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An Experimental Study on Emission Trading Behaviors of Generation Companies

Jie Huang, *Member, IEEE*, Yusheng Xue, *Member, IEEE*, Chao Jiang, Fushuan Wen, Feng Xue, *Senior Member, IEEE*, Ke Meng, *Member, IEEE*, and Zhao Yang Dong, *Senior Member, IEEE*

***Abstract*—The overall performance of emission trading (ET), a market-based emission regulation tool, strongly relies on participants' participation and responses. In order to improve market design, it is important for policy makers to understand the participants' trading behaviors in different market environments. However, human behaviors cannot be easily modeled with conventional analytical methods due to its "bounded rationality" characteristics. In this paper, based on the complementary features between experimental and agent-based computational methods, a hybrid interactive simulation methodology is proposed to solve human behaviors related problems. Human-subjected experiment based on European Union Emissions Trading System price data in 2006 is conducted, the results show that there is no fixed emission trading interval for generation companies, and the strategic behaviors of market participants are observed. Major driving factors of emission trading are categorized into emission price, emission quantity and time related factors, which are in accordance with empirical analysis results on EU ETS 2005–2006 transaction dataset. Furthermore, more human-subjected experiments are conducted under different emission price scenarios to obtain samples for quantitative analysis. Based on thousands of samples obtained, the joint influences of driving factors on emission trading behaviors are analyzed. The quantitative analysis results obtained can reflect the trading patterns of human participants, which provide basis for constructing computer agents that can act as useful substitutes for human participants.**

***Index Terms*—Bounded rationality, decision making, emission trading, experimental economics, generation company.**

I. Introduction

THE exhaustion of fossil fuels and the climate change have brought intensive attention to energy conservation and emission reduction. emission trading (ET) has been widely adopted by policy makers around the world, which deals with environmental externality by defining property right and market based mechanisms. The ongoing ET schemes include the European Union Emissions Trading System (EU ETS), the Australian Emissions Trading System, the New Zealand Emissions Trading System, the Regional Greenhouse Gas Initiative (RGGI), the California Emissions Trading System, and the Tokyo Emissions Trading System (Tokyo ETS), etc. [1].

China is also making great efforts to mitigate energy exhaustion and climate change. The State Council of China issued the Comprehensive Work Plan for Conserving Energy and Reducing Emissions and the Work Plan for Controlling Greenhouse Gas Emissions for the "Twelfth Five-Year" Plan period in August 31, 2011 and December 1, 2011, consecutively. The Chinese government plans to reduce the CO_2 emission intensity per unit of GDP by 17% at the end of the "Twelfth Five-Year" Plan period, and reduce about 45% emission intensity by 2020. The establishment of emission market is explicitly stated in these plans as well. Until now, the pilot carbon emission trading scheme mentioned in the National "Twelfth Five-Year Plan" has been launched in two provinces (Hubei and Guangdong) and five cities (Beijing, Tianjin, Shanghai, Chongqing, and Shenzhen). The first trades in these pilot schemes took place in September 2012, when four cement-manufacturing companies in Guangdong province invested millions of dollars each in carbon-pollution permits to expand operations [2].

As an important part of energy industry and also an intense emission source, the electricity sector is key to tackling climate change. The implementation of ET and other emission regulation measures will impose impacts on the electricity sector. Generation companies (GenCos) are therefore the major participants of ET.

As a special commodity, the exchange of electricity is constrained by the physical characteristics of power systems. Making trading strategies in multi-level electricity markets with the physical constraints is already a very challenging task for GenCos. ET will introduce additional constraints, trading market and control variable to the GenCos' portfolio optimization problem, which makes the existing challenges even more complex. GenCos will have to make more flexible multi-market trading strategies considering multi-market price dynamics, to maximize their profits. Clear insights of the GenCos' trading behaviors in different ET environments, can not only help new entrants to understand the operation mechanism of emission trading, but also help policy makers to design more incentively compatible emission markets.

Manuscript received February 27, 2014; revised July 11, 2014 and September 21, 2014; accepted October 28, 2014. This work was supported in part by State Grid Corporation of China (Fundamental and Prospective Project: Risk Analysis and Control of Power System Reliability under Emission Reduction Environment), and in part by Project 51307153 supported by National Natural Science Foundation of China (NSFC). Paper no. TPWRS-00285-2014.

J. Huang, Y. Xue, and F. Xue are with State Grid EPRI, Nanjing, China (e-mail: huangjie1@sgepri.sgcc.com.cn; xueyusheng@sgepri.sgcc.com.cn; xue-feng@sgepri.sgcc.com.cn).

C. Jiang is with Nanjing University of Science & Technology, Nanjing, China (e-mail: jiangchao1@sgepri.sgcc.com.cn).

F. Wen is with Zhejiang University, Hangzhou, China (e-mail: fushuan.wen@gmail.com).

K. Meng is with the Centre for Intelligent Electricity Networks (CIEN), The University of Newcastle, Callaghan, Australia (e-mail: ke.meng@newcastle.edu.au).

Z. Y. Dong is with the School of Electrical and Information Engineering, The University of Sydney, Sydney, Australia (e-mail: joe.dong@sydney.edu.au).

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Digital Object Identifier 10.1109/TPWRS.2014.2366767

This rest of the paper is organized as follows. In Section II, existing modeling methods are summarized and compared. A hybrid interactive simulation methodology is proposed in Section III. In Sections IV and V, human-subjected experiments are conducted to study the trading strategies of GenCos in emission market using the EU ETS 2006 price data and random generated price scenarios, and quantitative analysis results are provided. Discussions and further research suggestions are given in the last section.

II. Existing Modeling Methods of GenCos' Emission Trading Behavior

In the context of emission regulation, GenCos will make decisions in both electricity market and emission market to maximize their overall profits as in (1). Here, q_t and $q_{e,t}$ are the trading volumes in electricity and emission market, p_t and $p_{e,t}$ are market prices:

$$\max \quad \sum_{t=1}^{T} q_t p_t + \sum_{t=1}^{T} q_{e,t} p_{e,t} \tag{1}$$

$$\text{s.t.}$$

$$\underline{q}_t \le q_t \le \bar{q}_t \tag{1a}$$

$$\sum_{t=1}^{T} \gamma_{e,t} q_t \le \sum_{t=0}^{T} q_{e,t}. \tag{1b}$$

Transmission constraint can be reflected in the electricity price p_t by solving optimal power flow. Here, (1a) is the technical constraint of generation units, where $\underline{q}_t$ and $\bar{q}_t$ are the lower and upper bounds of generation output. (1b) is the emission constraint, which is a flexible constraint that do not have to be met at any moment. GenCos only have to hold enough emission allowances before the end of compliance period T. In (1b), $\gamma_{e,i}$ is the emission rate, $q_{e,t}$ is emission trading volume at time t, and $q_{e,0}$ refers to the initial free emission allowance allocation.

The compliance period of emission regulation is one or two years in most ETS, thus emission trading strategies can be flexible for GenCos, who can take advantages of this flexible constraint to make coordinated trading strategies between electricity and emission market, to maximize their overall profit in multi-markets.

Existing modeling methods for GenCos' decision making in emission market include optimization, game equilibrium and simulation models. However, uncertainties in different markets, constraints of different time-scales, along with market participants' subjective behaviors that are sensitive to market condition variations, have made it difficult to build effective mathematical models.

A. Optimization Models

Optimization models are formulated as an optimization program in which single firm pursues maximum profit or minimum cost [3]. In [4] the impact of emission cost on generation scheduling is studied by multi-period stochastic optimization. In [5] a GenCo's trading strategies in electricity, fuel and emission markets are studied using fuzzy differential evolution algorithm. In [6], a profit maximization model of CO_2 capture power plant (CCPP) is derived in the context of a cap-and-trade carbon emission market, which can support the decision making of power production and CO_2 capture schedules. In [7], an information gap decision theory (IGDT) based analytical approach is proposed to obtain GenCo's trading position in fuel, emission and electricity markets, which considers uncertainty in prices of electricity, congestion, fuel and emission permits.

The optimized strategies are obtained through mathematical derivations. Usually, strong assumptions are made in order to obtain analytical solutions. The key issues in optimization models are price forecasting and prediction of competitors' behaviors [8].

B. Equilibrium Models

Equilibrium models focus on multi-participants game equilibrium solutions based on game theory. Popular equilibrium models include Bertrand, Cournot, Stackelberg, supply function equilibrium, etc. In [9] equilibrium model is adopted to focus on the analysis of ETS impacts on the entire market function rather than on an individual company. In [10], an electric power supply chain equilibrium model which incorporates fuel, power and emission trading market is proposed, the effects of emission trading, renewable energy generation and congestion on equilibrium solutions are studied.

C. Simulation Models

Agent-based computational economics (ACE) has been widely used to study electricity markets, as well as the GenCos' emission trading strategies [11]. GenCos are modeled as adaptive learning agents by reinforcement learning algorithms to participate in electricity market and emission market in [12], [13]. For the purpose of simplification, the large time-scale and flexible emission constraint is converted to several small time-scale constraints, GenCos will balance their emission on daily [12] or weekly [13] basis.

The development of experimental economics provided new methodologies to address economics problems [14]. By setting up mathematical models of objective modules to act as experiment environment, the subjective behaviors of human participants can interact with the objective mathematical models as model inputs [15].

III. Hybrid Interactive Simulation Methodology

A. Generalized Congestions and Multi-Side Gaming

The power industries nowadays are facing more challenges from external domains such as emission regulation, primary energy supplies, natural disasters, and etc. In order to unify the research of both internal and external factors affecting the operations of electricity sector, a novel concept of generalized congestions (GCs) is proposed in [16]. The congestion concept in conventional sense incurred by transmission constraint is expanded to include other factors that could obstruct the energy flows, such as environment, energy quality, primary energy, regulation, etc.

Emission trading is a typical regulation measure of GenCos' social responsibility on environmental protection, which introduces external generalized congestion, while the regulation of power market introduce internal generalized congestion. As can

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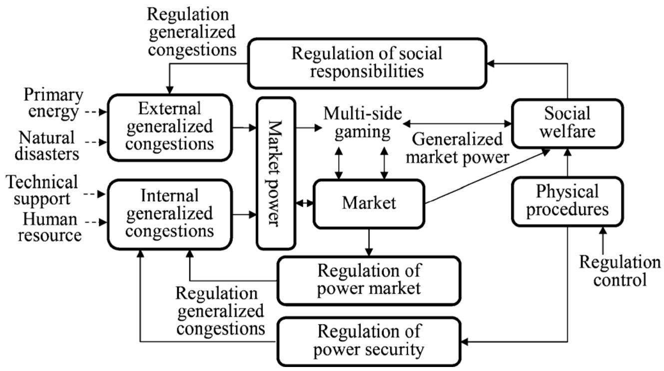

Fig. 1. Interactions among generalized congestions, market power, and generalized market power.

be seen in Fig. 1, both internal and external GCs will influence market efficiency and social welfare through the multi-side gaming of market participants. So the priority issue in GCs research is to understand the strategic behaviors of market participants under different GCs.

A novel research tool Dynamic Simulation platform for Power Market and Power System (DSPMPS) has been designed and developed [17] by our research team for GCs related researches, which supports experimental economic based cross domain dynamic interactive simulation and coordinate system dynamics with different time-scales, including emission trading, power system, and power market operation.

B. Hybrid Interactive Simulation Method

In power system analysis, mathematical models of physical components will be formulated for numerical simulation. Based on simulation results, in-depth knowledge will be extracted, providing decision support for both power system operation and planning. The decision-making behavior of participants in economic activities, in the same sense, can be considered as special "components" with subjective characteristics of human beings. However, these "components" are difficult to model mathematically.

Experimental economics is a useful methodology to study human behaviors and emerging market effects under a controlled experiment environment, which can act as a beneficial supplement to existing research method. However, experimental economics still leave much to be desired. Among others, it is not easy to have enough qualified human participants to conduct large-scale and repetitive experiments, and for those long-term experiments with frequent small time-scale decisions to make, experiments with human participant may be time-consuming. Therefore, it is necessary to adopt other research methods as supplements.

In fact, the relationship between experimental and agent-based computational methods are complementary rather than mutual exclusive. In order to exploit the complementary characteristics among different research methods, a hybrid interactive simulation research method is proposed in this paper (as in Fig. 2).

The basic idea behind this hybrid method is using human-subjected experiments, combined with the exploitation of existing

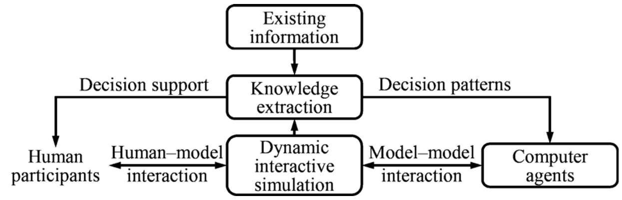

Fig. 2. Proposed hybrid interactive simulation method.

TABLE I
PARAMETERS OF DIFFERENT GENCOS

GenCos	Units	Installed Capacity (MW)	Fuel Cost (€/MWh)	Emission Rate (t/MWh)
RENEWABLE	BIO	80×6	60.0	0.00
	WIND	1500×1	70.0	0.00
GAS_A	GAS_CCGT	240×6	32.0	0.35
GAS_B	GAS_CCGT	240×2	32.0	0.35
	GAS_OCGT	50×10	50.0	0.70
COAL_A	COAL_GEN_A	360×2	20.0	0.85
COAL_B	COAL_GEN_B	200×11	25.0	1.00
COAL_C	COAL_GEN_C	80×11	30.3	1.20

information, to design and improve decision patterns for computer agents, in order to construct a hybrid simulation environment. Existing information (such as the historical ETS data) can be used to summarize decision pattern prototypes by empirical analysis or by interviews and questionnaires with market participants. Human-subjected experiments can help to explore behaviors of human participants. The controlled experiments can test how they behave under different scenarios. More in-depth analysis of the simulation results can help discovering new decision patterns or improving existing decision patterns, so that to augment the decision patterns available for computer agents. In this way, a hybrid simulation environment can be developed iteratively.

As the first article of this methodology, this paper concentrates our efforts on using human-subjected experiments to extract emission trading driving factors and study the joint influences of driving factors on human participants' emission trading behaviors. In the following sections, human-subjected experiments based on EU ETS 2006 price and randomly generated price scenarios will be conducted.

IV. HUMAN-SUBJECTED EMISSION TRADING EXPERIMENTS

A. Arrangement of Experiment

In this case study, six GenCos with different generation units are defined in the experiments, parameters of which can be found in Table I.

Daily market price of EU ETS in 2006 is used as the emission price scenario (as in Fig. 3).

Benchmarking method is adopted for initial emission allowances allocation. According to the power output and average emission rate at Business as Usual (BaU) scenario, the 10% reduction target and 90% free allocation proportion, the initial allocation can be determined (as in Table II).

To assure the quality of experiment participants, six Ph.D. students are invited to act as GenCos, who are familiar with the operation mechanism of electricity and emission market. The

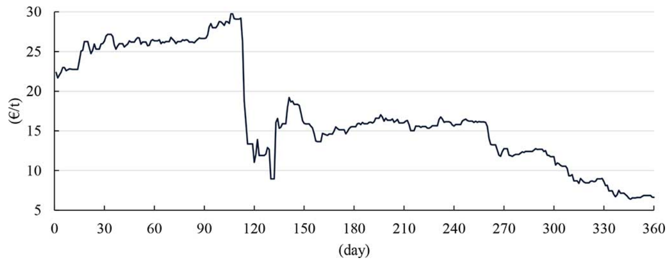

Fig. 3. EU ETS Emission Price in 2006.

TABLE II
FREE ALLOCATION OF EMISSION ALLOWANCE

GenCos	BaU Power Output (MWh)	BaU Average Emission Rate (t/MWh)	Allowance Allocation (kt)
RENEWABLE	1.87E+05		112.9
GAS_CCGT	2.73E+05		165.9
GAS_OCGT	1.77E+05	0.75	106.9
COAL_A	2.67E+05		161.9
COAL_B	8.16 E+05		494.7
COAL_C	2.84 E+05		171.9

role of each GenCo is assigned randomly to each participants. All participants are price takers in emission market. Each participant can estimate the price trend in his/her mind, based on price dynamics of the past days.

In the experiment, the reported marginal cost of each generation unit to the electricity market consists of marginal fuel cost c_f and emission cost $c_e = \gamma_{e,t} p_{e,t}$. As this experiment focuses on the trading strategy in emission market, it is assumed that there are no strategic behaviors in the electricity market, the marginal generation cost will be reported to the electricity market automatically.

Human participants can focus on emission trading strategies. Based on the information displayed through the human-computer interface, participants can choose the time and volume of emission trading based on their own judgments.

B. Key Findings of the Experiment

1) Flexible Timing of Emission Trading: The daily trading volumes are recorded by the simulation platform during simulation (as in Figs. 4–9). Based on the experiment results, no fixed trading interval (daily, weekly, or monthly) can be observed from the participants' trading behaviors. The timing of emission trading is based on each participant's emission balance and the price dynamics of emission market, which is easy to understand considering the elastic constraint characteristic of emission regulation. In the experiment, the annual unbalanced emission ΔQ_e is estimated according to average emission quantity and emission trading volumes in the past days to provide a reference value of participants' emission compliance situation. The estimation of annual unbalanced emission $\Delta\tilde{Q}_{e,t}$ at day t can be calculated as in (2):

$$\Delta\tilde{Q}_{e,t} = \frac{T}{t-1}\sum_{i=1}^{t-1}\gamma_{e,i}q_i - \sum_{i=0}^{t-1}q_{e,i}. \tag{2}$$

The emission trading frequency of each GenCo is summarized in Table III, in which the "emission balance" indicates the emission allowance position of each GenCo if without trading. Here, "Long" indicates that the initial allowance allocation is adequate to cover the GenCo's annual emission with extra allowance that can be sold, and "Short" indicates the initial allowance allocation is not adequate and extra allowances need to be purchased for emission compliance.

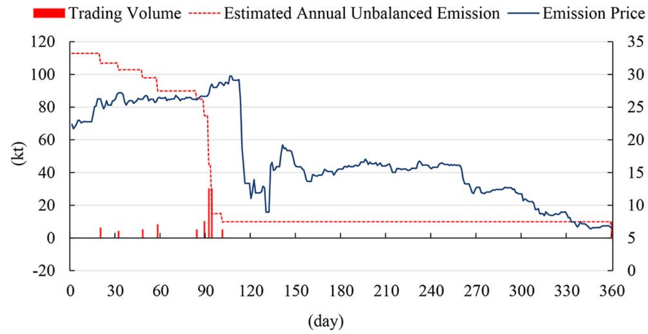

Fig. 4. Daily trading volume (RENEWABLE).

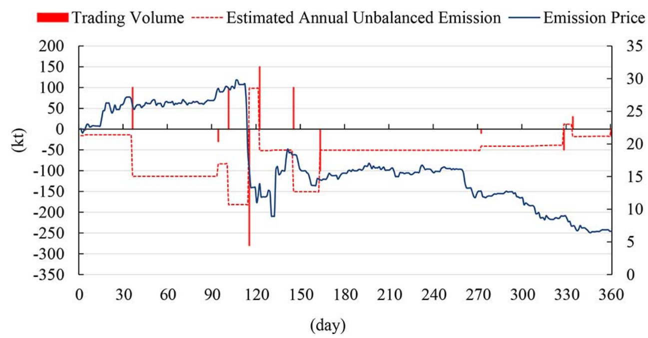

Fig. 5. Daily trading volume (GAS_A).

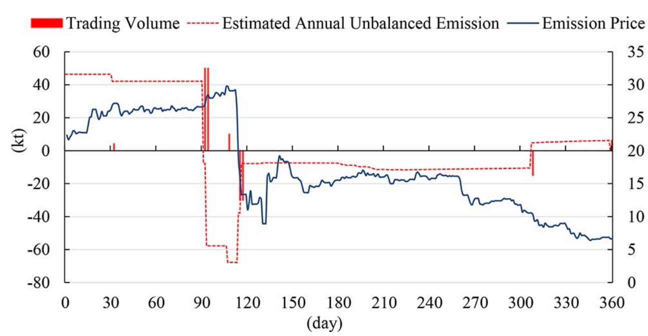

Fig. 6. Daily trading volume (GAS_B).

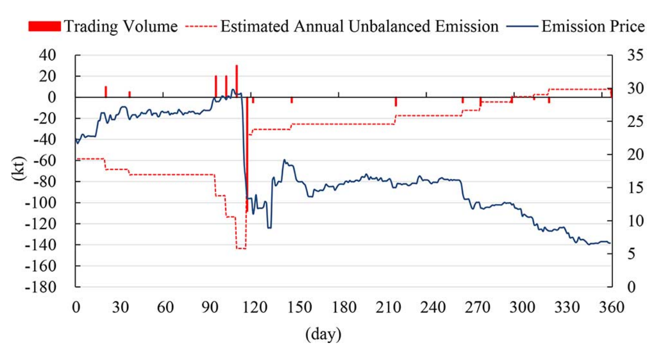

Fig. 7. Daily trading volume (COAL_A).

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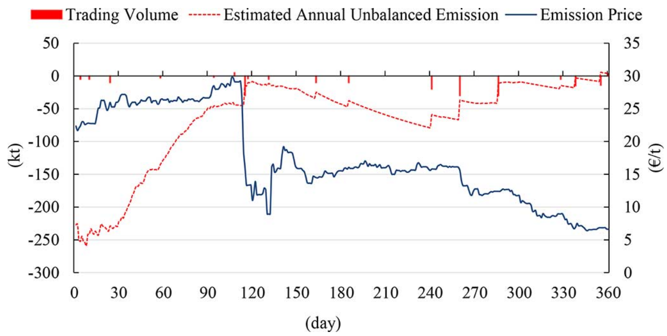

Fig. 8. Daily trading volume (COAL_B).

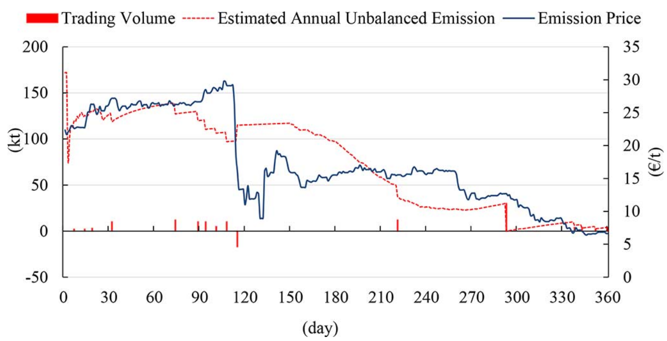

Fig. 9. Daily trading volume (COAL_C).

TABLE III
NUMBER OF EMISSION TRADES OF EACH GENCO
(HUMAN-SUBJECTED EXPERIMENT)

GenCos	Emission Balance (kt)	Sales	Purchases	Total
RENEWABLE	112.9 (Long)	9	0	9
GAS_A	-10.7 (Short)	5	6	11
GAS_B	45.5 (Long)	4	3	7
COAL_A	-58.4 (Short)	5	9	14
COAL_B	-189.2 (Short)	1	16	17
COAL_C	103.5 (Long)	14	1	15

TABLE IV
PARTICIPATION IN EU ETS, 2006 [18]

		Purchases 0	Purchases 1	Total
Sales	0	204	78	282
	1	113	271	384
Total		317	349	666

It can be found that human participants do not participate in emission trading actively as assumed in most multi-agent studies. Empirical analysis of EU ETS transaction data in the first compliance period (2005–2006) [18] also points out high degree of non-participation in emission trading. 204 out of the total 666 firms do not participate in ET at all (as in Table IV). When participation occurs, few trades happen per firm per year, about one third of these firms trade 5 times at most.

2) Strategic Behaviors of Human Participants: The major advantage of experimental method is its capability to consider strategic behaviors of human participants. In Table V, the annual emission balance quantities of GenCos with same position (Long/Short) are aggregated to calculate the unbalanced emission quantity needed for each trade. The results show that for those "Short" GenCos, 6.2 kt unbalanced emission can trigger one trade, while 8.5 kt unbalanced emission can trigger one trade for "Long" GenCos. It indicates that in this experiment, "Short" GenCos are more active in emission market than "Long" GenCos. For "Short" GenCos, emission compliance means extra cost. While for "Long" GenCos, emission compliance means extra incomes. This is a typical "loss aversion" phenomena [19] for human participants when making decisions in behavioral economics, who will have tendency to strongly prefer avoiding losses to acquiring gains.

TABLE V
NUMBER OF EMISSION TRADING OF GENCOS WITH DIFFERENT POSITIONS

GenCos	Emission Balance (kt)	Trades	(kt/trade)
Short	-258.3	42	6.2
Long	262.0	31	8.5

TABLE VI
REVENUE OF GENCOS IN EMISSION MARKET
(HUMAN-SUBJECTED EXPERIMENT)

GenCos	Emission Balance (kt)	Revenue (€×10^6)
RENEWABLE	112.9	2.88
GAS_A	-10.7	1.97
GAS_B	45.5	2.19
COAL_A	-58.4	0.13
COAL_B	-189.2	-2.74
COAL_C	103.5	2.13

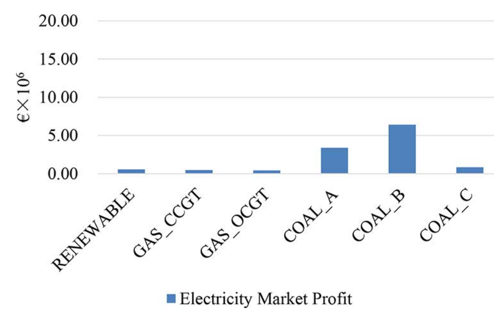

Fig. 10. GenCos' profits without emission regulation.

Table VI concludes the revenue in emission market of each GenCo. Arbitrage behaviors in emission market are observed in this experiment. It is interesting to notice that through arbitrage, GenCos who are short at initial allowance allocation can gain profits in the emission market, such as GAS_A and COAL_A.

Figs. 10 and 11 show GenCos' profits without and with emission regulation.

Due to the pass-through of emission cost, the electricity price is raised in a deregulated environment so that GenCos enjoy "windfall" profits in electricity market. In this experiment, most GenCos (except GenCo "COAL_B") can gain profits in the emission market by selling extra allowance or arbitraging. Among them, the most environmental friendly GenCos (such as "RENEWABLE" and "GAS_CCGT") can enjoy significant profit lifting.

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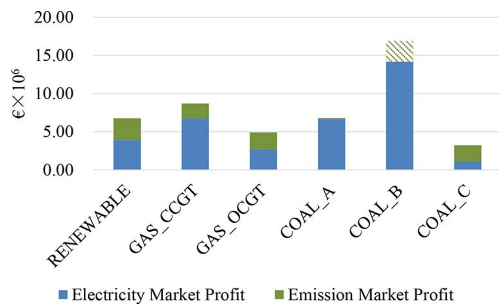

Fig. 11. GenCos' profits with emission regulation.

TABLE VII
MAIN DRIVING FACTORS FOR EMISSION TRADING

Category	Details
Emission Price	Price dynamics of emission market
Emission Quantity	Estimation of unbalanced emission quantity
Compliance Time	Time urgency for compliance

C. *Driving Factors for Emission Trading Behaviors*

After the experiment, each participant is requested to specify his/her main driving factors of emission trading. The driving factors for emission trading can be summarized into three categories: emission price, emission quantity, and compliance time related (as shown in Table VII). Participant will make trading decisions considering the time evolution of these factors.

Among these driving factors, emission quantity and compliance time related factors are objective factors that can be calculated mathematically, while the emission price related factor is hard to calculate as it is very subjective and will be influenced by many other factors. In some multi-agent emission trading researches, price threshold or expected emission price are pre-set before simulation to aid computer agents making trading decisions [10]. However, how to determine the value of these prices still need further researches. Usually, average price is an alternative of price threshold, the computer agent can decide whether to trade by comparing the daily price with average price.

Existing empirical analysis study [18] divided the driving factors of emission trading into firm specific and market specific factors. Firm-specific driving factors include firm size, sector, and ownership structure. Market-specific factors include free allowance allocation size and allowance position. The participations in the emission market are driven by a combination of firm-specific characteristics and market-specific factors. It is also found that the purchasing actions strongly concentrated at the end of each compliance year and at the end of each calendar year.

Driving factors extracted from the human-subjected experiments are in accordance with the empirical study results. Furthermore, human-subjected experiments can provide in-depth information through repetitive simulations and comprehensive analysis under different scenarios.

V. QUANTITATIVE ANALYSIS OF THE DRIVING FACTORS' INFLUENCES

More samples are needed to obtain clear insights of the joint influences of the above mentioned driving factors on emission trading behaviors. So in this section three human participants (participant P1, P2, and P3) are invited to play the role of GenCo "COAL_A". For each human participant, human-subjected experiments are conducted under 20 randomly generated emission price scenarios.

A. *Mathematical Formulations of Driving Factors*

The emission price ratio $r_{p,t}$ can be formulated as in (3). $p_{e,t}$ is the emission price at day t and $p^*_{e,t}$ is the recent average emission price at day t (which is, seven days average price in this paper):

$$r_{p,t} = \frac{p_{e,t} - p^*_{e,t}}{p_{e,t}} \times 100\%. \tag{3}$$

Here, $r_{p,t} < 0$ indicates that the present emission price is lower than recent average, and $r_{p,t} > 0$ indicates the present emission price is higher than recent average.

Both emission quantity and compliance time reflect the compliance urgency. The difference is that the former reflects the urgency in quantity, while the latter reflects the urgency in time. Thus, the compliance urgency ratio $r_{u,t}$ combining emission quantity and compliance time related driving factors is formulated as in (4):

$$r_{u,t} = \frac{\frac{T}{t-1}\sum_{i=1}^{t-1}\gamma_{e,i}q_i - \sum_{i=0}^{t-1} q_{e,i}}{\frac{T-(t-1)}{t-1}\sum_{i=1}^{t-1}\gamma_{e,i}q_i} \times 100\%. \tag{4}$$

The numerator of (4) is the estimated unbalanced emission quantity at the end of the compliance period, and the denominator is the estimated emission in the remaining days till the end of the compliance period. Here, $r_{u,t} < 0/r_{u,t} > 0$ indicates that a shortage/abundance of emission allowance is expected. The larger $|r_{u,t}|$ is, the more urgent for participant who is short of emission allowance to buy extra emission allowances, and the more urgent for participant who is abundant of emission allowance to sell redundant allowances.

B. *Quantitative Analysis of the Experiment Results*

The value of $[r_{p,t}, r_{u,t}]$ can denote different system state, which is divided into 6×8 value intervals in the analysis. The number of the system state appeared in each value interval can be obtained from the experiment results under 20 emission price scenarios. Then, by counting the participant's number of trading in each value interval, and divided by the number of the system state appeared in that value interval, the emission trading probability at each interval can be calculated.

For each human participant, 7200 samples of $[r_{p,t}, r_{u,t}]$ are obtained. Table VIII concludes the trading frequency and average trading volume (both sales and purchases) of each human participants.

GenCo "COAL_A" is "short" at initial allowance allocation. It can be found in Table VIII that participant P1 only purchase allowance for compliance, while participant P2 and P3 try to arbitrage in the emission market. The average trading volume of P3 is much higher than P1 and P2, with less trading times.

TABLE VIII
TRADING TIMES AND AVERAGE TRADING VOLUME

Participant	Average Trading Volume (kt)	Sales	Purchases
P1	3.26	0	282
P2	1.63	105	491
P3	18.14	20	79

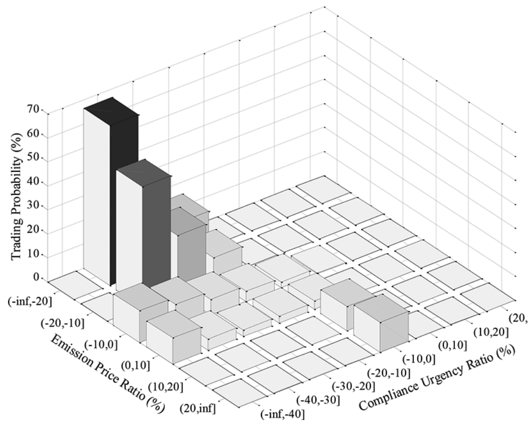

Fig. 12. Trading probability distribution of Participant P1.

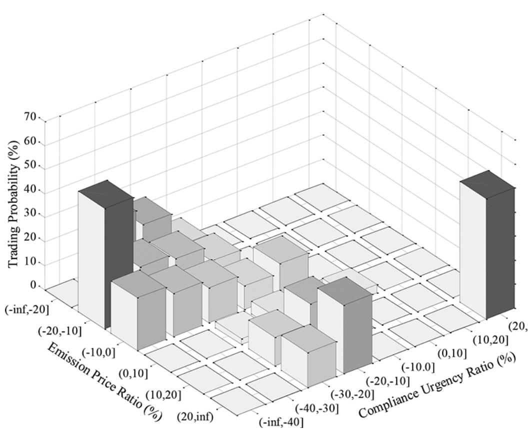

Fig. 13. Trading probability distribution of Participant P2.

After quantitative analysis of the experiment results, emission trading probability distribution of the three participants can be obtained (as shown in Figs. 12–14).

Participant P1 and P2 have similar distributions. The lower value of $r_{u,t}$ is, or the lower value of $r_{p,t}$ is, the higher probability for participant P1 and P2 to purchase allowance in the emission market. The correlation between the two ratios can also be observed, the lower the value of $r_{u,t}$ is, the lower value of $r_{p,t}$ are required to stimulate purchasing actions.

P1 and P2 adopt relatively frequent emission trading strategies to avoid risks. However, P3 shows more tendency to arbitrage in the emission market, who will trade large amount of allowances at lower price, and try to sell the extra allowance at higher price.

C. Suggestions for Constructing Computer Agents

From the experiment results of the three human participants, it can be found that even when playing the same role in the experiment, participants may show different trading patterns. For

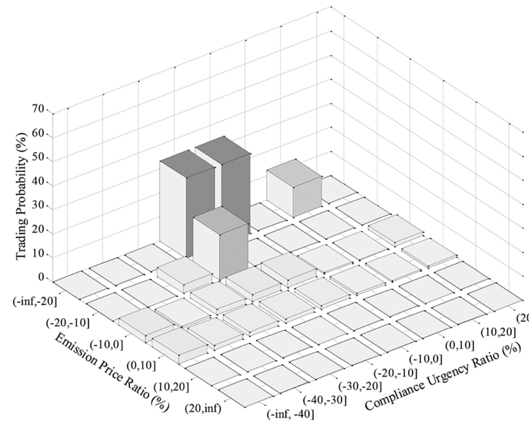

Fig. 14. Trading probability distribution of Participant P3.

human participants with the same trading patterns (such as participant P1 and P2), their trading samples can be aggregated to construct a computer agent with specific trading pattern. However, as for the samples of human participants with significantly different trading patterns, the aggregation may be meaningless.

In the next step of this research, it is important to analyze the trading patterns of different human participants in details, and find ways to parameterize them. Then, it is suggested to construct probabilistic logic decision-making model for computer agents based on the experiment results, to simulate the behaviors of human beings.

VI. CONCLUSION

When studying human participants involved research problems, the essential issue is to model the human behaviors, which is a very challenging work. To complement existing research methods, a hybrid interactive simulation method is proposed in this paper, which attempts to combine experimental and computational methods to study human behaviors. As a preliminary application of this hybrid simulation method, this paper focuses on studying GenCos' emission trading strategies by human-subjected experiments. Major emission trading driving factors are firstly extracted based on experiment using EU ETS 2006 price data, which is in accordance with recent empirical analysis results on EU ETS 2005–2006 transaction dataset. Furthermore, repetitive human-subjected experiments under different price scenarios are conducted to draw more samples for quantitative analysis. Based on thousands of samples obtained, the joint influences of driving factors on human participants' emission trading behaviors are analyzed quantitatively. The analysis results can provide solid foundation for constructing computer agents. Further researches will focus on improving the hybrid interactive simulation methodology in aspects like experiment organization, patterns recognition and validation method. Large-scale hybrid simulation environment with the coexistence of human participants and agents can be set step by step.

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Jie Huang (S’10–M’11) received the Ph.D. degree from Nanjing University of Science & Technology, Nanjing, China, in 2011.

He is now a senior engineer in State Grid Electric Power Research Institute (SGEPRI), State Grid Corporation of China. His research interests include electricity market modeling and simulation, risk management, and policy issues related with emission trading.

Yusheng Xue (M’87) received the Ph.D. degree in electrical engineering from the University of Liege, Belgium, in 1987.

He is now the Honorary President of State Grid Electric Power Research Institute (SGEPRI), State Grid Corporation of China. His research interests include nonlinear stability, control, and power system automation.

Dr. Xue became a Member of Chinese Academy of Engineering in 1995.

Chao Jiang received the B.Sc. degree from Nanjing University of Science & Technology, Nanjing, China, in 2010. Currently, he is pursuing the Ph.D. degree at Nanjing University of Science & Technology.

His research interests include power market and emission market modeling, experimental economics, and environmental policies.

Fushuan Wen received the B.E. and M.E. degrees from Tianjin University, China, in 1985 and 1988, respectively, and the Ph.D. degree from Zhejiang University, China, in 1991, all in electrical engineering.

He joined the faculty of Zhejiang University in 1991, and has been a full professor since 1997, and the director of Zhejiang University-Insigma Joint Research Center for Smart Grid since 2010. His current research interests include power industry restructuring, power system alarm processing, fault diagnosis and restoration strategies, and smart grids.

Feng Xue (M’10–SM’12) received the Ph.D. degree from the University of Bath, U.K., in 2008.

His main research field is power system analysis and control.

Ke Meng (M’10) received the Ph.D. degree from The University of Queensland, Australia.

He is with the Centre for Intelligent Electricity Networks (CIEN), The University of Newcastle, Australia. His research interest includes pattern recognition, power system stability analysis, wind power, and energy storage.

Zhao Yang Dong (M’99-SM’06) received the Ph.D. degree from the University of Sydney, Australia, in 1999.

He is now Head of School and Professor of the School of Electrical and Information Engineering, the University of Sydney, Ausgrid Chair Professor and Director of the Centre for Intelligent Electricity Networks (CIEN), the University of Newcastle, Australia. He previously held academic and industrial positions with the Hong Kong Polytechnic University, the University of Queensland, Australia, and Transend Networks, Australia. His research interest includes smart grid, power system planning, power system security, load modeling, renewable energy systems, electricity market, and computational intelligence and its application in power engineering.

Prof. Dong is an editor of the IEEE TRANSACTIONS ON SMART GRID and the IEEE POWER ENGINEERING LETTERS.