

Contents lists available at ScienceDirect

Applied Energy

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



A two-stage inexact-stochastic programming model for planning carbon dioxide emission trading under uncertainty

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ARTICLE INFO

Article history:
Received 23 June 2009
Received in revised form 7 September 2009
Accepted 12 September 2009
Available online 13 October 2009

Keywords:
Carbon dioxide
Energy
Interval programming
Stochastic
Two-stage
Trading
Uncertainty

ABSTRACT

In this study, a two-stage inexact-stochastic programming (TISP) method is developed for planning carbon dioxide (CO_2) emission trading under uncertainty. The developed TISP incorporates techniques of interval-parameter programming (IPP) and two-stage stochastic programming (TSP) within a general optimization framework. The TISP can not only tackle uncertainties expressed as probabilistic distributions and discrete intervals, but also provide an effective linkage between the pre-regulated greenhouse gas (GHG) management policies and the associated economic implications. The developed method is applied to a case study of energy systems and CO_2 emission trading planning under uncertainty. The results indicate that reasonable solutions have been generated. They can be used for generating decision alternatives and thus help decision makers identify desired GHG abatement policies under various economic and system-reliability constraints.

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1. Introduction

Currently, a large amount of electricity relies primarily on nonrenewable energy supplies, such as coal, natural gas and petroleum [1]. Greenhouse gas (GHG) is primary gas emitted from these fossil fuels combustion, and increasing concentration of GHG [e.g., carbon dioxide (CO₂)] is likely to accelerate the rate of global warming [2-8]. The present measured concentration of CO₂ in the atmosphere is approximately 30% higher than Pre-Industrial Revolution (1850s) levels [5]. Many scientists concern about the increase of global CO₂ and other GHG emissions, which lead to the increase in surface temperature, the change in the global climate, and the rise in sea level. Some of them question that whether energy supplies can meet GHG mitigation standards with increasing electricity demands. Moreover, a number of researchers are in a puzzle about how to balance increasing electricity demands (due to the population growth and the economic development), less fossil fuel consumption, and mandated requirement for reducing GHG emission [1].

A large number of research works were undertaken for the planning of GHG mitigation in integrated energy and environmental management systems. For example, economic incentive (typically a carbon tax) was proposed to promote less carbonintensive fuels and to develop alternatives [9]. Renewable energy sources or less GHG intensive fuels were used, such as nuclear power and natural gas [10-12]. Sequestration facilities were built up and used to capture GHG emitted from power plants during electricity generation process [12,13]. Besides, GHG emission trading was envisaged within the Kyoto protocol as one of the so-called flexible mechanisms, it was introduced to help attain reduction of GHG emission in a cost-effective way [14-16]. Previously, deterministic methods were extensively used for managing GHG emission in energy systems [17-23]. However, an integrated energy and environmental management system often contains various uncertainties that may exist in electricity demand and supply, electricity generation processes, related economic parameters, GHG emission inventories, and errors in the measurement instruments. For example, GHG emissions from the electricity generation sector can be influenced by stochastic events such as electricity demand, which may fluctuate from time to time. Meanwhile, the quality of information on generated energy and cost/benefit coefficients are not sufficient, which may vacillate within a certain interval.

As a result, a number of research efforts were conducted for dealing with various uncertainties in the integrated energy and environmental management systems, such as interval mathematical programming (IMP) and stochastic mathematical programming (SMP) [24–29]. IMP allows uncertainties to be directly

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communicated into the optimization process and resulting solutions, it does not lead to more complicated intermediate models and does not require distribution information for model parameters [30]. Nevertheless, IMP has difficulties when the right-hand sides of a model are highly uncertain, especially with uncertainties expressed as possibilistic and/or probabilistic distributions, which may lead to the loss of valuable information in many real-world decision-making problems [31,32]. In comparison, SMP is effective for decision problems whose coefficients (input data) are uncertain but could be represented as chances or probabilities, which has been extensively applied to energy systems planning [33-36]. Two-stage stochastic programming (TSP) is a typical SMP method, which is an effective alternative for tackling problems where an analysis of policy scenarios is desired and the right-hand-side coefficients are random with known probability density functions (PDFs) [3,37–39]. In TSP, the first-stage decision is to be made before uncertain information is revealed, whereas the second-stage one (recourse) is to adapt to the previous decision based on the further information; the second-stage decision is used to minimize 'penalties' that may appear due to any infeasibility [38,40-45]. However, the major problem of stochastic programming method is that there are increased data requirements for the specification of the probability distribution of the coefficients which may affect the practical applicability [46]. For example, in an integrated energy and environmental system, a planner may know that the daily pollutant and/or GHG emission rate fluctuates within a certain interval, but he may find it is difficult to state a meaningful probability distribution for this variation [31,47]. Therefore, one potential approach for better accounting for the uncertainties and economic penalties is to incorporate the interval-parameter programming (IPP) and TSP techniques within a general optimization framework. This will lead to a two-stage inexact-stochastic linear programming method. For example, Li et al. [29] developed an inexact fuzzy-robust two-stage programming model for managing sulfur dioxide abatement in an energy system under uncertainty, where fuzzy programming was introduced into a TSP framework to deal with uncertainties presented in terms of fuzzy sets and random variables. Huang and Loucks [39] proposed an inexact twostage stochastic programming (ITSP) model to address the uncertainties. In their study, the concept of inexact optimization was incorporated within a two-stage stochastic programming framework. The model was applied to a case study of water resources management. Moreover, few research works focused on the TSP method for GHG emission trading planning within an integrated energy and environmental management system.

Therefore, the objective of this study aims to develop a two-stage inexact-stochastic programming (TISP) method for CO₂ emission trading planning within an integrated energy and environmental management system. The developed TISP will integrate techniques of IPP and TSP into a general optimization framework. Uncertainties expressed as probabilistic distributions and interval values will be reflected. A case study will then be provided for demonstrating applicability of the developed method. A number of policy scenarios that are associated with different mitigation levels of CO₂ emission permits will be analyzed. The results can help decision makers not only discern optimal energy-allocation patterns, but also gain deep insights into the tradeoffs between CO₂ emission trading and economic objective.

The paper is organized as follows: Section 2 describes the statement of energy and environmental management problem, and formulates the CO₂ emission trading and non-trading models; Section 3 provides the results analysis of the case study; Section 4 discusses the potential limitations and extensions of the proposed TISP method; Section 5 presents conclusions of the work; Appendix A depicts the detailed methodology of the proposed model.

2. Modeling formulation

In an integrated energy and environmental management system, uncertainties may exist in CO₂ generation process and various impact factors, such as CO₂ emission inventory, control measures, and related costs. These uncertainties may affect the endeavors in modeling CO₂ emissions in a power system, which is important for making the integrated energy and environmental management planning. For example, CO₂ emission inventory from the electricity generation sector may vary with the electricity demand, which can be represented as a random variable; the information of cost and benefit coefficients is not sufficient, thus these coefficients can be expressed as interval numbers. An integrated energy and environmental management system can be generally characterized by one or several sources (i.e., the power plant). A large number of CO₂ emissions from these power plants may lead to adverse impacts on climate change. For example, increasing amount of CO₂ in the atmosphere may affect weather condition changes, sea/land ice cover decreases, biodiversity changes, and ecosystem changes.

Since it is generally either technically infeasible or economically impossible to design processes leading to zero emission of CO₂, authorities and decision makers always seek to control the CO₂ emission to level at which the effect is minimized [29]. Therefore. CO₂ mitigation strategy for a power system should include a criterion of allowable levels of CO₂ emissions (i.e., the CO₂ emissions permits) and a scheme for making effective employ of the CO2 emissions permits. In order to effectively use of emissions permits, it is necessary to carry out the CO₂ emissions trading scheme. Moreover, amounts of CO₂ emissions vary qualitatively and quantitatively from one power plant to another, which can result in huge variations in the cost of achieving targets of emission limits. This difference in cost can also encourage managers of power plants to carry out CO₂ emissions trading scheme [48]. Through trading scheme, each power plant is no longer constrained by its own emission permit but theoretically by the aggregate number of CO₂ emission limit from the power system, which can maximize the system benefit at a certain level of CO₂ emission permit. Since potential energy-demand may vary with the population increase and economic development, which can be expressed as random variable with probability P_{ih} in one case; besides, some uncertain parameters in power system may be expressed as discrete intervals (e.g., the target amount of generated energy, the energy system cost and benefit, the range of CO2 emission permit, the handling capacity of control measure); furthermore, decisions need to be made periodically over time, and a link to a predefined policy is desired [5,29,49,50]. Therefore, the question under consideration is how to maximize the net benefit of the power system under CO₂ trading scheme while meeting CO₂ emission permit. Thus, the application of TISP model in CO2 emission trading scheme is considered to be feasible for: (i) meeting the CO₂ emission permit requirement; (ii) maximizing the net benefit of the power system with trading scheme; (iii) recognizing appropriate mitigation plan for CO₂ emissions.

A hypothetical problem is advanced to illustrate the applicability of the TISP approach. The planning horizon of this study is 15 years with three planning periods. This is because, from a long-term planning point of view, CO₂ emission rates may keep increasing due to economic development and energy-demand increase, and the related cost of power system may also vary among different time periods. In this study, three power plants (i.e. one gas-fired power plant, one petroleum-fired power plant, and one coal-fired power plant) are considered as major CO₂ emission sources over the planning horizon. In each power plant, two measures are used to reduce the amount of CO₂ emission: (i) capture and storage (CS), and (ii) chemical absorption (CA). The climate

may be adversely affected by the emitted CO_2 from three sources. The study system is shown in Fig. 1. The target level of generated energy from each power plant in three periods are different, while different amounts of generated energy can result in varied CO_2 emission levels that are expressed as random variables.

In this study, a number of scenarios with different mitigation levels of CO_2 emission permits will be considered (i.e., the value of μ will change from 0% to 90%). Abbreviations and scenarios are given in Table 1. Ten typical scenarios (i.e., S1-T, S3-T, S5-T, S7-T, S9-T, S1-NT, S3-NT, S5-NT, S7-NT, and S9-NT) are described as follows:

- (i) S1-T, S3-T, S1-NT and S3-NT are based on an aggressive policy for system benefit maximization. The power system considers developing the power generation with loose CO₂ emission limit. In addition, 0% and 20% reductions of CO₂ emission permit should be obtained over the planning period. Thus, these scenarios correspond to decisions that can satisfy the region's increasing power demand.
- (ii) S5-T and S5-NT are mainly based on a balance between system benefit and CO₂ emission reduction. There is a tradeoff among economic objective, power energy-demand, and CO₂ emission mitigation.
- (iii) S7-T, S9-T, S7-NT and S9-NT are mainly based on a policy for the CO₂ emission minimization. The study system considers developing the power generation plans subject to strict CO₂ emission permission. Under these scenarios, 60% and 80% CO₂ emission mitigation should be achieved over the planning horizon.

In the study system, gas-fired, petroleum-fired and coal-fired power plants are considered, where petroleum-fired and coal-fired power plants are major sources of CO_2 generation. Table 2 shows the targets for energy generated and net benefits in each power plant during different periods when required CO_2 emission permits are satisfied. Table 3 shows operating costs of pollution control techniques during different periods, which may vary with the type of power plant. Table 4 lists power demand and supply indices under different probability distributions. Besides, total CO_2 emission allowances are regulated as $[66.00, 73.70] \times 10^6$ tonnes in period 1, $[66.55, 73.76] \times 10^6$ tonnes in period 2, and $[66.11, 73.81] \times 10^6$

Table 1The list of scenarios.

Abbreviation	Trading scheme
S1	Scenario 1 without mitigation of total CO ₂ emission permit
S2	Scenario 2 with 10% mitigation of total CO ₂ emission permit
S3	Scenario 3 with 20% mitigation of total CO ₂ emission permit
S4	Scenario 4 with 30% mitigation of total CO ₂ emission permit
S5	Scenario 5 with 40% mitigation of total CO ₂ emission permit
S6	Scenario 6 with 50% mitigation of total CO ₂ emission permit
S7	Scenario 7 with 60% mitigation of total CO ₂ emission permit
S8	Scenario 8 with 70% mitigation of total CO ₂ emission permit
S9	Scenario 9 with 80% mitigation of total CO ₂ emission permit
S10	Scenario 10 with 90% mitigation of total CO ₂ emission permit

Note: In the manuscript, symbol "Si-T" means scenario *i* under the trading scheme, and symbol "Si-NT" denotes scenario *i* under the non-trading scheme.

Table 2The target of generated energy and net benefit in each power plant.

Power plant	k = 1	k = 2	k = 3				
The target of generated energy in each power plant (10 ⁹ kW h)							
Gas	[25.00, 30.00]	[25.50, 30.50]	[26.00, 31.00]				
Petroleum	[23.00, 23.50]	[23.50, 24.00]	[24.00, 24.50]				
Coal	[27.00, 27.50]	[27.50, 28.00]	[28.00, 28.50]				
The net benefit of	The net benefit of each power plant (\$/kW h)						
Gas	[0.065, 0.070]	[0.070, 0.075]	[0.075, 0.080]				
Petroleum	[0.055, 0.060]	[0.060, 0.065]	[0.065, 0.070]				
Coal	[0.060, 0.065]	[0.065, 0.070]	[0.070, 0.075]				

Table 3The operating costs of pollution control techniques (\$/tonne).

Power plant	Measure	k = 1	k = 2	k = 3
Gas	CS	[13.00, 15.00]	[18.00, 20.00]	[23.00, 25.00]
	CA	[28.00, 30.00]	[33.00, 35.00]	[38.00, 40.00]
Petroleum	CS	[14.00, 16.00]	[19.00, 21.00]	[24.00, 26.00]
	CA	[29.00, 31.00]	[34.00, 36.00]	[39.00, 41.00]
Coal	CS	[15.00, 17.00]	[20.00, 22.00]	[25.00, 27.00]
	CA	[30.00, 32.00]	[35.00, 37.00]	[40.00, 42.00]

 10^6 tonnes in period 3, respectively. The capacities of CS technique in gas, petroleum and coal power plants are $[9.90, 11.40] \times 10^6$,

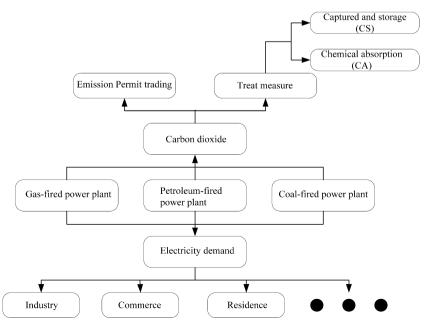


Fig. 1. The sketch map of power system.

Table 4The power demand and supply index under different probability distributions.

Power plant	Level	P_{ih}	b^{\pm}_{ih}
Gas	h = 1	0.60	[1.034, 1.162]
	h = 2	0.20	[0.945, 1.031]
	h = 3	0.20	[0.862, 0.943]
Petroleum	h = 1	0.60	[1.033, 1.161]
	h = 2	0.20	[0.944, 1.030]
	h = 3	0.20	[0.861, 0.942]
Coal	h = 1	0.60	[1.032, 1.160]
	h = 2	0.20	[0.943, 1.029]
	h = 3	0.20	[0.860, 0.941]

 $[9.30, 10.80] \times 10^6$ and $[9.60, 11.10] \times 10^6$ tonnes, respectively. Annual CO₂ emission loadings for the three power plants (i.e., gas, petroleum and coal) are 0.0006, 0.0009 and 0.00095 tonne/ kW h, respectively. Efficiencies of CS and CA for CO2 emission mitigation are 1.0 and [0.80, 0.90], respectively. Although this is a hypothetical case study, the representative cost and technical data in Tables 2-4 are investigated and counted from a number of related literatures [51–53]. In fact, many factors may affect the value of CO₂ emission loading, the system benefit, and the treating cost. For example, the values of CO₂ emission loading are affected by the types of fuels, the combustion conditions, the amount of electricity generation, and the labor fee; the benefit for the power plant may change according to the fuel quality, the prices of fuels, and the levels of regional economic development; cost for the excess CO₂ treating are estimated based on raised collection, storage, transportation, and disposal costs. Correspondingly, CO₂ emission loading, system benefit and operating costs could be sensitive variables which can be defined as intervals with known upper- and lowerbounds but unknown distribution information.

In order to reduce the cost for CO₂ treatment, emission trading is considered for the three power plants. Based on the local CO₂ emission management policies, a target quantity of CO₂ emission quota is allocated to each power plant. If this quantity is satisfied, the power generation system will bring net benefits. If this quantity exceeds the regulated level, power plants will have to take measures to decrease the CO₂ emission. In response to such regulation, the power plants need to optimize CO₂ treated to achieve a maximized system net benefit while to satisfy the GHG emission requirement. Through the program of CO₂ emission trading, each power plant can sell credit to other power plants with higher electric power profitability. The CO₂ emission permits can thus be reallocated to the most efficient power plants instead of proportionally allocated to each power plant. Consequently, the proposed TISP method is suitable for tackling such a problem. When CO₂ is tradable, the TISP model can be formulated as follows:

Maximize
$$f_1^{\pm} = \sum_{i=1}^{3} \sum_{k=1}^{3} C_{ik}^{\pm} M_{ik}^{\pm} - \sum_{i=1}^{3} \sum_{j=1}^{2} \sum_{k=1}^{3} \sum_{h=1}^{3} P_{ih} D_{ijk}^{\pm} Y_{ijkh}^{\pm}$$
 (1a)

subject to
$$0 \leqslant \sum_{i=1}^{2} \eta_{j} Y_{ijkh}^{\pm} \leqslant E_{ikh}^{\pm}, \quad \forall i, k, h$$
 (1b)

$$E_{ikh}^{\pm} - \sum_{j=1}^{2} \eta_j Y_{ijkh}^{\pm} \leqslant S_{ik}^{\pm}, \quad \forall i, k, h$$
 (1c)

$$\sum_{i=1}^{3} S_{ik}^{\pm} \leqslant (1-\mu)T_{k}^{\pm}, \quad \forall \ k$$
 (1d)

$$Y_{i1kh}^{\pm} \leqslant W_{i1}^{\pm}, \quad \forall i, k, h \tag{1e}$$

$$M_{i\nu}^{\pm} \geqslant 0, \quad \forall i, k$$
 (1f)

$$Y_{iibh}^{\pm} \geqslant 0, \quad \forall i, j, k, h$$
 (1g)

where M^\pm_{ik} , Y^\pm_{ijkh} , C^\pm_{ik} , D^\pm_{ijk} , T^\pm_k , E^\pm_{ikh} , W^\pm_{ij} , η^\pm_j and S^\pm_{ik} denote the sets of inexact numbers. i is the name of power plant (i.e., gas-fired units, petroleum-fired units and coal-fired units, respectively); *i* is the type of the CO_2 control measure (CS, CA); k is the time period (k = 1, 2, 3); h is the CO₂ emissions level (h = 1, 2, 3); f_1^{\pm} is the net benefit of the power system with CO₂ emissions trading scheme (\$); M_{ik}^{\pm} is the target amount of energy to be generated from power plant i during period k, which is derived based on the power target of each power plant pre-regulated by the authorities (kW h) (i.e., the first-stage decision variable); Y_{iikh}^{\pm} is the amount of excess CO_2 treated by control measure j during period k under level h, which is related to the randomness of energy-demand (tonne); Pih is probability of occurrence of CO_2 emissions; C_{ik}^{\pm} is net benefit per kW h to power plant i if required CO2 emission allowance is satisfied (\$/ kW h); D_{iik}^{\pm} is operating cost for excess CO₂ released from power plant i which is treated by control measure j during period k (\$/ tonne); T_{ν}^{\pm} is discharge limit of total CO_2 emissions for the whole power system during period k (tonne); E_{ikh}^{\pm} is the amount of CO_2 emissions from power plant *i* during period *k* under level *h* (tonne); W_{ii}^{\pm} is the handling capacity of control measure j (tonne); η_{i}^{\pm} is the efficiency of control measure j; S_{ik}^{\pm} is the reallocated emission permit to power plant i with trading scheme (tonne); μ is the percentage of reduced total CO₂ emission permit (i.e., mitigation level).

Since CO_2 emission inventory from the electricity generation sector may vary with the power demand, the relationship between CO_2 emission and power demand can be expressed as follows:

$$E_{ikh}^{\pm} = b_{ih}^{\pm} l_i M_{ik}^{\pm}, \quad \forall i, k, h \tag{2}$$

where b_{ih}^{\pm} is the power demand and supply index; l_i is the amount of CO₂ emission loading per kW h electricity for power plant i (tonne/kW h).

In the TISP model, since the target of energy generation for each power plant (M_{ik}^+) is expressed as interval number, decision variable z_{ik} is introduced to identify the optimal target values (i.e., the first-stage decision variables) [39]. Let $M_{ik}^+ = M_{ik}^- + \Delta M_{ik} z_{ik}$, where $\Delta M_{ik} = M_{ik}^+ - M_{ik}^-$ and $z_{ik} \in [0, 1]$. Thus, when M_{ik}^+ reach their upper bounds (i.e., when $z_{ik} = 1$), a higher net benefit of the power system would be achieved. However, a high risk of violating the emission permit for each power plant would be generated, leading to higher operating costs of control measures for excess CO_2 emission. When M_{ik}^+ approach to their lower-bounds (i.e., when $z_{ik} = 0$), the system may have a relatively low net benefit with a low risk of violating the CO_2 emission permit. Then, according to Huang and Loucks [39], model (1) can be transformed into the following two deterministic submodels, which correspond to the upper- and lower-bounds of the desired objective function value.

Submodel (1)

Maximize
$$f_1^+ = \sum_{i=1}^3 \sum_{k=1}^3 C_{ik}^+ (M_{ik}^- + \Delta M_{ik} z_{ik})$$

 $-\sum_{i=1}^3 \sum_{k=1}^2 \sum_{k=1}^3 \sum_{h=1}^3 P_{ih} D_{ijk}^- Y_{ijkh}^-$ (3a)

subject to
$$0 \leqslant \sum_{j=1}^{2} \eta_{j}^{-} Y_{ijkh}^{-} \leqslant E_{ikh}^{-}, \quad \forall i, k, h$$
 (3b)

$$E_{ikh}^{-} - \sum_{i=1}^{2} \eta_{j}^{-} Y_{ijkh}^{-} \leqslant S_{ik}^{-}, \quad \forall i, k, h$$
 (3c)

$$\sum_{i=1}^{3} S_{ik}^{-} \leqslant (1-\mu)T_{k}^{-}, \quad \forall \ k \tag{3d}$$

$$Y_{i1kh}^- \leqslant W_{i1}^-, \quad \forall \ i, k, h \tag{3e}$$

$$Y_{iikh}^- \geqslant 0, \quad \forall \ i,j,k,h$$
 (3f)

Submodel (2)

Maximize
$$f_1^- = \sum_{i=1}^3 \sum_{k=1}^3 C_{ik}^- (M_{ik}^- + \Delta M_{ik} z_{ik})$$

 $-\sum_{i=1}^3 \sum_{i=1}^2 \sum_{k=1}^3 \sum_{h=1}^3 P_{ih} D_{ijk}^+ Y_{ijkh}^+$ (4a)

$$\text{subject to} \quad 0 \leqslant \sum_{j=1}^2 \eta_j^+ Y_{ijkh}^+ \leqslant E_{ikh}^+, \quad \forall \ i,k,h \tag{4b}$$

$$E_{ikh}^{+} - \sum_{i=1}^{2} \eta_{j}^{+} Y_{ijkh}^{+} \leqslant S_{ik}^{+}, \quad \forall \ i, k, h$$
 (4c)

$$\sum_{i=1}^{3} S_{ik}^{+} \leqslant (1-\mu)T_{k}^{+}, \quad \forall \ k$$
 (4d)

$$Y_{i1kh}^+ \leqslant W_{i1}^+, \quad \forall i, k, h$$

$$Y_{ijkh}^+ \geqslant 0, \quad \forall i, j, k, h$$

$$(4e)$$

$$(4f)$$

$$Y_{ijkh}^+ \geqslant 0, \quad \forall \ i,j,k,h$$
 (4f)

On the other hand, when CO₂ is not tradable, the CO₂ emission for each power plant will be limited by its own emission permit. Under this case, the TISP model (without considering CO₂ trading) can be formulated as follows:

$$\text{Maximize} \quad f_2^{\pm} = \sum_{i=1}^3 \sum_{k=1}^3 C_{ik}^{\pm} M_{ik}^{\pm} - \sum_{i=1}^3 \sum_{j=1}^2 \sum_{k=1}^3 \sum_{h=1}^3 P_{ih} D_{ijk}^{\pm} Y_{ijkh}^{\pm} \qquad (5a)$$

subject to
$$0 \leqslant \sum_{j=1}^{2} \eta_{j} Y_{ijkh}^{\pm} \leqslant E_{ikh}^{\pm}, \quad \forall i, k, h$$
 (5b)

$$E_{ikh}^{\pm} - \sum_{j=1}^{2} \eta_{j} Y_{ijkh}^{\pm} \leqslant \frac{l_{i} M_{ik \text{ max}}^{\pm}}{\sum_{i=1}^{3} l_{i} M_{ik \text{ max}}^{\pm}} (1 - \mu) T_{k}^{\pm}, \quad \forall i, k, h \qquad (5c)$$

$$Y_{i1kh}^{\pm} \leqslant W_{i1}^{\pm}, \quad \forall i, k, h$$

$$M_{ik}^{\pm} \geqslant 0, \quad \forall i, k$$
(5d)
(5e)

$$M_{ik}^{\pm} \geqslant 0, \quad \forall i,k$$
 (5e)

$$Y_{iikh}^{\pm} \geqslant 0, \quad \forall i, j, k, h \tag{5f}$$

where f_2^{\pm} is the net benefit of the power system without considering CO_2 emission trading (\$); $M_{ik \text{ max}}^{\pm}$ is the upper target of generated energy in period k from power plant i (kW h). Similarly, model (5) can be converted into two submodels as follows:

Submodel (1)

Maximize
$$f_2^+ = \sum_{i=1}^3 \sum_{k=1}^3 C_{ik}^+ (M_{ik}^- + \Delta M_{ik} Z_{ik})$$

 $-\sum_{i=1}^3 \sum_{k=1}^2 \sum_{k=1}^3 \sum_{k=1}^3 P_{ih} D_{ijk}^- Y_{ijkh}^-$ (6a)

subject to
$$0 \leqslant \sum_{j=1}^{2} \eta_{j}^{-} Y_{ijkh}^{-} \leqslant E_{ikh}^{-}, \quad \forall i, k, h$$
 (6b)

$$E_{ikh}^{-} - \sum_{j=1}^{2} \eta_{j}^{-} Y_{ijkh}^{-} \leqslant \frac{l_{i} M_{ik}^{+}}{\sum_{i=1}^{3} l_{i} M_{ik}^{+}} (1 - \mu) T_{k}^{-}, \quad \forall i, k, h \quad (6c)$$

$$Y_{iikh}^- \leqslant W_{ii}^-, \quad \forall i, k, h
Y_{iikh}^- \geqslant 0, \quad \forall i, j, k, h$$
(6d)
(6e)

Submodel (2

Maximize
$$f_2^- = \sum_{i=1}^3 \sum_{k=1}^3 C_{ik}^- (M_{ik}^- + \Delta M_{ik} Z_{ik})$$

 $-\sum_{i=1}^3 \sum_{i=1}^2 \sum_{k=1}^3 \sum_{h=1}^3 P_{ih} D_{ijk}^+ Y_{ijkh}^+$ (7a)

subject to
$$0 \leqslant \sum_{j=1}^{2} \eta_{j}^{+} Y_{ijkh}^{+} \leqslant E_{ikh}^{+}, \quad \forall i, k, h$$
 (7b)

$$E_{ikh}^{+} - \sum_{j=1}^{2} \eta_{j}^{+} Y_{ijkh}^{+} \leqslant \frac{l_{i} M_{ik}^{+}}{\sum_{i=1}^{3} l_{i} M_{ik}^{+}} (1 - \mu) T_{k}^{+}, \quad \forall i, k, h \quad (7c)$$

$$Y_{ijkh}^{+} \leqslant W_{i1}^{+}, \quad \forall i, k, h$$

$$Y_{ijkh}^{+} \geqslant 0, \quad \forall i, j, k, h$$

$$(7d)$$

$$(7e)$$

$$Y_{iikh}^{+} \geqslant 0, \quad \forall \ i,j,k,h \tag{7e}$$

3. Results analysis

In this study, 20 scenarios corresponding to different CO₂ mitigation levels and different trading schemes (i.e., trading and nontrading) were examined by the TISP model. Fig. 2 shows the solutions for optimized system benefits obtained from the TISP model, which are the sum of the first-stage benefit from the energy generation and the second-stage random cost for mitigating CO2 emission. In Fig. 2, solid lines represent the benefit obtained from trading scheme, and dashed lines represent the benefit obtained from non-trading scheme. The results demonstrate that system benefit under trading scheme is much higher than that under non-trading scheme. Moreover, with the increase of the mitigation level, the optimized net system benefits under trading and nontrading schemes are both decrease. For example, the optimized system benefit would be decreased from \$ $[16.07, 17.35] \times 10^9$ (S1-T) to \$ [10.16, 11.98] \times 10⁹ (S10-T) under trading scheme. Under non-trading scheme, the optimized system benefit would be $[16.06, 17.35] \times 10^9$ (S1-NT) decreased from \$ $[10.14, 11.96] \times 10^9$ (S10-NT). All of the system benefits are intervals; the actual value of each variable varies within its lower and upper bounds, the resulting system benefit will change correspondingly between its lower and upper bounds with varied reliability levels. In practice, planning for the lower-bound system benefit would lead to a lower risk of violating the allowable CO₂ emission level. Conversely, planning with a higher benefit will correspond to a higher probability of violating the allowance. Therefore, there is a tradeoff between the system benefit and CO2 emission-allowance violation risk. In addition, the maximum difference of system benefits under trading and non-trading schemes would occur in scenario 5 (i.e., the optimized system benefits would be $[14.39, 15.96] \times 10^9$ under S5-T and \$ [14.31, 15.87] \times 10⁹ under S5-NT). This implies the high efficiency of CO₂ trading would be achieved under scenario 5. Consequently, S5-T and S5-NT were chosen as two basic scenarios, and detailed interpretation and analysis for the results under S5-T and S5-NT would be provided as follows.

3.1. Solutions under scenarios S5-T and S5-NT

Figs. 3–5 show the optimal solutions for CO₂ emission treated by different measures for the three power plants under scenarios S5-T and S5-NT. Under scenario S5-T (i.e., under trading scheme), for gas-fired power plant in period 1, the CO₂ emission permit would be $[8.71, 9.52] \times 10^6$ tonnes; the amounts of excess CO₂ treated by CS would be $[9.90, 11.40] \times 10^6$ tonnes (probability = 0.6),

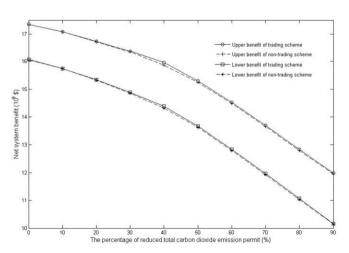


Fig. 2. Net system benefits under different mitigation level.

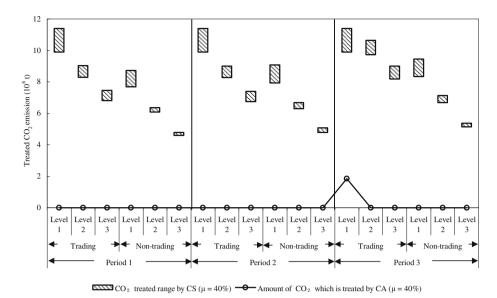


Fig. 3. Solutions for CO₂ emissions from the gas-fired power plant under S5-T and S5-NT ("S5-T" and "S5-NT" denote the "scenario 5 under trading" and "scenario 5 under non-trading", respectively).

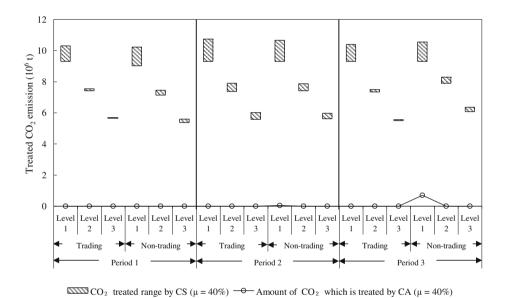
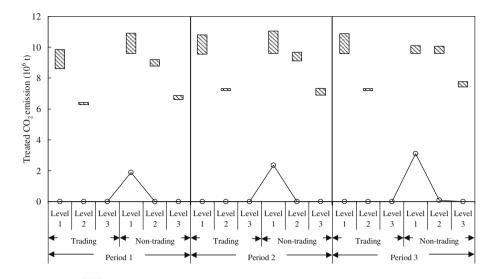


Fig. 4. Solutions for CO₂ emissions from the petroleum-fired power plant under S5-T and S5-NT ("S5-T" and "S5-NT" denote the "scenario 5 under trading" and "scenario 5 under non-trading", respectively).

[8.30, 9.04] × 10⁶ tonnes (probability = 0.2) and [6.80, 7.46] × 10⁶ tonnes (probability = 0.2). Under scenario S5-T, for petroleum-fired power plant in period 1, the CO₂ emission permit would be [12.55, 14.25] × 10⁶ tonnes; the amounts of excess CO₂ treated by CS would be [9.30, 10.31] × 10⁶, [7.42, 7.54] × 10⁶, and [5.66, 5.68] × 10⁶ tonnes, respectively. Under scenario S5-T, for coal-fired power plant in period 1, the CO₂ emission permit would be [18.34, 20.46] × 10⁶ tonnes; the amounts of excess CO₂ emission treated by CS would be [8.62, 9.85] × 10⁶, [6.30, 6.43] × 10⁶, and 4.13 × 10⁶ tonnes, respectively. The results indicate that, for the three power plants, no excess emission would be allocated to CA.

Under scenario S5-NT (i.e., under non-trading scheme), for gasfired power plant during period 1, the amounts of excess CO_2 emission treated by CS would be $[7.69, 8.72] \times 10^6$, $[6.09, 6.36] \times 10^6$, and $[4.60, 4.78] \times 10^6$ tonnes, respectively; in comparison, the CO $_2$ emission permit under scenario S5-NT would be [10.92, 12.19] \times 10 6 tonnes. For petroleum-fired power plant during period 1, the amounts of excess CO $_2$ treated by CS would be [9.02, 10.23] \times 10 6 , [7.14, 7.46] \times 10 6 , and [5.38, 5.60] \times 10 6 tonnes, respectively; the CO $_2$ emission permit would be [12.83, 14.33] \times 10 6 tonnes. For coal-fired power plant during period 1, the amounts of excess CO $_2$ treated by CS would be [9.60, 10.91] \times 10 6 , [8.79, 9.18] \times 10 6 , and [6.62, 6.89] \times 10 6 tonnes, respectively; the CO $_2$ emission permit would be [15.85, 17.70] \times 10 6 tonnes. For gas-fired and petroleum-fired power plants, no excess CO $_2$ would be allocated to CA under scenario S5-NT; however, for the coal-fired power plant, the amount of excess emissions treated by CA under scenario S5-NT would be 1.89 \times 10 6 tonnes when power generation level is high.

The results indicate that CO_2 emission and mitigation under scenarios S5-T and S5-NT are different from each other. For



 CO_2 treated range by CS ($\mu = 40\%$) $-\Theta$ Amount of CO_2 which is treated by CA ($\mu = 40\%$)

Fig. 5. Solutions for CO₂ emissions from the coal-fired power plant under S5-T and S5-NT ("S5-T" and "S5-NT" denote the "scenario 5 under trading" and "scenario 5 under non-trading", respectively).

gas-fired power plant during period 1, the excess amount of CO_2 treated by CS under S5-T is higher than that under S5-NT. For petroleum-fired power plant during period 1, the excess amount of CO_2 treated by CS under S5-T is also higher than that under S5-NT. For coal-fired power plant during period 1, the excess amounts of CO_2 treated by CS and CA under S5-T are lower than those under S5-NT. This is mainly attributable to two facts: (i) CS has the highest efficiency and lowest operating cost in treating the excess CO_2 emission; (ii) the policy for CO_2 trading has effects on the CO_2 emission and mitigation.

3.2. Solutions under scenarios S1-T and S3-T

Figs. 6–8 show the optimal solutions for CO_2 emission treated by different measures for the three power plants under scenarios S1-T and S3-T. For the gas-fired power plant with different CO_2 emission levels (Fig. 6). The amounts of excess CO_2 emission treated by CS under S1-T would be $[1.42, 2.08] \times 10^6$, 0 and 0 tonnes, respectively; the CO_2 emission permit under S1-T would be $[17.19, 18.84] \times 10^6$ tonnes. The amounts of excess CO_2 emission treated by CS under S3-T would be $[6.49, 7.25] \times 10^6$, 4.89×10^6 ,

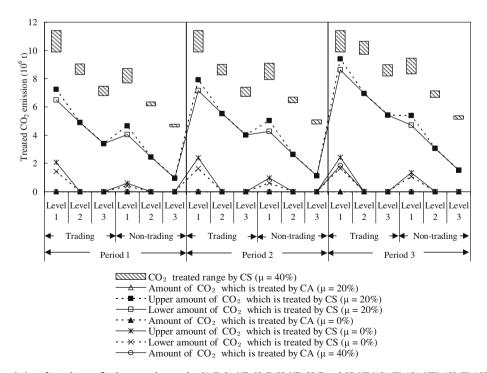


Fig. 6. Solutions for CO₂ emissions from the gas-fired power plant under S1-T, S1-NT, S3-T, S3-NT, S5-T and S5-NT ("S1-T", "S1-NT", "S3-T", "S3-NT", "S5-T", and "S5-NT" denote the "scenario 1 under trading", "scenario 1 under trading", "scenario 3 under trading", "scenario 5 under trading", "scenario 5 under non-trading", respectively).

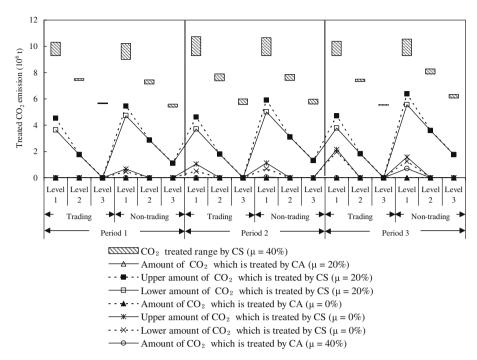


Fig. 7. Solutions for CO₂ emissions from the petroleum-fired power plant under S1-T, S1-NT, S3-T, S3-NT, S5-T and S5-NT ("S1-T", "S1-NT", "S3-T", "S3-NT", "S5-T", and "S5-NT" denote the "scenario 1 under trading", "scenario 1 under trading", "scenario 3 under trading", "scenario 5 under non-trading", "scenario 5 under non-trading", respectively).

and 3.39×10^6 tonnes, respectively; the CO₂ emission permit under S3-T would be [12.12, 13.67] \times 10⁶ tonnes. For the petroleum-fired power plant with different CO₂ emission levels (as shown in Fig. 7). The amounts of excess CO₂ emission treated by CS under S1-T would be zero; the CO₂ emission permit under S1-T would be [21.85, 24.56] \times 10⁶ tonnes. The amounts of excess CO₂ emission treated by CS under S3-T would be [3.64, 4.53] \times 10⁶, 1.76 \times 10⁶,

and 0 tonnes, respectively; the CO₂ emission permit under S3-T would be [18.21, 20.03] \times 10^6 tonnes. For the coal-fired power plant with different CO₂ emission levels (Fig. 8). The excess CO₂ emission treated by CS under S1-T would be zero; the CO₂ emission permit under S1-T would be [26.96, 30.31] \times 10^6 tonnes. The amounts of excess CO₂ emission treated by CS under S3-T would be [4.49, 5.04] \times 10^6 , 2.17×10^6 , and 0 tonnes, respectively; the

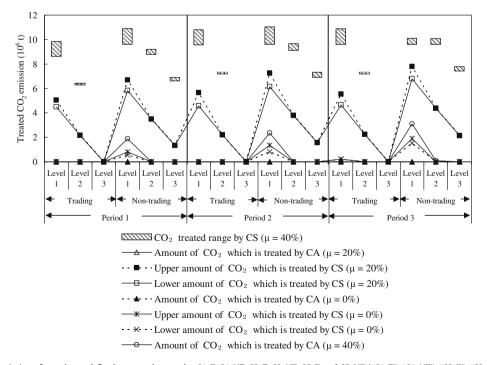


Fig. 8. Solutions for CO₂ emissions from the coal-fired power plant under S1-T, S1-NT, S3-T, S3-NT, S5-T and S5-NT ("S1-NT", "S3-NT", "S3-NT", "S5-NT", and "S5-NT" denote the "scenario 1 under trading", "scenario 1 under trading", "scenario 3 under trading", "scenario 5 under trading", "scenario 5 under non-trading", respectively).

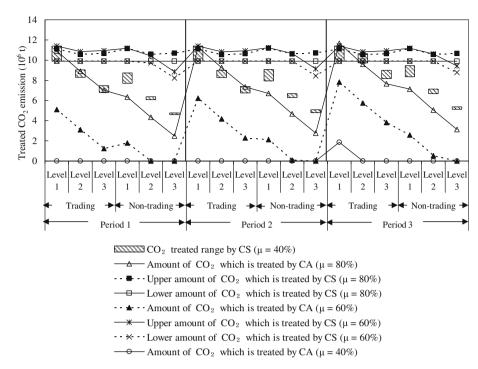


Fig. 9. Solutions for CO₂ emissions from the gas-fired power plant under S5-T, S5-NT, S7-T, S7-NT, S9-T and S9-NT ("S5-NT", "S7-NT", "S7-NT", "S9-T", and "S9-NT" denote the "scenario 5 under trading", "scenario 5 under trading", "scenario 5 under trading", "scenario 7 under trading", "scenario 9 under trading", "scenario 9 under non-trading", respectively).

 CO_2 emission permit under S3-T would be [22.47, 25.26] \times 10^6 tonnes. The results indicate that, for the three power plants, no excess emission would be allocated to CA under S1-T and S3-T. Generally, when μ is lower than 40% (i.e., S1-T and S3-T), more excess CO_2 emission would be treated by CS, while less CO_2 would be treated by CA. Besides, the optimized net system benefits would be \$ [16.07, 17.35] \times 10 9 under S1-T and \$ [15.33, 16.74] \times 10 9 under

S3-T, higher than the net system benefit obtained from S5-T (i.e., $[14.39, 15.96] \times 10^9$).

3.3. Solutions under scenarios S1-NT and S3-NT

Figs. 6–8 also show the optimal solutions for CO₂ emission treated by different measures for the three power plants under

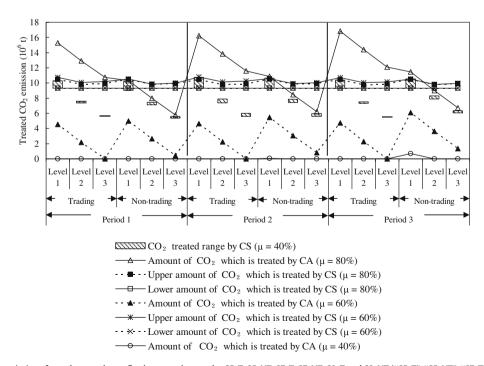


Fig. 10. Solutions for CO₂ emissions from the petroleum-fired power plant under S5-T, S5-NT, S7-T, S7-NT, S9-T and S9-NT ("S5-T", "S7-NT", "S7-NT", "S7-NT", "S9-T", and "S9-NT" denote the "scenario 5 under trading", "scenario 5 under trading", "scenario 7 under trading", "scenario 7 under non-trading", "scenario 9 under non-trading", respectively).

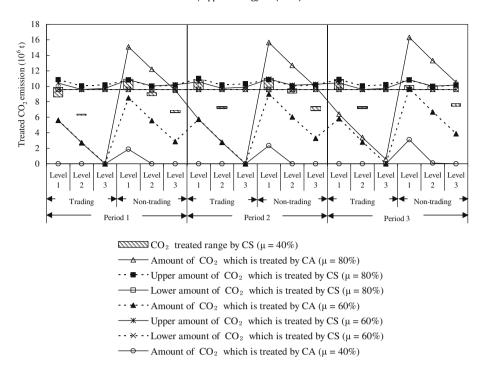


Fig. 11. Solutions for CO₂ emissions from the coal-fired power plant under S5-T, S5-NT, S7-T, S7-NT, S9-T and S9-NT ("S5-T", "S5-NT", "S7-NT", "S7-NT", "S9-T", and "S9-NT" denote the "scenario 5 under trading", "scenario 5 under trading", "scenario 5 under trading", "scenario 7 under trading", "scenario 9 under trading", "scenario 9 under trading", respectively).

scenarios S1-NT and S3-NT. For the gas-fired power plant with different CO_2 emission levels (Fig. 6). The amounts of excess CO_2 emission treated by CS under S1-NT would be $[0.41, 0.59] \times 10^6$, 0 and 0 tonnes, respectively; the CO_2 emission permit under S1-NT would be $[18.20, 20.32] \times 10^6$ tonnes. The excess CO_2 emission treated by CS under S3-NT would be $[4.05, 4.66] \times 10^6$, 2.45×10^6 , and 0.96×10^6 tonnes, respectively; the CO_2 emission permit under S3-NT would be $[14.56, 16.26] \times 10^6$ tonnes. For the petroleum-fired power plant with different CO_2 emission levels (Fig. 7). The excess CO_2 emissions treated by CS under S1-NT would

be $[0.46,0.68] \times 10^6$, 0 and 0 tonnes, respectively; the CO₂ emission permit under S1-NT would be $[21.39,23.88] \times 10^6$ tonnes. The amounts of excess CO₂ emission treated by CS under S3-NT would be $[4.74,5.45] \times 10^6$, 2.86×10^6 , and 1.10×10^6 tonnes, respectively; the CO₂ emission permit under S3-NT would be $[17.11,19.10] \times 10^6$ tonnes. For the coal-fired power plant with different CO₂ emission levels (Fig. 8). The amounts of excess CO₂ emission treated by CS under S1-NT would be $[0.55,0.81] \times 10^6$, 0 and 0 tonnes, respectively; the CO₂ emission permit under S1-NT would be $[26.42,29.50] \times 10^6$ tonnes. The amounts of excess

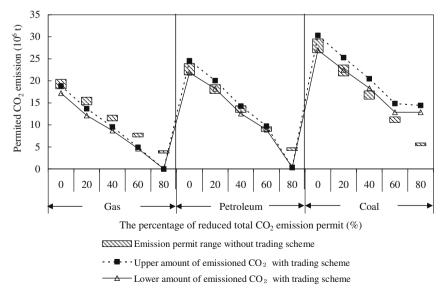


Fig. 12. Solutions for CO₂ emission permits during the period 1 under S1-T, S1-NT, S3-T, S3-NT, S5-T, S5-NT, S7-NT, S9-T and S9-NT ("S1-T" denote the "scenario 1 under trading", "S1-NT" denote the "scenario 3 under trading", "S3-NT" denote the "scenario 3 under trading", "S3-NT" denote the "scenario 3 under trading", "S5-NT" denote the "scenario 7 under trading", "S7-NT" denote the "scenario 7 under trading", "S7-NT" denote the "scenario 7 under trading", "S7-NT" denote the "scenario 9 under trading", "S9-T" denote the "scenario 9 under trading").

 CO_2 emission treated by CS under S3-NT would be $[5.83, 6.71] \times 10^6$, 3.50×10^6 , and 1.34×10^6 tonnes, respectively; the CO_2 emission permit under S3-NT would be $[21.13, 23.60] \times 10^6$ tonnes. For the three power plants, no excess emission would be allocated to CA under S1-NT and S3-NT.

In summary, when μ is lower than 40% (i.e., S1-NT and S3-NT), more CO_2 emission surplus would be treated by CS, while less CO_2 would be treated by CA. Besides, the optimized net system benefits would be \$ [16.06, 17.35] × 10⁹ under S1-NT and \$ [15.32, 16.72] × 10⁹ under S3-NT, higher than the net system benefit obtained from S5-NT (i.e., \$ [14.31, 15.87] × 10⁹). In addition, Figs. 9–11 present the optimal results for CO_2 emission treated by different measures for the three power plants under scenarios S7-T, S7-NT, S9-T and S9-NT. The analysis for the solutions these

scenarios can be similarly interpreted based on the results presented in Figs. 9–11.

3.4. Comparisons of results under CO₂ trading and non-trading schemes

Figs. 12–14 show the CO_2 emission permits of each power plant obtained through trading and non-trading schemes. The results indicate that CO_2 emission quota allocation plan under trading scheme is significantly different from that under non-trading. For the gas-fired power plant in period 1 (Fig. 12), the amount of allowable CO_2 emission under trading scheme would be lower than that under non-trading scheme except for scenarios S9–T and S9–NT (μ = 80%). For the petroleum-fired and coal-fired power plants

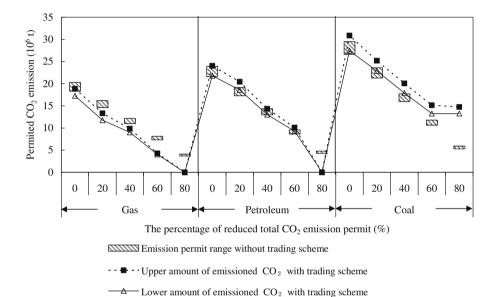


Fig. 13. Solutions for CO₂ emission permits during the period 2 under S1-T, S1-NT, S3-T, S3-NT, S5-T, S5-NT, S7-NT, S9-T and S9-NT ("S1-T" denote the "scenario 1 under trading", "S1-NT" denote the "scenario 3 under trading", "S3-NT" denote the "scenario 3 under trading", "S3-NT" denote the "scenario 3 under trading", "S5-NT" denote the "scenario 7 under trading", "S7-NT" denote the "scenario 7 under trading", "S7-NT" denote the "scenario 7 under trading", "S7-NT" denote the "scenario 9 under trading", "S9-T" denote the "scenario 9 under trading").

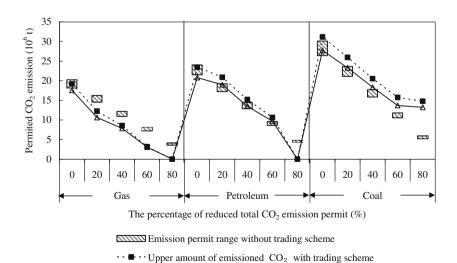


Fig. 14. Solutions for CO₂ emission permits during the period 3 under S1-T, S1-NT, S3-T, S3-NT, S5-T, S5-NT, S7-NT, S9-T and S9-NT ("S1-T" denote the "scenario 1 under trading", "S1-NT" denote the "scenario 3 under trading", "S3-NT" denote the "scenario 3 under trading", "S3-NT" denote the "scenario 3 under trading", "S5-NT" denote the "scenario 7 under trading", "S7-NT" denote the "scenario 7 under trading", "S7-NT" denote the "scenario 7 under trading", "S7-NT" denote the "scenario 9 under trading", "S9-T" denote the "scenario 9 under trading").

-Lower amount of emissioned CO₂ with trading scheme

during period 1 (Fig. 12), the allowable CO₂ emissions under trading scheme would be higher than those under non-trading scheme except for scenarios S9-T and S9-NT (μ = 80%). The amounts of CO₂ emission permits for gas- and petroleum-fired power plants under S9-T are lower than that under S9-NT, while the CO₂ emission permit for coal-fired power plant under S9-T is higher than that under S9-NT. This indicates that trading action is also appears in scenario 9, partial CO₂ emission permits of gas- and petroleum-fired power plant are assign to coal-fired power plant. Such reallocations of emission permits denote that the CO₂ emission is tradable, and trading scheme can reallocate CO₂ emission permits effectively. In addition, total treatment costs of CO₂ which surplus from three power plants are decreased under trading scheme, even with increased net power system benefit. These solutions suggest that trading can maximize the system benefit under a certain level of CO₂ emission permit.

3.5. Comparisons of results under different mitigation levels

It can be seen that the allocation plans in scenarios S1-T, S3-T, S7-T, S9-T, S1-NT, S3-NT, S7-NT, and S9-NT are significantly different with plans in S5-T and S5-NT. Solutions shown in Figs. 6-8 suggest that when the mitigation level is lower than 40% (i.e., S1-T, S3-T, S1-NT and S3-NT), the change of mitigation level causes a great transformations of excess CO₂ treated by CS both under trading and non-trading schemes. However, the change of mitigation level has a little influence on the amounts of CO₂ treated by CA. Therefore, CO₂ surplus from each power plant would be mainly treated by CS. Besides, the lower the mitigation level, the lower the amount of excess CO₂ which should be treated. This is due to the following facts: when the mitigation level is low, the CO₂ emission permits allocated to each power plant are relative high. So, less CO₂ surplus from each power plant would be treated, and high system benefit may be gained. However, these scenarios may lead to lower degree of CO₂ mitigation assurance for slowing climate change.

Solutions shown in Figs. 9–11 suggest that when the mitigation level is greater than 40% (i.e., S7-T, S9-T, S7-NT and S9-NT), the change of mitigation level causes great influence on the amount of excess CO2 treated by CS and CA both under trading and nontrading schemes. Moreover, the higher the mitigation level, the larger the amount of excess CO₂ should be treated. CO₂ surplus from each power plant in these situations would be treated by CS and CA. However, when mitigation level is greater than 60%, the amounts of surplus CO₂ which would be treated by CS are nearly stable. This suggests that, when the mitigation level is high, the CO₂ emission permits allocated to each power plant are relative low. Therefore, lots of CO₂ surplus from three power plants should be treated, which cause CS may reach their maximal handling capacities. Thus a large amount of CO₂ should be treated by CA, and low system benefit would be gained. However, higher degree CO₂ mitigation assurance for slowing climate change will be got at the same time.

Solutions of trading and non-trading models offer an effective linkage between the predefined environmental policies and the associated economic implications (e.g., low benefits and high costs caused by improper policies). The net system benefit of power system under trading scheme is obviously higher than that under non-trading scheme. CO₂ emission permits for each power plant are optimized through CO₂ emission permits trading scheme, and the trading scheme would be more effectual under the condition that the mitigation level of CO₂ total emission permit is around 40%. Besides, the amounts of excess CO₂ emission treated by CS and CA are influenced by the mitigation level of CO₂ total emission permit, due to different CO₂ management policies. This may also lead to the changing of the net system benefit for power system. These solutions suggest that CO₂ emission trading is effective for

CO₂ permit reallocation, and different policies for CO₂ management are associated with different levels of CO₂ management cost and CO₂ mitigation-failure risk.

4. Discussion

Although the TISP method has been applied to CO₂ emission trading planning within an integrated energy and environmental management system, there are also potential limitations and extensions of the proposed method. Firstly, the TISP method can hardly adequately reflect the dynamic variations of system conditions, especially for sequential structure of large-scale problems [44]. In fact, in the real-world problems, the credit surpluses in the former period could be accumulated in the later period, but the TISP model cannot reflect such a variation. To deal with such a dynamic feature, a number of multi-stage stochastic programming (MSP) methods were developed as extensions of dynamic stochastic optimization methods. The multi-stage models improved upon the two-stage stochastic programming methods by permitting revised decisions in each time stage based on the uncertainty realized so far. Therefore, it may be significant to extend the TISP into multi-stage method. Besides, the proposed TISP method can be incorporated with other inexact optimization techniques to handle various types of uncertainties under trading scheme, which will maximize system benefits and reinforce decision support for real-world problems.

Moreover, the proposed TISP method could also be applied to the Kyoto Protocol (KP)'s flexible mechanism, including both the clean development mechanism (CDM) and joint implementation (JI). CDM and JI are two so-called flexible mechanisms of the KP designed to allow its parties flexibility in achieving their quantified emission limitation and reduction commitments [54]. Under these mechanism projects that reduce emissions or remove carbon dioxide from the atmosphere generate emission certificates: Certified Emission Reductions (CERs) in the case of the CDM, Emission Reduction Units (ERUs) in the case of JI [54]. Although the basic concept of CDM and II is similar, it is important to bear in mind that CDM and JI are completely independent from each other and that there are significant differences between the two, particularly with respect to the status of implementation and their scope. CDM has the objective to support developing countries in achieving a sustainable development path, while at the same time assisting industrialized countries in achieving their Kyoto Protocol commitments [55]. It typically results in a transfer of GHG abatement technologies to developing countries in exchange for the GHG emission reduction credits [55,56]. For example, the developed countries can offer money and technology to help developing countries establish low-carbon energy demonstration projects (such as wind energy demonstration project) to generate emission certificates. The cost saving potential of wind energy is quite significant [57]. Moreover, Wind generation also leads to a significantly lower market price particularly during peak periods [57]. JI allows industrialized countries, who got binding Kyoto targets (Annex-I-Countries) to charge reductions of greenhouse gas (GHG) emissions which they effected in other Annex-I-Countries, e.g. by technology transfers, with their own emissions-credits [58]. The recipient countries emissionscredits are accordingly debited [58]. The CDM contrary to JI results in an increasing of the total volume of emissions permits. When implement the CDM and II mechanisms, uncertainties may exist in GHG emission and reduction processes, emission quota allocation, various impact factors (such as GHG emission inventory, control measures, emission reduction credits, wind speed forecasts, and related costs). Therefore, the proposed TISP method can also be applied to the KP's flexible mechanism (both CDM and II). This is due to the facts that (i) the IPP technique can tackle uncertainties

of emission quota allocation in CDM and JI; TSP can not only tackle uncertainties of GHG emission, but also reflect the issue what decision should be made when the emission exceed the regulated quota; (ii) the TISP method can provide an effective linkage between the pre-regulated environmental policies and the associated economic penalties when the promised targets are violated. Therefore, the application of TISP model to CDM and JI mechanisms could be effective in: (i) developing new energy sources, mitigation technologies, and adaptation measures in the energy system [59]; (ii) making a valuable contribution to enact and adjust international climate policy [59]; (iii) designing a multi-level governance framework for renewable energies that is attractive for foreign CDM investment as well as for domestic industry development [56].

5. Conclusions

In this study, a two-stage inexact-stochastic linear programming (TISP) method has been developed for planning CO₂ emission mitigation with trading scheme. The TISP method can effectively deal with uncertainties presented as both probabilities and intervals within a multi-period, multi-demand-level, and multi-option context. Solutions of the model provide an effective linkage between the pre-regulated energy and environmental policies and the associated economic implications (e.g., losses and penalties caused by improper policies). The solutions are combinations of deterministic, interval and distributional information, and can thus facilitate the reflection for different forms of uncertainties. The interval solutions can help managers obtain multiple decision alternatives, as well as provide bases for further analyses of tradeoffs between system benefit and system-failure risk. The developed model can also help analyze various trading policies under different CO₂ emission allowances and mitigation efficiencies.

The developed method has been applied to a case study of CO₂ emission trading for a regional power system. The results obtained indicate that CO₂ emission scheme can be efficiently performed to maximize the power net benefits through trading when the level of CO₂ emission permit is low. In addition, a number of scenarios corresponding to different CO₂ emission management policies under varied mitigation levels of total emission permits have been analyzed. The results indicate that CO₂ emission trading is effective for CO₂ permit reallocation and different policies for CO₂ management are associated with different levels of CO2 management cost and CO₂ mitigation-failure risk. Although application of TISP model to CO₂ emission trading is a new attempt and the TISP may be further enhanced or extended, the results obtained imply that the developed model is applicable and effective in CO2 emission mitigation through coupled mechanism between emission trading and control measure.

Acknowledgments

This research was supported by the Major State Basic Research Development Program of MOST (2005CB724200, 2009CB825105), the Natural Science Foundation of China (50979001), and the Natural Sciences and Engineering Research Council of Canada. The authors are extremely grateful to the editors and the anonymous reviewers for their insightful comments and suggestions.

Appendix A

When uncertainties of the right-hand-side of the model are expressed as PDFs and decisions need to be made periodically over time, the problem can be formulated as a TSP model [60]. In the TSP optimization framework, decision variables are divided into two subsets: those that must be determined before the realizations

of random variables are known and those (recourse variables) that are determined after the realized values of the random variables are available [60]. Generally, a TSP model can be formulated as follows [29,42,61]:

$$z = \max C^{T} X - E_{\omega \in \Omega}[Q(X, \omega)]$$
(A.1a)

subject to

 $x \in X$

with

 $Q(x, \omega) = \min f(\omega)^T y$

subject to

$$D(\omega)y \le h(\omega) + T(\omega)x$$
 (A.1b)

 $y \in Y$

where $X \in \mathbb{R}^{n_1}$, $C \in \mathbb{R}^{n_1}$, and $Y \in \mathbb{R}^{n_2}$. Here, ω is a random variable from space (Ω, F, P) with $\Omega \subseteq \mathbb{R}^K$, $f: \Omega \to \mathbb{R}^{n_2}$, $h: \Omega \to \mathbb{R}^{m_2}$, $D: \Omega \to R^{m_2 \times n_2}$, and $T: \Omega \to R^{m_2 \times n_1}$. Eq. (A.1a) with variables xcomposes the first-stage decision, which needs to be made before the realization of uncertain parameters ω . Eq. (A.1b) with variables y composes the second-stage decision. For a given set of first-stage variables x, the second-stage problem decomposes into independent linear subproblems. Each subproblem corresponds to a realization of the uncertain parameters. The above TSP model is generally nonlinear, and the set of feasible constraints is convex only for some particular distributions [29]. However, the TSP problem can be equivalently formulated as a linear programming (LP) model. According to Huang and Loucks [39] this nonlinear TSP model can be converted into a LP one by letting random variables (i.e., ω) take discrete values ω_h with probability levels p_h , where h = 1, 2, ..., Hand $\sum p_h = 1$. Consequently, model (A.1) can be converted as follows [29,60]:

Maximize
$$f = C_{T_1}X - \sum_{h=1}^{H} p_h D_{T_2}Y$$
 (A.2a)

subject to $A_{r_1}X + A_{r_2}Y \leq w_h$, $r_1, r_2 \in M$,

$$M = 1, 2, \dots, m, \quad \forall h \tag{A.2b}$$

$$x_j \geqslant 0, \ x_j \in X, \ j = 1, 2, \dots, n_1$$
 (A.2c)

$$y_{jh} \ge 0, \ y_{jh} \in Y, \ j = 1, 2, \dots, n_2$$
 (A.2d)

However, the parameter of a model may fluctuate within a certain interval, and it is difficult to state a meaningful probability distribution for this variation. Interval-parameter programming (IPP) can deal with uncertainties in objective function and system constraints which can be expressed as interval without distribution information. In this method, interval numbers are acceptable as its uncertain inputs. An IPP model can be expressed as [62]:

Maximize
$$f^{\pm} = C^{\pm}X^{\pm}$$
 (A.3a)

subject to
$$A^{\pm}X^{\pm} \leqslant B^{\pm}$$
 (A.3b)

$$X^{\pm} \geqslant 0$$
 (A.3c)

where $A^{\pm} \in \{R^{\pm}\}^{m \times n}$, $B^{\pm} \in \{R^{\pm}\}^{m \times 1}$, $C^{\pm} \in \{R^{\pm}\}^{1 \times n}$ and $X^{\pm} \in \{R^{\pm}\}^{n \times 1}$ (R^{\pm} denotes a set of interval numbers). An interval number X^{\pm} can be defined as an interval with known upper- and lower-bounds but unknown distribution information [63]. It can be expressed as $[X^{-}, X^{+}]$, representing a number (or an interval) which can have a minimum value of X^{-} and a maximum one of X^{+} [63]:

$$X^{\pm} = [X^{-}, X^{+}] = \{ a \in X | X^{-} \leqslant a \leqslant X^{+} \}$$
 (A.4)

where X^- and X^+ are the lower and upper bounds of X^{\pm} , respectively. When $X^- = X^+$, X^{\pm} becomes a deterministic number. An interactive solution algorithm is developed to solve the above problem through analyzing the detailed interrelationships between parameters and variables and between the objective function and constraints [30]. According to the algorithms proposed by Huang et al. [31,64], the solution for model (A.3) can be obtained through a two-step method, where a submodel corresponding to f^* (when the objective function is to be maximized) is first formulated and solved, and then the relevant submodel corresponding to f can be formulated based on the solution of the first submodel [30]. Therefore, the final solution of $f^*_{opt} = [f^-_{opt}, f^+_{opt}]$ and $X^+_{opt} = [X^-_{opt}, X^+_{opt}]$ can be obtained. A set of basic definitions for interval numbers and an interactive solution process was developed by Huang et al. [64]. Thus, integration of IPP and TSP will be considered for dealing with uncertainties presented as probabilities and intervals in the planning of energy planning and GHG emission trading management systems. This will lead to a two-stage inexact-stochastic programming model as follows [29]:

Maximize
$$f^{\pm} = C_{T_1}^{\pm} X^{\pm} + \sum_{h=1}^{H} p_h D_{T_2}^{\pm} Y^{\pm}$$
 (A.5a)

subject to $A_{r_1}^{\pm}X^{\pm} + A_{r_2}^{\pm}Y^{\pm} \leqslant w_h^{\pm}, \ r_1, \ r_2 \in M;$

$$M = 1, 2, \dots, m \tag{A.5b}$$

$$A_{r_3}^{\pm}X^{\pm}+A_{r_4}^{\pm}Y^{\pm}\,\geqslant\,B^{\pm},\ r_3,\ r_4\in M;$$

$$M=1,2,\ldots,m \tag{A.5c}$$

$$x_i^{\pm} \geqslant 0, \ x_i^{\pm} \in X^{\pm}; \quad j = 1, 2, \dots, n_1$$
 (A.5d)

$$y_{jh}^{\pm} \geqslant 0, \ y_{jh}^{\pm} \in Y^{\pm}, \quad j = 1, 2, ..., \ n_2; \quad \forall \ h$$
 (A.5e)

where x_j^{\pm} and y_{ih}^{\pm} represent first- and second-stage decision variables, respectively; the right-hand side coefficients in (A.5b) are presented as PDFs, and the left- and right-hand side coefficients in (A.5c) are available as discrete intervals [29].

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