existing quantitative models have and would help an increasing number of enterprises adapt themselves to the ETS and improve their technologies, adding up to an impressive mitigating effect at the macroscopic level.

3.2.4 Future research

Optimization models and statistical models were prevailing in existing ETS research for enterprises, effectively exploring ETS-related decisions and potential impacts, respectively. Interestingly, some powerful AI models have been incorporated to help optimization models search for optimal solutions [118,119]. With the boom in computer science and big data technologies, more powerful AI models have emerged and can also be introduced in ETS research to substantially improve decision optimization for enterprises and more effectively study the intrinsic linkage between ETS and enterprises.

3.3 Third parties

Third parties, i.e., independent audits, is the ETS regulator to verify the truthfulness of the emissions and emission reductions reported by an enterprise, and to supervise its compliance with ETS by controlling its emissions under the allowance quota. However, there were quite few quantitative analyses on third parties. The available research focused on MRV work, i.e., measuring, reporting and verifying the emissions from an enterprise. In particular, emissions or emission reductions were first estimated based on different methods, such as the Waxman-Markey standard [38], the EU ETS approach [38,40], the California cap-and-trade programme approach [38], and a method used in the Japanese Iron and Steel Federation [40], and then compared with the measuring data monitored by the Coriolis mass flowmeter [139] and continuous emission monitoring systems [40] or the fitted data by marginal abatement cost curves [38]. Due to the key role of third parties in an ETS, more powerful quantitative models apart from the above traditional statistical models are strongly recommended to streamline the MRV work for not only accurate estimates of emissions and emission reductions but also low regulation costs.

3.4 ETS markets

The ETS market is the platform or medium through which various ETS-involved agents (and the associated factors) interact with each other. Given that ETS is a market-driven policy and functions through market mechanism, a thorough understanding of the ETS market and its spillover on other goods markets can provide insightful implications to guarantee the efficacy.

3.4.1 Research hotspots

Existing research has built a great diversity of quantitative models to study factors in ETS market and the spillover effects between ETS and goods markets.

(1) Market factors in the ETS market mainly include carbon price [73], certified emission reduction (CER) price [51,73], futures [41,140], options [141], trading volumes [142], carbon price returns [142] and volatilities [142,143]. On the one hand, existing research has been devoted to capturing the dynamic trends of these market factors in the ETS market [51,64] and their relationships with each other (particularly carbon and CER prices [73]), which provides policy implications for both policy design [109,144] and investment decisions [145]. In addition, existing models have attempted to explore an effective pricing mechanism for ETS markets, exploring a reasonable carbon or CER price to balance the mitigation effect and financial costs of ETS policy [146,147].

(2) Market spillover between ETS and goods markets has been extensively studied. In particular, a rich group of quantitative analyses have been conducted to capture how the ETS market impacts and is impacted by different goods markets, especially for energy commodities (electricity [64,148], coal [149,150], solar electricity [151], wind electricity [151], etc.) and emissions-intensive commodities [152]. For each market, the key factors were introduced into quantitative models for analyses, including commodity prices [153,154], stock index [151], returns [51], volatility [39], sales [154], transaction volume [155], exports and imports [152], employment [156], generation [151], demand [157], etc.

3.4.2 Quantitative models

Relative to other agents, the diversity of proposed quantitative models was at a quite large level, particularly featuring a promising type of ensemble models (such as decomposition and ensemble models).

(1) Simulation models, particularly CGE [42,152,155], SD [158,159] and ABM [145,153], have been employed to explore the spillovers among ETS and different goods markets. In particular, CGE models, as a typical simulation model, have been used to capture the macroscopic relationship across ETS and goods markets under a general equilibrium, involving various ETS and economic factors [15,42,155]. SD models, based on feedback loops, have been formulated to describe the intrinsic relationship between the interactive factors in ETS and different goods markets [157,158]. ABM, a bottom-top simulation model, has not only vividly detailed the microscopic ETS-related activities in the ETS markets and economic activities in commodity markets for heterogeneous agents (i.e., generators [153], consumers [160], and operators [160]), but also captured the macroscopic impacts of all agents, which can help understand the market mechanism in an ETS market [145] and the spillovers between ETS and/or goods markets [160].

(2) For optimization models, some game models have been used to detail ETS-related and economic activities of various conflicting participants (i.e., heterogeneous enterprises) in the

ETS market [161] or goods market under an ETS [43,144] at a microscopic level, and to capture market trends [43] at a macroscopic level when all participants reach noninferior decisions in a Nash equilibrium.

(3) Both statistical and AI models have been introduced to extensively analyse factors in the ETS and goods markets. As for statistical models, timeseries models (e.g., autoregressive moving average model [97] and wavelet analysis [140]) have been used to capture and forecast the dynamic trends in carbon price [162], CER price [140] and their returns [140,162]; and multivariate models (e.g., VAR [51,142,149], GARCHs [143,156] and other regression analyses) have been used to capture the relationship between factors in ETS and goods markets. To address complexity and nonlinearity, increasing number of AI models have been introduced to model the factors in the ETS markets, such as extreme learning machine [44], SVM [44,87], DT [87] and deep learning [98].

(4) Interestingly, some ensemble models have recently emerged in modelling carbon price [44] and CER price [44], with decomposition and ensemble models being a promising case, with three steps. First, the complex carbon price is decomposed into simple components at different time scales, via a multi-scale analysis (e.g., wavelet analysis [163] and empirical mode decomposition (EMD) [44]). Second, a statistical (e.g., clustering analysis [44]) or AI model (e.g., extreme learning machine [44,163]) is employed to model the components at different scales individually. Third, the individual results at different scales are integrated into the final outputs.

3.4.3 General findings

Different quantitative models have consistently revealed the high-level complexity and nonlinearity feature of the ETS market, and the strong, large-scale and intrinsic spillover effect between the ETS and goods markets. In particular, simulation models found that a change in carbon price would directly impact fossil energy demand and highly emission-intensive production, and further influence all other goods markets; the complexity of the ETS market lies in the existence of numerous competing and conflicting interactive agents, which was the top challenge in modelling ETS market. Due to such complexity, linear statistical models have been shown to be ineffective in modelling ETS-related factors, while nonlinear AI tools have become increasingly popular. Nevertheless, a new type of ensemble models, i.e., decomposition & ensemble models, was recently proposed based on the idea of “divide and conquer”. In a decomposition & ensemble model, the complex ETS factors (e.g., carbon price) are first decomposed into relatively simple components at different time scales (or frequencies), via a multi-scale analysis (e.g., wavelet analysis and EMD); then, a statistical or AI model is employed to individually analyse each component; finally, the individual results are integrated into the final outputs. This design can substantially reduce the modelling difficulty by decomposing the complex system of ETS market into relatively simple components that can be easily modelled.

3.4.4 Future research

The diversity of proposed quantitative models for ETS market was large relative to other agents. A variety of simulation models, optimization models, statistical models and AI models have been built to model the ETS market from different perspectives. However, these above traditional models found it challenging to capture the nonlinearity and complexity of the ETS system. Accordingly, a promising style of ensemble models, i.e., decomposition and ensemble models, have recently emerged as a rising star largely reducing the modelling difficulty. Actually, such an interesting idea of decomposition and ensemble has been fully proven effective in addressing different complex systems (e.g., energy market [43]), in which powerful variants using other competitive decomposition (e.g., ensemble EMD [164,165]) and modelling techniques (e.g., deep learning [166,167]) have been proposed. Therefore, extending such a promising type of models might be an interesting direction for ETS modelling in the future.

4. Conclusions

Given that ETS is typical complex system, a variety of quantitative models have been applied to analyse it, offering specific (quantitative) implications for the ETS-involved agents to resolve their respective ETS-related challenges. This paper is the first attempt to review full-scale types of quantitative models used in ETS literature, aiming at detailing how different types of quantitative models serve each type of agents involved in an ETS system. In particular, diverse agents involved in ETS are considered, and for each agent, a systematic analysis is conducted on the research hotspots (ETS-related challenges), quantitative models (how to address the problems), main findings (policy implications) and future research (potential improvements). As shown by both descriptive and scientometric statistics, an increasing number of quantitative models have been proposed to help ETS-involved agents effectively carry out their respective ETS-related problems, including the government (i.e., the ETS designer), enterprises (the ETS targets), third parties (the ETS regulator) and ETS markets (the ETS platform). Interestingly, the results reveal the key role of China in ETS research using quantitative models: China was the largest contributor to ETS research using quantitative models (representing 37.68% of the total articles), and Chinese ETS markets ranked 2nd in the top research hotspots (28% of the total articles).

For a clear understanding, the main features of different models in ETS research are extracted and compared, i.e., the key components (e.g., model variables, parameters and data), model outputs, hotspots, advantages and disadvantages, as shown in Table 2. Popular models for ETS research can fall into six categories, which are different from other each with distinct strategies of quantifications (how to describe an ETS system via different model components; see the 2nd column of Table 2) and solutions (the methods or criteria to determine the optimal results; 3rd row). Optimization models (with popular models of DEA, game model, programming model, etc. in ETS research) optimize ETS-related decisions for the best fitness (e.g., maximal profits, minimal mitigation costs and maximal mitigation effect), using fitness functions, decision variables and constraints as the key components to reflect the related targets, ETS-related decisions and the rules in an ETS, respectively. Simulation models (e.g., CGE, ABM and SD) simulate the potential impacts of candidate ETS-related policies and determine a satisfactory one with agreeable results. Generally, a simulation model involves a set of modules to describe the economic, environmental and ETS systems, uses a social accounting matrix and the related economic or environmental data as the model input to train the model, and reruns the model under a series of policy scenarios with different ETS designs to estimate the associated impacts in terms of changes in results. Assessment models (e.g., AHP, TOPSIS and life cycle approach) evaluate the efficacy of an existing ETS policy, with scores, indicators and weights as the key components to quantify such efficacy, the factors associated and importance of a factor, respectively. Statistical models (e.g., VAR, GARCH, etc.) investigate the profound relationships (in terms of model parameters) across various factors (in terms of dependent and independent variables) in ETS in a relatively simple (usually linear) form, using statistical methods (such as least square estimation) to estimate the model parameters. AIs (e.g., ANN, DT and SVM) aim to capture the underlying mechanisms of an ETS system similarly to statistical models, but use a relatively complex structure to capture the nonlinear relationship of factors and iterative training to estimate model parameters rather than a statistical method. Ensemble models combine a series of individual models (any of the above categories) in a given framework (i.e., ensemble strategy). Three types of ensemble models were popularly used in ETS research, i.e., AI-based optimization models (incorporating AIs into optimization models for searching optimal solutions), combined statistical & AI models (using statistical and AI models to analyse the ETS system), and decomposition & ensemble models (decomposing the complicated ETS system into relatively simple subsystems, analysing each subsystem individually, and combining the individual results into the final results).

Each type of quantitative models has its own advantages and disadvantages (see the last two columns in Table 2), which determines their dominance in research areas for ETS modelling (see the 4th column of Table 2). To find optimal ETS-related decisions or policy designs, optimization models, simulation models and assessment models were popularly used, even from different analysis perspectives. Generally, optimization models hold a relatively flexible, simple framework, using the basic components of fitness, decision variables and constraints to quantify the targets (what to do), solutions (how to do) and rules (to be followed when doing) of any ETS-related problems. Due to the instinct virtues of flexibility, simplicity and universality, optimization models were the most popular models in ETS research, particularly helping enterprises make different ETS-related decisions (for production, sales, investments, technology updating, ETS trading, etc.) and the government to design ETS policies (e.g., for allowance allocation). As a basic model, optimization models can be extended into other models, for example, CGE model (introducing various economic and ETS-related factors as decision variables and determining their relationships based on the theories of economics and energy economics) and some AI models (with the fitness of minimal estimation errors in describing an ETS system). However, effectively and correctly finding a global optimum is still a difficult problem for an optimization model, as these often fall into local optima.

Simulation models and assessment models find optimal ETS decisions or designs from opposite analysis perspectives (i.e., through *ex-ante* and *ex-post* analyses, respectively), which make them dominate different ETS policies (i.e., policy candidates that have not yet been implemented and existing policies that have already been implemented, respectively). Furthermore, simulation models and assessment models are formulated on different bases, primarily relying on a systematic theory that has been sufficiently studied (e.g., economics for CGE and dynamics for SD) and individual knowledge from certain experts, respectively. Therefore, they have different disadvantages: simulation models often suffer from the local optimum and parameter sensitivity and are time-consuming when introducing too many associated factors and parameters; assessment models are often criticized for subjectivity, particularly in determining evaluation indicators and their weights.

To understand the complicated structure of ETS system, statistical models and AI models have been proven effective, even using different fitting equations and estimation methods. Statistical models describe the relationship of ETS-related factors in a direct, simple (usually linear) form and estimate the related parameters using statistical methods (such as least squares estimation), with the virtues of interpretability and simplicity in operation; however, they often appear to be at a relatively low level of estimation accuracy, exactly due to such a simple, fixed structure and the associated data assumptions (e.g., linearity and stationary), which contradict reality. Against this background, a variety of AIs have been proposed and become increasingly prevalent due to their high accuracy, which utilize a relatively complex, flexible structure to capture the nonlinearity and complexity of ETS systems and powerful computer learning ability to train the model. However, this complex structure, in most cases with too many parameters, in turn, makes AIs suffer from the weaknesses of interpretability, parameter sensitivity and instability (attributable to many random model parameters).

In view of different strengths and weaknesses for different models, ensemble models have emerged and become a rising star in ETS research, aiming at combining a set of models to take advantage of their respective advantages to complement the disadvantages. For example, some studies using AI searching algorithms (e.g., genetic algorithm and particle swarm optimization) help optimization models effectively find optimal solutions, forming AI-based optimization models. Some studies used both statistical models (e.g., K-means clustering and regression models) and AI (e.g., error back propagation and extreme learning machines) to analyse the ETS system, forming combined statistical & AI models that can take full advantage of the interpretability and simplicity of statistical models (for rapidly determining the main factors, capturing the linearity components, etc.) and the high accuracy of AIs (for enhancing the accuracy, working out the nonlinearity and complexity components, etc.). To address the complexity of ETS systems, a new type of ensemble models, i.e., decomposition & ensemble models, was recently proposed based on the idea of "divide and conquer". In a decomposition & ensemble model, the complex ETS factors (e.g., carbon price) are first decomposed into relatively simple components at different time scales (or frequencies), via a multi-scale analysis (e.g., wavelet analysis and EMD); then, a statistical or AI model is employed to individually analyse each component; finally, the individual results are integrated into the final outputs. However, due to the involvement of too many parameters for both individual models and their linkages, ensemble models severely suffer from parameter sensitivity, high time consumption and the possible multiplication of model vulnerabilities if not organized properly. Due to these weaknesses, ensemble models have been relatively few used in existing ETS research.

Even with the considerable applications and innovations, there still exists much room to develop ETS research using quantitative models. Quantitative models have effectively helped enterprises make optimal ETS-related decisions and the government design ETS mechanisms, and captured the complex structure of an ETS market; nevertheless, there are quite few quantitative analyses facilitating MRV work for third parties. However, due to the key role of third parties in an ETS (i.e., supervising the compliance performance of enterprises and guaranteeing the final mitigation effect), more powerful quantitative models apart from traditional statistical models are strongly recommended to streamline the MRV work for not only accurate estimates of emissions and emission reductions but also reduced regulation costs. Though dominant in analysing other energy systems, AI models appear to be quite insufficient for the ETS system relative to statistical models. However, statistical models, holding strong data assumptions (e.g., linearity and stationarity which contradict reality), have been shown at a low accuracy level; therefore, introducing various powerful AI tools is an interesting direction for future ETS research, which can effectively capture the complexity and nonlinearity of ETS systems with the help of flexible structures and powerful computer learning capability. Most importantly, in view of different strengths and weaknesses of different models, ensemble models, based on the interesting idea of combining a series of models to take advantage of their respective merits to address the weaknesses, might be a rising star in ETS research. For example, simulation models and assessment models, from opposite perspectives (i.e., *ex-ante* and *ex-post* analyses, respectively) and based on different foundations (i.e., relatively mature theories and subjective expert opinions), are exactly complementary to each other; therefore, their combination can provide comprehensive results for optimal ETS-related decisions and policy designs. Furthermore, statistical and AI models can also be finely coupled, with the latter enhancing the accuracy of the former and, in turn, with the former improving the interpretability of the latter. However, due to the possible multiplication of model vulnerabilities, ensemble models should be carefully designed, particularly balancing model complexity and results improvement.

Table 2. Comparison among different types of quantitative models in ETS research.

	Model type	Model components (for ETS-problem quantification)	Model outputs	Hotspots	Advantages	Disadvantages
1	**Optimization models** (DEA, game model, programming model, etc.)	- **Fitness function**: maximal profit, minimal mitigation cost, maximal mitigation effect, etc. - **Variables**: ETS-related decisions or policy designs - **Constraints**: reflecting rules in an ETS, relationship of agents and their factors, etc.	Optimal ETS-related decisions (with the best fitness)	- **Enterprise**: ETS-related decisions and response to ETS. - **Government**: allowance allocation	Flexibility; Simplicity; Universality	Local optima
2	**Simulation models** (CGE, ABM, SD, etc.)	- **Modules** of economy (production, trading, income, savings, investments, etc.), environment and ETS - **Data**: social accounting matrix; economic or environmental data - **Parameters**: reflecting relationship between factors and structure of the system - **Policy scenario**: ETS design candidates	Optimal ETS designs (with agreeable economic and environmental impacts)	- **Government**: ETS design	*Ex-ante* analysis of candidate ETS; Incorporating relatively mature theories	Local optima; Low accuracy
3	**Assessment models** (AHP, TOPSIS, life cycle approach, etc.)	- **Scores**: a combination of targets (regarding equity, effectiveness, flexibility, costs, etc.) - **Indicators**: factors reflecting targets - **Weights**: importance of a target or factor against others	Optimal ETS policy (with the highest scores)	- **Government:** efficacy of an ETS	*Ex-post* analysis of existing ETS; Incorporating expert knowledge;	Subjectivity
4	**Statistical models** (VAR, difference in difference, GARCH, etc.)	- **Dependent variables**: the targeted factors - **Independent variables**: the related factors - **Parameters**: reflecting relationship between factors - **Data**: historical observations of factors	Prediction and relationship of ETS-related factors (via least square estimation)	- **Market**: relationship of ETS-related factors; spillovers of ETS and other markets	Interpretability; Simplicity	Strong data assumptions; Fixed structures; Low accuracy
5	**AIs** (ANN, DT, SVM, etc.)	- **Dependent variables**: the targeted factors - **Independent variables**: the related factors - **Data**: historical observations of different market factors - **Parameters**: reflecting relationship between factors or determining training rules - **Data**: historical observations of factors	Prediction for ETS-related factors (via iterative training)	- **Market**: prediction	Without strong data assumptions; Flexibility; High accuracy	Weak interpretability; Parameter sensitivity; Instability
6	**Ensemble models** (combining any models of the above categories)	- **Individual models**: any of the above categories - **Ensemble strategy**: linkage of individual models and combination of individual results	Optimal ETS-related decisions or designs; ETS market prediction	- **Enterprises:** ETS-related decision making - **Market:** ETS-related factor prediction	Universality; Flexibility; High accuracy	Complexity; Time-consuming; Multiplication of models' vulnerabilities

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