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RESEARCH ARTICLE

Risk management for sulfur dioxide abatement under multiple uncertainties

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Abstract In this study, interval-parameter programming, two-stage stochastic programming (TSP), and conditional value-at-risk (CVaR) were incorporated into a general optimization framework, leading to an interval-parameter CVaR-based two-stage programming (ICTP) method. The ICTP method had several advantages: (i) its objective function simultaneously took expected cost and risk cost into consideration, and also used discrete random variables and discrete intervals to reflect uncertain properties; (ii) it quantitatively evaluated the right tail of distributions of random variables which could better calculate the risk of violated environmental standards; (iii) it was useful for helping decision makers to analyze the trade-offs between cost and risk; and (iv) it was effective to penalize the second-stage costs, as well as to capture the notion of risk in stochastic programming. The developed model was applied to sulfur dioxide abatement in an air quality management system. The results indicated that the ICTP method could be used for generating a series of air quality management schemes under different risk-aversion levels, for identifying desired air quality management strategies for decision makers, and for considering a proper balance between system economy and environmental quality.

Keywords risk management, conditional value-at-risk, interval optimization, two-stage programming, uncertainty, air quality management

1 Introduction

Two-stage stochastic programming (TSP), as a typical stochastic programming method, can effectively tackle optimization problems where an analysis of policy scenarios is desired and the related data are mostly uncertain (Birge and Louveaux, 1988). In applying this model, a decision is first undertaken before values of random variables are disclosed, and then, after the random events have occurred and their values are known, a recourse action is made in order to minimize “penalties” that may appear due to any infeasibilities (Ruszczyński, 1993). The initial action is called the first-stage decision, and the corrective action is named the second-stage decision. Over the past decades, the TSP model with the expected recourse function was widely explored (Huang and Loucks, 2000; Seifi and Hipel, 2001; Ahmed, 2004; Li et al., 2006; Cai et al., 2011a, b; Shao et al., 2011; Dong et al., 2012). However, a potential limitation of the conventional TSP model is that it can only account for the expectation as the optimization criterion without any consideration on the variability of the recourse values; hence, it is a risk neutral approach. As a result, the TSP model may become infeasible when the decision maker is risk averse under extra-high variability conditions.

A risk measurement method that could help tackle the above shortcomings is conditional value-at-risk (CVaR), which could capture the notion of risk in stochastic programming (Dentcheva and Ruszczynski, 2006; Miller and Ruszczynski, 2008; Lim et al., 2010). This method is modified from the value-at-risk (VaR) model which has become an essential tool in financial markets when quantifying portfolio market risk (Hsu et al., 2012). Previously, Dentcheva and Ruszczynski (2006) utilized a CVaR model for solving the problem of constructing a portfolio of finitely many assets . Miller and Ruszczynski (2008) introduced a risk-adjusted measure with CVaR to evaluate the market portfolios. These studies demonstrated that a CVaR-based model cannot only handle the expected loss under extreme conditions, but also calculate the risk through a linear model rather than nonlinear ones (Shao et

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al., 2011). The idea of introducing CVaR into the objective functions in the framework of a TSP model is contained by fairly recent research topics (Noyan, 2012). For instance, Schultz and Tiedemann (2006) introduced CVaR and integer programming into a TSP framework, and transformed it into an explicit mixed-integer linear programming model when the probability distribution is discrete and finite. Fabian (2008) proposed the decomposition frameworks for handling CVaR objectives and constraints in a TSP model. Schultz (2011) formulated a CVaR-based TSP method, and explored the structural properties of these optimization problems and the algorithms for the solutions. Noyan (2012) considered a CVaR-based TSP method, and employed it for supporting disaster management where uncertain information was addressed through a discrete scenario method. The CVaR-based TSP method can effectively help to analyze predefined policy scenarios to deal with uncertainties in stochastic formats, to reflect the expected losses from extreme events, and to balance the trade-off between system cost and risk. However, few previous studies were reported in applying inexact CVaR-based TSP methods to address multiple uncertainties that exist in air quality management systems.

In fact, in air quality management problems, various uncertainties exist in a number of system components as well as their interrelationships (Liu et al., 2003). The random characteristics of pollutants emission (e.g., sulfur dioxide (SO_2) generation rate) caused by combustion conditions (e.g., fuel property, temperature, pressure, and air inflow), the interval characteristics of pollution control technology (e.g., treatment efficiency, and control technology capacity), the dispersion processes of pollutants (e.g., pollutant emission amount, exit velocity and temperature, wind speed and direction, and atmospheric stability), the errors in estimated modeling parameters, and the vagueness of system objectives and constraints are possible sources of uncertainties (Byun et al., 2003; Athanasiadis and Mitkas, 2007). In general, the system objectives are often associated with a number of socio-economic and ecological factors such as economic cost, environmental protection, and ecological sustainability, while the constraints are related to pollutant discharges, capacity of pollution control technologies, environmental requirements, and policy regulations. Moreover, these uncertainties may be further exaggerated by not only interactions among various uncertain and dynamic impact factors, but also their associations with economic implications of violated environmental requirements (Li et al., 2006). Previously, a number of inexact optimization techniques, such as interval-parameter programming, stochastic-parameter programming, and fuzzy-parameter programming were developed for dealing with uncertainties in air quality management problems (Lejano et al., 1997; Wang and Milford, 2001; Zolezzi, 2001; Ma and Zhang, 2002; Liu et al., 2003; Haurie et al., 2004; Li et al., 2006; An and Eheart, 2007; Li et al., 2008; Lv et al., 2011). Generally, fuzzy-parameter programming can deal with imprecision or vagueness (expressed by membership functions) in decision-making problems; however, it may lead to complicated submodels that are not applicable to practical problems (Inuiguchi and Sakawa, 1998; Liu et al., 2003; Tan et al., 2011). Although stochastic-parameter programming, including TSP and CVaR-based TSP, can directly incorporate various probabilistic uncertainties within the optimization frameworks, the increased data requirements for specifying the parameters' probability distributions may affect its practical applicability (Marti and Ploöchinger, 1990; Li et al., 2006). For uncertainties that cannot be quantified as membership or distribution functions, interval-parameter programming provides an alternative way to directly communicate uncertainties into the optimization process without leading to more complicated intermediate models (Dai and Huang, 2012). Nevertheless, it may become infeasible when its right-hand-side parameters are highly uncertain (Li et al., 2008). Moreover, the interval-parameter programming cannot reflect the trade-off between system costs and risks of violated environmental standards caused by the extra high SO_2 generated levels.

Consider an air quality management system in a region where multiple pollution-control technologies are used to reduce the air pollutants discharged by multiple emission sources. Moreover, these pollutants may disperse along the atmosphere with temporal and spatial variations, and influence the air quality of multiple receptor zones. Any change in one activity may lead to a series of environmental effects. Uncertainties exist in a number of impact factors and pollution-related processes, such as pollutant generation amounts, treatment efficiencies, emissions, and transport, as well as impacts on related environmental standards; Moreover, such uncertainties may be further multiplied by their associations with economic penalties if the promised targets are violated (Huang and Chang, 2003; Lv et al., 2011). Furthermore, variations in SO_2 generation rates may result in extra high SO_2 generated levels even if the probability that such conditions happen is small. In fact, such extra high SO_2 generated levels would increase the risk of violated environmental standards. Therefore, incorporation of various uncertainties, economic penalties, and risks within a general mathematical programming framework is desired for supporting air quality management and planning.

As an extension of previous efforts, an interval-parameter CVaR-based two-stage programming (ICTP) method will be developed for air quality management, where techniques of interval-parameter programming, two-stage stochastic programming (TSP), and conditional value-at-risk (CVaR) will be incorporated within a general framework. The developed ICTP will be used for handling uncertainties expressed as probability distributions and interval values, and also for effectively analyzing predefined policy scenarios. Moreover, the ICTP method will help control the system risks of violated environmental standards, and avoid the serious problems related to excessive emissions of air pollutants. A case study will then be provided for demonstrating applicability of the developed methodology. The results can help decision makers to not only manage air quality problems, but also gain insight into the tradeoffs between environmental and economic objectives.

2 Methodology

When uncertainties of the right sides of the model are expressed as probability distribution functions, and decisions need to be made periodically over time (i.e., SO_2 generation rates are random), the problem can be formulated as a TSP model (Huang and Loucks, 2000). A general form of the TSP model can be formulated as follows (Birge and Louveaux, 1988):

$$\min \mathbb{E}[f(\boldsymbol{x},\omega)] = \min\{\boldsymbol{c}^{\mathrm{T}}\boldsymbol{x} + \mathbb{E}_{\omega\in\Omega}[Q(\boldsymbol{x},\omega)] : \boldsymbol{x} \in X\}, \tag{1a}$$

with

$$Q(\mathrm{x},\omega) = \min\{\boldsymbol{q}(\omega)^{\mathrm{T}}\boldsymbol{y}(\omega) : \boldsymbol{y} \in Y\}, \tag{1b}$$

subject to

$$\boldsymbol{D}(\omega)\boldsymbol{y}(\omega) + \boldsymbol{T}(\omega)\boldsymbol{x} \geqslant \boldsymbol{h}(\omega), \tag{1c}$$

where $\boldsymbol{c} \in \mathbb{R}^{n_1}$, $X \subseteq \mathbb{R}^{n_1}$, and $Y \subseteq \mathbb{R}^{n_2}$; ω is a random variable from probability space (Ω,F,P) with $\Omega \to \mathbb{R}^k$, $\boldsymbol{q} : \Omega \to \mathbb{R}^{n_2}$, $\boldsymbol{h} : \Omega \to \mathbb{R}^{m_2}$, $\boldsymbol{D} : \Omega \to \mathbb{R}^{m_2 \times n_2}$, and $\boldsymbol{T} : \Omega \to \mathbb{R}^{m_2 \times n_1}$; $\mathbb{E}$ denotes the expectation operates; $\boldsymbol{x}$ and $\boldsymbol{y}$ are the vectors of first-stage and second-stage decision variables, respectively. Moreover, $f(\boldsymbol{x},\omega) = \boldsymbol{c}^{\mathrm{T}}\boldsymbol{x} + Q(\boldsymbol{x},\omega)$ is the total cost function of the first-stage problem [i.e., model (1a)] and $Q(\boldsymbol{x},\omega)$, known as the recourse function, is the objective function of the second-stage problem [i.e., model (1b)]. Model (1) is risk-neutral two-stage stochastic programming model in the sense that it focuses on the optimization of an expectation objective and ignores the risk associated with the variability of random variables. CVaR as a risk measurement method can capture the notion of risk in stochastic programming. Therefore, we consider the CVaR-based TSP method as follows:

$$\min\{\mathbb{E}[f(\boldsymbol{x},\omega)] + \lambda \mathrm{CVaR}_\beta[f(\boldsymbol{x},\omega)] : \boldsymbol{x} \in X\}, \tag{2}$$

where CVaR_β denotes the conditional value-at-risk at level β; λ is a nonnegative weight to trade-off expected cost with risk, which is specified by decision makers according to their risk preferences. Birbil et al. (2009) indicated that $\mathrm{CVaR}_\beta(Z + a) = \mathrm{CVaR}_\beta(Z) + a$ for $a \in \mathbb{R}$ and $Z \in \mathcal{Z}$. Then, we have $\mathrm{CVaR}_\beta[f(\boldsymbol{x},\omega)] = \boldsymbol{c}^{\mathrm{T}}\boldsymbol{x} + \mathrm{CVaR}_\beta[Q(\boldsymbol{x},\omega)]$, and

$$\mathbb{E}[f(\boldsymbol{x},\omega)] + \lambda \mathrm{CVaR}_\beta[f(\boldsymbol{x},\omega)] \tag{3a}$$

$$= (1+\lambda)\boldsymbol{c}^{\mathrm{T}}\boldsymbol{x} + \mathbb{E}[Q(\boldsymbol{x},\omega)] + \lambda \mathrm{CVaR}_\beta[Q(\boldsymbol{x},\omega)]. \tag{3b}$$

Suppose the random vector ω ($\omega \in \mathbb{R}^m$) has a probability density function $p(\cdot)$, and $Q(\boldsymbol{x},\omega)$ is continuous in $\boldsymbol{x}$ and measurable in ω where $\mathbb{E}\{|Q(\boldsymbol{x},\omega)|\}<\infty$ for each $\boldsymbol{x} \in X$. Given the decision variable $\boldsymbol{x}$, the probability of $Q(\boldsymbol{x},\omega)$ not exceeding a threshold of α is represented as $\psi(x,\alpha) = \int_{Q(\boldsymbol{x},\omega)\leqslant\alpha} p(\omega)\mathrm{d}\omega$. Given a confidence level β and a fixed $\boldsymbol{x}$, the VaR is defined by $\mathrm{VaR}_\beta(x) = = \min\{\alpha \in \mathbb{R} : \psi(x,\alpha) \geqslant \beta\}$. And then, $\mathrm{CVaR}_\beta(\boldsymbol{x})$ defined as the expected value of the loss that exceeds $\mathrm{VaR}_\beta(\boldsymbol{x})$, can be written as follows,

$$\mathrm{CVaR}_\beta(x) = \frac{1}{1-\beta}\int_{Q(\boldsymbol{x},\omega)\geqslant \mathrm{VaR}_\beta(x)} Q(\boldsymbol{x},\omega)p(\omega)\mathrm{d}\omega. \tag{4}$$

Since model (4) is convoluted and implicit, Rockafellar and Uryasev (2000) developed an equivalent function to solve model (4) as follows:

$$F_\beta(\boldsymbol{x},\alpha) = \alpha + \frac{1}{1-\beta}\int_{\omega\in\mathbb{R}^m}\{\max\{0,\ [Q(\boldsymbol{x},\omega)-\alpha]\}\}p(\omega)\mathrm{d}\omega, \tag{5}$$

where $F_\beta(\boldsymbol{x},\alpha)$ is shown to be convex and continuously differentiable with respect to α, and $\min_x \{\mathrm{CVaR}_\beta(x)\}$ is equals to $\min_\alpha \{F_\beta(\boldsymbol{x},\alpha)\}$. By introducing an auxiliary variable z, the minimization of $\mathrm{CVaR}_\beta[Q(\boldsymbol{x},\omega)]$ is equivalent to the following model (Tong et al., 2010):

$$\min_{(x,\alpha,z)} \left\{\alpha + \frac{1}{1-\beta}\mathbb{E}_{\omega\in\mathbb{R}^m}[z(\omega)]\right\}, \tag{6a}$$

subject to

$$\boldsymbol{x} \in X, \tag{6b}$$

$$z(\omega) \geqslant Q(\boldsymbol{x},\omega) - \alpha, \tag{6c}$$

$$z(\omega) \geqslant 0. \tag{6d}$$

Accordingly, the CVaR-based TSP method [model (2)] can be transformed into the following form:

$$\min f = (1+\lambda)\boldsymbol{c}^{\mathrm{T}}\boldsymbol{x} + \mathbb{E}[Q(\boldsymbol{x},\omega)] + \lambda\left\{\alpha + \frac{1}{1-\beta}\mathbb{E}_{\omega\in\mathbb{R}^m}[z(\omega)]\right\}, \tag{7a}$$

subject to

$$z(\omega) \geqslant Q(\boldsymbol{x},\omega) - \alpha, \tag{7b}$$

$$z(\omega) \geqslant 0, \tag{7c}$$

$$\alpha \geqslant 0, \tag{7d}$$

$$\boldsymbol{x} \in X, \tag{7e}$$

with

$$Q(\boldsymbol{x},\omega) = \min \boldsymbol{q}(\omega)^{\mathrm{T}} \boldsymbol{y}(\omega), \tag{7f}$$

subject to

$$\boldsymbol{D}(\omega)\boldsymbol{y}(\omega) + \boldsymbol{T}(\omega)\boldsymbol{x} \geqslant \boldsymbol{h}(\omega), \tag{7g}$$

$$\boldsymbol{y} \in Y. \tag{7h}$$

By letting random variables (i.e., ω) take the discrete value ω_s with the probability level p_s ($s = 1,2,...,v$ and $\sum p_s = 1$), model (7) can be equivalently formulated as a following linear programming model (Noyan, 2012):

$$\min f = (1+\lambda)\boldsymbol{c}^{\mathrm{T}}\boldsymbol{x} + \sum_{s=1}^{v} p_s(\boldsymbol{q}_s)^{\mathrm{T}}\boldsymbol{y}_s + \lambda\left(\alpha + \frac{1}{1-\beta}\sum_{s=1}^{v} p_s z_s\right), \tag{8a}$$

subject to

$$\boldsymbol{T}_s\boldsymbol{x} + \boldsymbol{D}_s\boldsymbol{y}_s \geqslant \boldsymbol{h}_s,\ s = 1,2,...,v, \tag{8b}$$

$$\boldsymbol{x} \in X, \tag{8c}$$

$$\boldsymbol{y}_s \geqslant 0,\ s = 1,2,...,v, \tag{8d}$$

$$z_s \geqslant (\boldsymbol{q}_s)^{\mathrm{T}}\boldsymbol{y}_s - \alpha,\ s = 1,2,...,v, \tag{8e}$$

$$\alpha \in \mathbb{R},\ z_s \geqslant 0,\ s = 1,2,...,v. \tag{8f}$$

Model (8) can deal with uncertainties in the right-hand sides of constraints presented as probability distributions when coefficients in the left-hand sides of constraints and in the objective function are deterministic. However, in real-world optimization problems, the quality of available information is mostly not satisfactory enough to be presented as probabilities (Li et al., 2006). Such uncertainties cannot be solved through model (8). The interval-parameter programming is effective in tackling uncertainties expressed as interval values with known lower and upper bounds but unknown distribution functions (Huang et al., 1994). Therefore, through incorporating interval-parameter programming and CVaR-based TSP method within a general optimization framework, an interval-parameter CVaR-based TSP (ICTP) method can be formulated as follows:

$$\min f^{\pm} = (1+\lambda)(\boldsymbol{c}^{\pm})^{\mathrm{T}}\boldsymbol{x}^{\pm} + \sum_{s=1}^{v} p_s(\boldsymbol{q}_s^{\pm})^{\mathrm{T}}\boldsymbol{y}_s^{\pm} + \lambda\left(\alpha^{\pm} + \frac{1}{1-\beta}\sum_{s=1}^{v} p_s z_s\right), \tag{9a}$$

subject to

$$\boldsymbol{T}_s^{\pm}\boldsymbol{x}^{\pm} + \boldsymbol{D}_s^{\pm}\boldsymbol{y}_s^{\pm} \geqslant \boldsymbol{h}_s^{\pm},\ s = 1,2,...,v, \tag{9b}$$

$$z_s \geqslant (\boldsymbol{q}_s^{\pm})^{\mathrm{T}}\boldsymbol{y}_s^{\pm} - \alpha^{\pm},\ s = 1,2,...,v, \tag{9c}$$

$$\alpha^{\pm} \in \{\mathbb{R}^{\pm}\},\ z_s \geqslant 0, s = 1,2,...,v, \tag{9d}$$

$$\boldsymbol{x} \in X, \tag{9e}$$

$$\boldsymbol{y}_s \geqslant 0,\ s = 1,2,...,v. \tag{9f}$$

Model (9) can be transformed into two deterministic submodels corresponding to the lower and upper bounds of the objective function. This transformation process is based on an interactive algorithm, which is different from the best/worst case analysis (Huang et al., 1994). The interval solutions associated with varying levels of constraint-violation risk can then be obtained through solving the two submodels sequentially. The submodel corresponding to the lower-bound objective function (f^-) can be first formulated as follows:

$$\min f^- = (1+\lambda)\left(\sum_{j=1}^{k_1} c_j^- x_j^- + \sum_{j=k_1+1}^{n_1} c_j^- x_j^+\right) + \sum_{s=1}^{v}\left(\sum_{j=1}^{k_2} p_s q_{js}^- y_{js}^- + \sum_{j=k_2+1}^{n_2} p_s q_{js}^- y_{js}^+\right) + \lambda\left(\eta^- + \frac{1}{1-\alpha}\sum_{s=1}^{v} p_s z_s\right), \tag{10a}$$

subject to

$$\sum_{j=1}^{k_1} |t_{js}|^+ \mathrm{Sign}(t_{js}^+) x_j^- + \sum_{j=k_1+1}^{n_1} |t_{js}|^- \mathrm{Sign}(t_{js}^-) x_j^+ + \sum_{j=1}^{k_2} |d_{js}|^+ \mathrm{Sign}(d_{js}^+) y_{js}^- + \sum_{j=k_2+1}^{n_2} |d_{js}|^- \mathrm{Sign}(d_{js}^-) y_{js}^+ \geqslant h_s^-, \forall s, \tag{10b}$$

$$\sum_{j=1}^{k_2} |q_{js}|^- \mathrm{Sign}(q_{js}^-) y_{js}^- + \sum_{j=k_2+1}^{n_2} |q_{js}|^- \mathrm{Sign}(q_{js}^-) y_{js}^+ \leqslant z_s + \eta^-, \forall s, \tag{10c}$$

$$z_s \geqslant 0, \forall s, \quad (10d)$$

$$\eta^- \geqslant 0, \quad (10e)$$

$$x_j^- \geqslant 0,\ j = 1,2,\ldots,k_1, \quad (10f)$$

$$x_j^+ \geqslant 0,\ j = k_1+1, k_1+2,\ldots,n_1, \quad (10g)$$

$$y_{js}^- \geqslant 0,\ \forall s,\ j = 1,2,\ldots,k_2, \quad (10h)$$

$$y_{js}^+ \geqslant 0,\ \forall s,\ j = k_2+1, k_2+2,\ldots,n_2, \quad (10i)$$

where $x_j^\pm$, $j = 1,2,\ldots,k_1$, are interval variables with positive coefficients in the objective function; $x_j^\pm$, $j = k_1+1, k_1+ +2,\ldots,n_1$, are interval variables with negative coefficients; $y_{js}^\pm$, $j = 1,2,\ldots,k_2$ and $s = 1,2,\ldots,v$, are interval random variables with positive coefficients in the objective function; $y_{js}^\pm \geqslant 0$, $j = k_2+1, k_2+2,\ldots,n_2$ and $s = 1,2,\ldots,v$, are interval random variables with negative coefficients. Solutions of η_{opt}^-, $x_{j,\text{opt}}^-$ $(j = 1,2,\ldots,k_1)$, $x_{j,\text{opt}}^+$ $(j = k_1+1, k_1+2,\ldots,n_1)$, $y_{js,\text{opt}}^-$ $(j = 1,2,\ldots,k_2)$, and $y_{js,\text{opt}}^+$ $(j = k_2+1, k_2+2,\ldots,n_2)$ can be obtained through submodel (10). Based on the above solutions, the second submodel for f^+ can be formulated as follows:

$$\min f^+ = (1+\lambda)\left(\sum_{j=1}^{k_1} c_j^+ x_j^+ + \sum_{j=k_1+1}^{n_1} c_j^+ x_j^-\right) + \sum_{s=1}^{v}\left(\sum_{j=1}^{k_2} p_s q_{js}^+ y_{js}^+ + \sum_{j=k_2+1}^{n_2} p_s q_{js}^+ y_{js}^-\right) + \lambda\left(\eta^+ + \frac{1}{1-\alpha}\sum_{s=1}^{v} p_s z_s\right), \quad (11a)$$

subject to

$$\sum_{j=1}^{k_1} |t_{js}|^- \mathrm{Sign}(t_{js}^-) x_j^+ + \sum_{j=k_1+1}^{n_1} |t_{js}|^+ \mathrm{Sign}(t_{js}^+) x_j^- + \sum_{j=1}^{k_2} |d_{js}|^- \mathrm{Sign}(d_{js}^-) y_{js}^+ + \sum_{j=k_2+1}^{n_2} |d_{js}|^+ \mathrm{Sign}(d_{js}^+) y_{js}^- \geqslant h_s^+,\ \forall s, \quad (11b)$$

$$\sum_{j=1}^{k_2} |q_{js}|^+ \mathrm{Sign}(q_{js}^+) y_{js}^+ + \sum_{j=k_2+1}^{n_2} |q_{js}|^+ \mathrm{Sign}(q_{js}^+) y_{js}^- \leqslant z_s + \eta^+,\ \forall s, \quad (11c)$$

$$z_s \geqslant 0,\ \forall s, \quad (11d)$$

$$\eta^+ \geqslant \eta_{\text{opt}}^-, \quad (11e)$$

$$x_j^+ \geqslant x_{j,\text{opt}}^-,\ j = 1,2,\ldots,k_1, \quad (11f)$$

$$0 \leqslant x_j^- \leqslant x_{j,\text{opt}}^+,\ j = k_1+1, k_1+2,\ldots,n_1, \quad (11g)$$

$$y_{js}^+ \geqslant y_{js,\text{opt}}^-,\ \forall s,\ j = 1,2,\ldots,k_2, \quad (11h)$$

$$0 \leqslant y_{js}^- \leqslant y_{js,\text{opt}}^+,\ \forall s,\ j = k_2+1, k_2+2,\ldots,n_2, \quad (11i)$$

Solutions of η_{opt}^+, $x_{j,\text{opt}}^+$ $(j = 1,2,\ldots,k_1)$, $x_{j,\text{opt}}^-$ $(j = k_1+1, k_1+2,\ldots,n_1)$, $y_{js,\text{opt}}^+$ $(j = 1,2,\ldots,k_2)$, and $y_{js,\text{opt}}^-$ $(j = k_2+1, k_2+2,\ldots,n_2)$ can be obtained through submodel (11). Through integrating solutions of submodels (10) and (11), interval solution for model (9) under a set of p_s $(s = 1,2,\ldots,v)$ levels can be obtained.

3 Case study

Air pollution issues have been of substantial concern because they are related to not only a variety of human activities and economic implications, but also to multiple human health risks (Liu et al., 2003). Hence, effective planning for air quality management is important for facilitating sustainable socioeconomic development. In air quality management systems, uncertainties may exist in a variety of impact factors and pollution-related processes, such as pollutant characteristics, emission rates, mitigation measures, pollutant transport, and pollution impacts. These uncertainties would inevitably affect the efforts in modeling pollutant transport in the atmosphere, which is important for relating source conditions to ambient air quality (Li et al., 2006). For example, the operating cost of SO_2 control technology may be imprecise, which can be represented as an interval parameter (with lower- and upper- bounds). Moreover, SO_2 generation rates may vary with the operating process and adopted fuel, which can be expressed as a random variable (with a probability distribution). In general, an air quality management system can be characterized by one or several emission sources that generate negative impacts on a given receptor zone (Li et al., 2006; Lv et al., 2011). The allowable pollutant emission amounts promised for each source are critical in ensuring a healthy air quality level. Moreover, if the emission allowance is not exceeded, it will cost a standard fee for pollution control. Otherwise, if the allowance is exceeded, the surplus (excess) emission will be subject to the following economic penalties (Lv et al., 2011): 1) operating cost for mitigating the excess pollution, 2) expenditure for buying additional allowances, and 3) a fine from the government. When penalties occur, the final pollutant emission amount will be the summation of both fixed-allowable and probabilistic surplus ones. Furthermore, the extra high SO_2 generated levels may occur with a small probability due to the variation characteristic of random variables (i.e., SO_2 generation rates), while such conditions would increase the risk of violated environmental standards. The risk cost calculated by CVaR, is used to quantify the risk of violated environmental standards. Therefore, the problem under consideration is how to minimize the system cost, including expected cost and risk cost, for pollution abatement while satisfying the overall environmental goal. Specifically, formulation of desired plans for air pollution is critical for: 1) satisfying the environmental requirements, 2) reducing the risk of violated environmental standards, 3) minimizing the expected cost (i.e., the sum of regular and penalty costs) and risk cost, and 4) identifying effective management policies.

In this study, two power plants (i = 1, 2), a chemical industry plant (i = 3), a petroleum refinery (i = 4), and a steel mill (i = 5) are considered as SO_2 emission sources. Five receptor zones including one residential zone (p = 1), one scenic zone (p = 2), two agricultural zones (p = 3 and p = 5), and one industrial zone (p = 4) are affected by the SO_2 emission from five emission sources. Figure 1 shows their locations in the hypothetical system. Investigations on the local observed meteorological data show that the stability of class D and east wind have the highest occurrence frequency. The effective stack height of five emission sources are estimated at 252 m, 265 m, 150 m, 110 m, and 100 m, respectively (Liu et al., 2003). The receptor zones are adversely affected by the SO_2 generated from the five emission sources. Because the sulfur content of the coals used varied and the related combustion conditions are different, the relevant SO_2 emission rates can be expressed as random variables (Li et al., 2006). Meanwhile, the stochastic variability of random SO_2 generation rates may result in the extreme expected loss. The data of SO_2 generation rates within the planning period are acquired through survey and forecast measures. 1,000 specimens of SO_2 generation rates are selected for each emission source. Thus, 5,000 specimens would be needed in the study. Kolmogorov–Smirnov tests are then used to identify the probability distribution function (PDF) of SO_2 generation rates. Figure 2 shows the frequency of the SO_2 generation rate for each emission source, which indicates they follow the normal distribution. Next, the normal probability distribution functions can be assumed to be discrete with 20 scenarios (i.e., 20 probability levels from extra low to extra high). Table 1 presents the discrete results, which

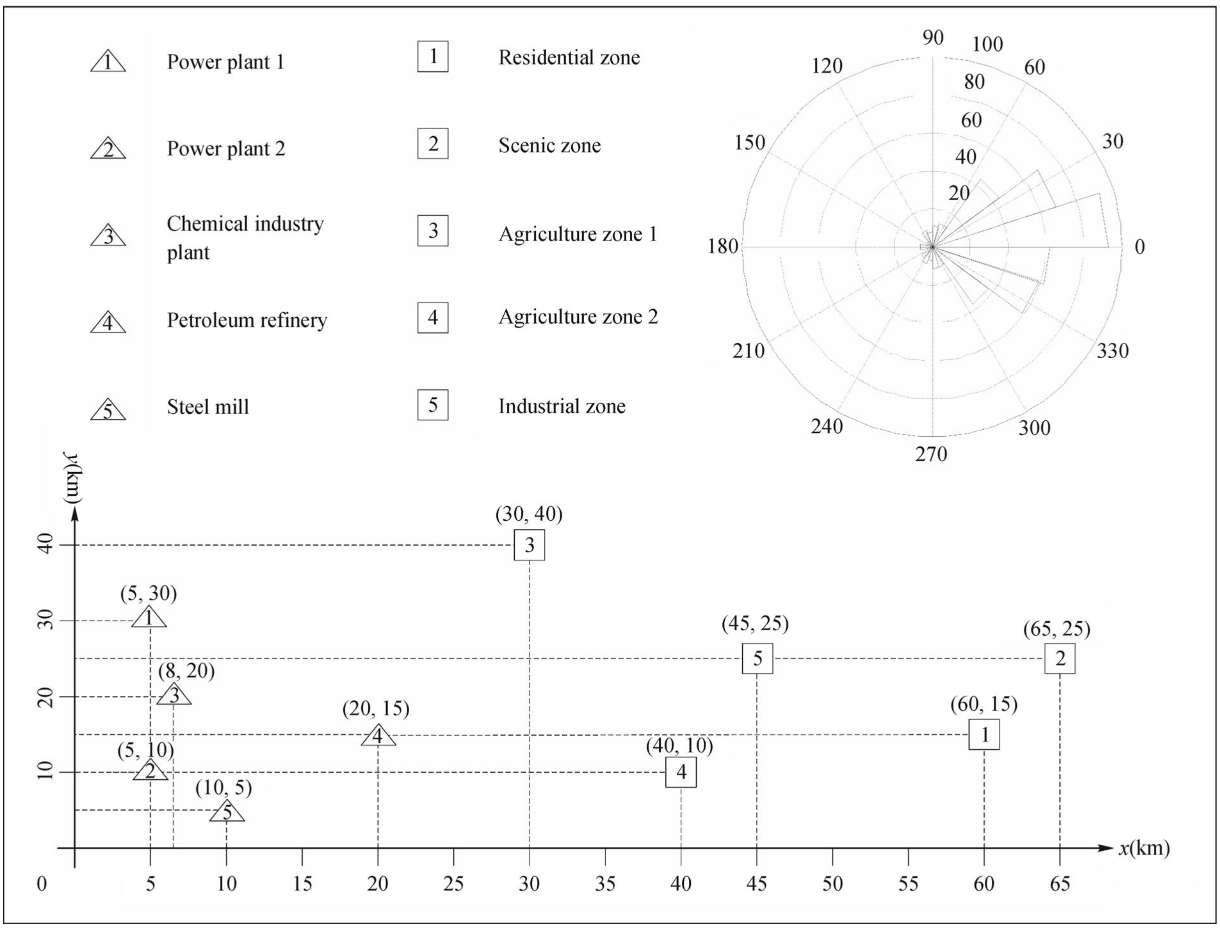

Fig. 1 The study system.

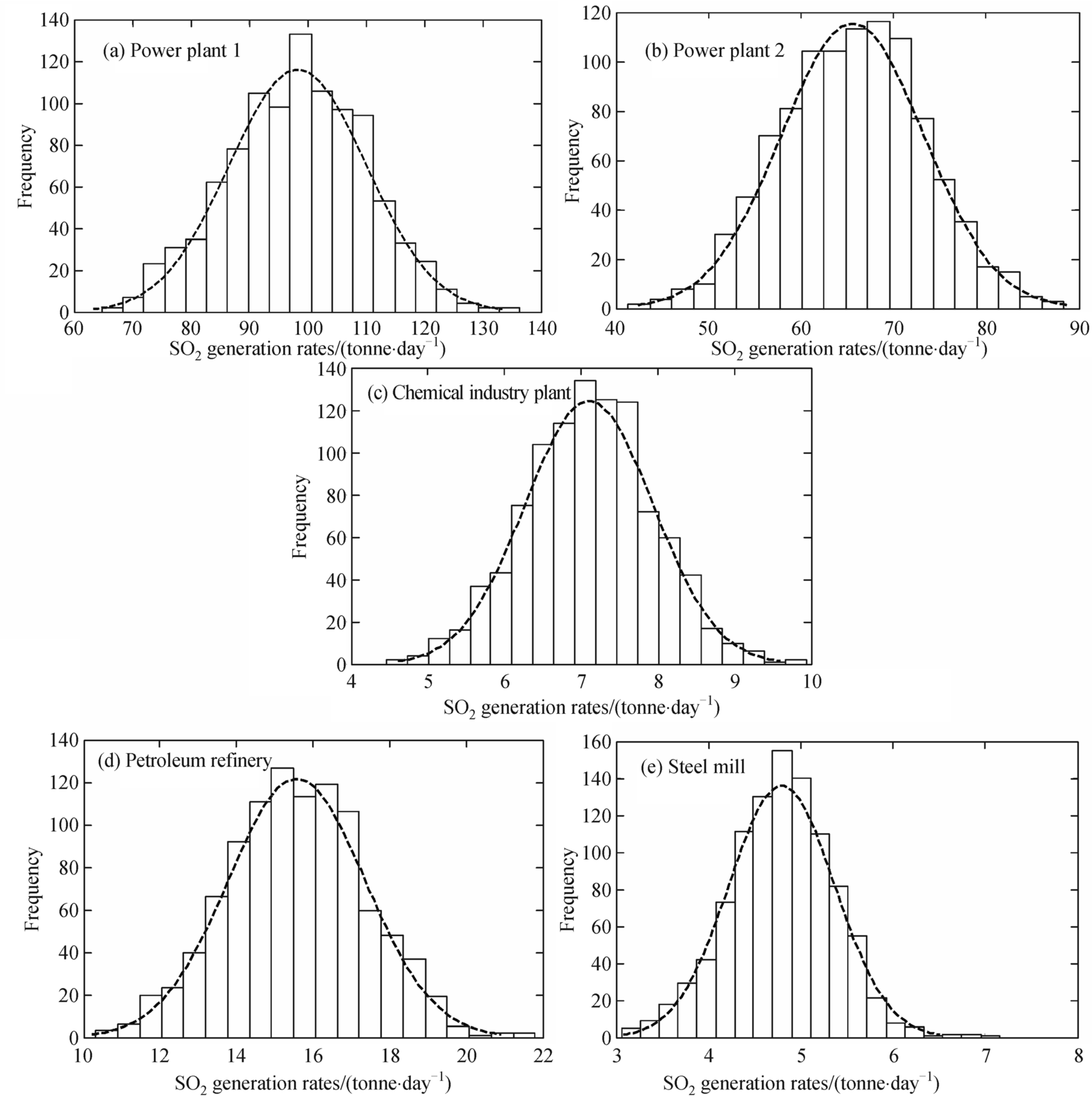

Fig. 2 The frequency of SO_2 generation rate for (a) power plant 1, (b) power plant 2, (c) chemical industry plant, (d) petroleum refinery and (e) steel mill.

show the interval SO_2 generation rates and the associated probabilities of occurrence. To keep the environmental quality at a more healthy level, the allowable emission amounts for five sources will be limited to a relatively low level which must be less than [40.0, 44.4], [26.0, 29.3], [3.7, 4.1], [7.5, 9.2] and [0.9, 1.5] tonnes/day, respectively. Moreover, the SO_2 loading capacities in the five receptor zones must be limited to under 0.15 mg/m^3, 0.05 mg/m^3, 0.15 mg/m^3, 0.25 mg/m^3, and 0.15 mg/m^3, respectively.

For the study system, even the use of low-sulfur coal (e.g., 0.2%) can hardly satisfy the SO_2 emission standard. Nevertheless, coals being mined naturally contain [0.2, 5]% of sulfur in China. Thus, to meet the environmental requirement, each emission source has to adopt pollution control technologies, including oxidation packed absorption (OPA), alkali absorption (AA), and limestone wet scrubbing (LWS), to mitigate the SO_2 emission and to avoid penalties from the government. Table 2 presents the parameters for different control technologies (i.e., efficiency, regular operation cost, and penalty operation cost) (Liu et al., 2003; Li et al., 2006; Lv et al., 2011). The efficiency of each pollution-control technology may vary with different operating conditions such as reagent ratios, temperature, and inlet SO_2 concentrations. Moreover, an elevated SO_2 level in the ambient air may cause a wide variety of human health threats and environmental impacts. According to the standard of the World Health Organization, the SO_2 loading level does not exceed the threshold of

Table 1 SO_2 generation rates under different probability levels

Scenario	Power plant 1		Power plant 2		Chemical industry plant		Petroleum refinery		Steel mill	
	Probability /%	Emission amount /(tonne·day^{-1})	Probability /%	Emission amount /(tonne·day^{-1})	Probability /%	Emission amount /(tonne·day^{-1})	Probability /%	Emission amount /(tonne·day^{-1})	Probability /%	Emission amount /(tonne·day^{-1})
S1	0.2	[64.8, 68.4]	0.2	[41.3, 43.7]	0.2	[4.5, 4.7]	0.3	[10.3, 10.9]	0.5	[3.1, 3.3]
S2	0.7	[68.4, 72]	0.4	[43.7, 46]	0.4	[4.7, 5]	0.6	[10.9, 11.5]	0.9	[3.3, 3.5]
S3	2.3	[72, 75.6]	0.8	[46, 48.4]	1.2	[5, 5.3]	2	[11.5, 12]	1.8	[3.5, 3.7]
S4	3.1	[75.6, 79.2]	1	[48.4, 50.7]	1.6	[5.3, 5.6]	2.3	[12, 12.6]	2.9	[3.7, 3.9]
S5	3.5	[79.2, 82.7]	3	[50.7, 53.1]	3.7	[5.6, 5.8]	4	[12.6, 13.2]	4.2	[3.9, 4.1]
S6	6.2	[82.7, 86.3]	4.5	[53.1, 55.4]	4.3	[5.8, 6.1]	6.6	[13.2, 13.8]	7.3	[4.1, 4.3]
S7	7.8	[86.3, 89.9]	7	[55.4, 57.8]	7.5	[6.1, 6.4]	9.2	[13.8, 14.3]	11.1	[4.3, 4.5]
S8	10.5	[89.9, 93.5]	8.1	[57.8, 60.1]	10.4	[6.4, 6.6]	11.1	[14.3, 14.9]	13	[4.5, 4.7]
S9	9.8	[93.5, 97]	10.4	[60.1, 62.5]	11.4	[6.6, 6.9]	12.7	[14.9, 15.5]	15.5	[4.7, 4.9]
S10	13.3	[97, 100.6]	10.4	[62.5, 64.8]	13.4	[6.9, 7.2]	11.3	[15.5, 16.1]	14	[4.9, 5.1]
S11	10.6	[100.6, 104.2]	11.3	[64.8, 67.2]	12.5	[7.2, 7.5]	11.9	[16.1, 16.6]	11	[5.1, 5.3]
S12	9.7	[104.2, 107.8]	11.6	[67.2, 69.5]	12.4	[7.5, 7.7]	10.6	[16.6, 17.2]	8.2	[5.3, 5.5]
S13	9.4	[107.8, 111.4]	10.9	[69.5, 71.9]	7.2	[7.7, 8]	6	[17.2, 17.8]	5.5	[5.5, 5.7]
S14	5.3	[111.4, 114.9]	7.7	[71.9, 74.2]	6	[8, 8.3]	4.8	[17.8, 18.4]	2.1	[5.7, 5.9]
S15	3.3	[114.9, 118.5]	5.2	[74.2, 76.6]	4.2	[8.3, 8.6]	3.7	[18.4, 18.9]	0.8	[5.9, 6.1]
S16	2.4	[118.5, 122.1]	3.5	[76.6, 79]	1.7	[8.6, 8.8]	1.9	[18.9, 19.5]	0.6	[6.1, 6.3]
S17	1.1	[122.1, 125.7]	1.7	[79, 81.3]	1	[8.8, 9.1]	0.5	[19.5, 20.1]	0.1	[6.3, 6.5]
S18	0.4	[125.7, 129.3]	1.5	[81.3, 83.7]	0.6	[9.1, 9.4]	0.1	[20.1, 20.7]	0.2	[6.5, 6.7]
S19	0.3	[129.3, 132.8]	0.5	[83.7, 86]	0.1	[9.4, 9.7]	0.2	[20.7, 21.2]	0.2	[6.7, 7]
S20	0.1	[132.8, 136.4]	0.3	[86, 88.4]	0.2	[9.7, 9.9]	0.2	[21.2, 21.8]	0.1	[7, 7.2]

Table 2 Parameters of pollution-control technologies

Technology	Efficiency/%	Regular operation cost/($·tonne^{-1})	Penalty operation cost/($·tonne^{-1})	Capacity/(tonne·day^{-1})
OPA	[75, 80]	[47, 54]	[70, 76]	[100, 110]
AA	[82, 90]	[65, 71]	[90, 99]	[75, 80]
LWS	[61, 70]	[32, 37]	[50,60]	[85,90]

50 μg/(m^3·year) in this study. The regular operation costs involve the capital and operating costs for mitigating SO_2 emissions through three pollution-control techniques. The penalty rates are significantly higher than the regular costs. The AA technology has the highest SO_2 removal efficiency, but it also has the highest operating cost due to the highest reagent cost.

This study focuses on the mitigation of SO_2 emission from multiple sources through different control measures. The pre-set policy formulated by local authorities is considered when a decision analysis is undertaken. Uncertainties that exist in the system components may be presented as PDFs and discrete intervals. Moreover, the risks from the variability of random parameters are quantified as CVaR. Therefore, the proposed ICTP method is suitable for tackling this type of management problem. Thus, we have:

$$\min f^{\pm} = (1+\lambda)\sum_{i=1}^{5}\sum_{j=1}^{3} X_{ij}^{\pm} AO_j^{\pm} + \sum_{i=1}^{5}\sum_{j=1}^{3}\sum_{s=1}^{20} p_{is} Y_{ijs}^{\pm} EO_j^{\pm} + \lambda\left(\alpha^{\pm} + \frac{1}{1-\beta}\sum_{i=1}^{5}\sum_{s=1}^{20} p_{is} z_{is}\right)$$

subject to

$$z_{is} \geqslant \sum_{j=1}^{3} EO_j^{\pm} Y_{ijs}^{\pm} - \alpha^{\pm},\ \forall i,s \qquad (12a)$$

[Constraint of auxiliary variable]

$$\sum_{i=1}^{5}\left(X_{ij}^{\pm}+Y_{ijs}^{\pm}\right)\leqslant TC_{j}^{\pm},\ \forall j,s \tag{12b}$$

[Constraint of capacity for each technology]

$$\sum_{j=1}^{3}\left(X_{ij}^{\pm}+Y_{ijs}^{\pm}\right)\geqslant G_{is}^{\pm},\ \forall i,s \tag{12c}$$

[Constraint of SO_2 mitigation requirement]

$$\sum_{j=1}^{3}\left(1-\eta_{j}^{\pm}\right)\left(X_{ij}^{\pm}+Y_{ijs}^{\pm}\right)\leqslant e_{i}^{\pm},\ \forall i,s \tag{12d}$$

[Constraint of SO_2 emission allowance]

$$\sum_{i=1}^{5}\sum_{j=1}^{3}t_{ip}u\left(1-\eta_{j}^{\pm}\right)\left(X_{ij}^{\pm}+Y_{ijs}^{\pm}\right)\leqslant a_{p}^{\pm},\ \forall p,s \tag{12e}$$

[Constraint of ambient air quality requirement]

$$\alpha^{\pm}\geqslant 0 \tag{12f}$$

$$z_{is}\geqslant 0,\ \forall i,s \tag{12g}$$

$$0\leqslant Y_{ijs}^{\pm}\leqslant X_{ij}^{\pm}\leqslant X_{ij,\max},\ \forall i,j,s \tag{12h}$$

[Non-negativity constraints]

where $f^{\pm}$ is the mean-risk function value (\$); i is the name of SO_2 emission source, i = 1, 2,…, 5; j is the type of SO_2 control technology, j = 1, 2, 3, where j = 1 for the OPA technology, j = 2 for the AA technology, and j = 3 for the LWS technology; s is the scenario of SO_2 emission rates, s = 1, 2,…, 20; p is the name of receptor zone, p = 1, 2,…, 5; λ and β are risk parameters; z_{is} is the auxiliary variable; $AO_j^{\pm}$ is the operating cost of control technology j for allowable SO_2 emissions (\$/tonne) (the first-stage cost parameter); $EO_j^{\pm}$ is the operating and penalty costs of control technology j for excess SO_2 emissions (\$/tonne) (the second-stage cost parameter), where $EO_j^{\pm} > AO_j^{\pm}$; $TC_j^{\pm}$ is the maximum allowable capacity of control technology j (tonne/day); $e_i^{\pm}$ is the SO_2 emission allowance for emission source i (tonne/day); $G_{is}^{\pm}$ is the amount of SO_2 generated from source i under scenario s of SO_2 generation rates (tonne/day); $\eta_j^{\pm}$ is the efficiency of control technology j; u is the unit conversion factor changing "tonne/day" into "mg/s," where the work time of emission sources varies between 8 and 10 h and the value of u equals $[2.78, 3.47] \times 10^4$; $X_{ij}^{\pm}$ is the amount of SO_2 generated from source i to be mitigated by control technology j, which can be derived based on the emission standard as pre-regulated by the authorities (the first-stage decision variable) (tonne/day); $Y_{ijs}^{\pm}$ is the amount by which the SO_2 emission allowance ($X_{ij}^{\pm}$) is exceeded when the SO_2 generation rate is $G_{is}^{\pm}$ with the probability p_{is} (tonne/day) (the second-stage decision variable); $a_p^{\pm}$ is the environmental loading capacity of receptor zone p (mg/m^3); t_{ip} is the contribution of unit pollutant emission rate at emission source i to receptor zone p. t_{ip} represents the mapping relationship between SO_2 emission source i and receptor zone p, which can be calculated based on the Gaussian dispersion model.

In the Gaussian dispersion model, the ground-level concentration of SO_2 at each arbitrary downwind location (x, y) can be estimated through the following equation:

$$C(x,y)=\frac{Q}{\pi\bar{u}\sigma_y\sigma_z}\exp\left[\left(\frac{-y^2}{2\sigma_y^2}\right)-\left(\frac{H^2}{2\sigma_z^2}\right)\right], \tag{13}$$

where H represents average effective stack height (m); Q denotes pollutant emission rate (mg/s); $\bar{u}$ is wind velocity (m/s); σ_y and σ_z represent standard deviations of the plume at y and z directions (m), respectively. Through fitting the Pasquill-Gifford curves, σ_y and σ_z can be calculated as follows (Turner, 1970):

$$\sigma_y = ax^b, \tag{14a}$$

$$\sigma_z = cx^d, \tag{14b}$$

where the coefficients a, b, c and d depend on Pasquill Stability Category. Let x_{ip} denote the distance between the i^{th} SO_2 emission source and p^{th} receptor zone at x directions (km). Meanwhile, let y_{ip} denote the distance between the i^{th} SO_2 emission source and p^{th} receptor zone at y directions (km). Therefore, the concentration contribution of the i^{th} emission source to the ground concentration in the p^{th} receptor zone can be estimated as follows:

$$C(x_{ip},y_{ip})=\frac{Q_i}{\pi\bar{u}acx_{ip}^{b+d}}\exp\left[\left(\frac{-y_{ip}^2}{2a^2x_{ip}^{2b}}\right)-\left(\frac{H^2}{2c^2x_{ip}^{2d}}\right)\right], \tag{15}$$

where Q_i denotes the pollutant emission rate of the i^{th} SO_2 emission source (mg/s). Consequently, the transfer factor t_{ip} can be defined as follows:

$$t_{ip}=\frac{x_{ip}^{-b-d}}{\pi\bar{u}ac}\exp\left[\left(\frac{-y_{ip}^2}{2a^2x_{ip}^{2b}}\right)-\left(\frac{H^2}{2c^2x_{ip}^{2d}}\right)\right]. \tag{16}$$

In model (12), the objective is to minimize the sum of system expected cost for SO_2 abatement and the CVaR quantifying the risk of violated environmental standard; the constraints include the SO_2 emission standards (or regulated allowances) and the allowable pollutant-loading levels. Figure 3 illustrates the general framework of the ICTP method model (12)], which is based on the interval-parameter programming, CVaR and TSP technologies. The solution algorithm of model (12) can then be summarized through using the following pseudo-code:

Step 1: Sample the SO_2 concentration for each emission

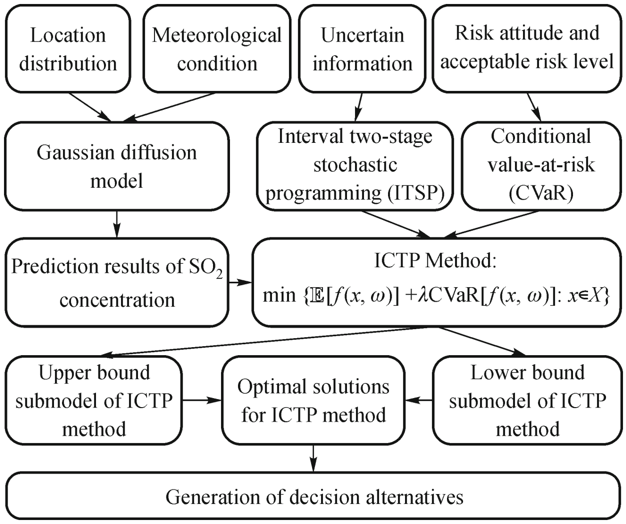

Fig. 3 The framework of the ICTP method.

source and obtain the related PDF;

Step 2: Employ the Gaussian dispersion model to calculate the transfer factor (t_{ip});

Step 3: Formulate the ICTP model [model (12)] for risk management of sulfur dioxide abatement;

Step 4: Introduce the discretized PDF and the transfer factor (t_{ip}) into model (12);

Step 5: Transform model (12) into two submodels, which correspond to f^- and f^+ respectively, based on the methodology developed in Section 2;

Step 6: Solve the two submodels, respectively, through the Lingo 9.0 optimization software;

Step 7: Obtain the solution of the ICTP model [model (12)] and get the optimal SO_2 emission allocation pattern under different risk levels;

Step 8: Stop.

4 Result analysis

In this study, two risk parameters, five levels of λ (i.e., 0.5, 1, 2, 5, 10) and three levels of β (i.e., 0.6, 0.8 and 0.99), were considered. Table 3 presents the solutions obtained through the ICTP method under $\lambda = 1$ and $\beta = 0.99$, for abating the allowable and excess SO_2 emissions (i.e., the first- and second-stage variables). The solutions presented as interval numbers indicate that the related decisions should be sensitive to the change of input parameters. An excess SO_2 emission will be generated if the SO_2 emission allowance is exceeded (i.e., excess SO_2 emission = SO_2 generation rate – SO_2 emission allowance). If the SO_2 generation rate is higher, a control technology with a higher efficiency should be installed to abate the excess emissions for meeting the air quality standard and reducing the economic penalties. Therefore, the amount treated by the AA technology should be assigned first in case of excess SO_2 emissions. For example, in power plant 1, the amounts of allowable SO_2 emission to be treated by OPA, AA, and LWS technology would be 30 tonnes/day, 30 tonnes/day, and 24 tonnes/day, respectively. In addition, some excess SO_2 emissions should be treated under varied SO_2 generation rates (with different probability levels). The amounts of excess emission mitigated by OPA, AA, and LWS technology would respectively be 10.3 tonnes/day, 18.7 tonnes/day, and [19.8, 23.4] tonnes/day under the highest SO_2 generation rate (in scenario 20 with the probability of 0.1%), while no excess emission was allotted under the lowest SO_2 generation rate (in scenario 1 with the probability of 0.2%).

Table 4 illustrates the optimized allocation pattern for the total SO_2 emission from the five sources to the OPA, AA, and LWS technologies under different risk levels. The results indicate that the optimized scheme for SO_2 emission allocation would be related to the risk levels (i.e., λ and β). For example, for $\beta = 0.6$, the amounts of total SO_2 emission abated by the OPA technology should be [34.2, 34.7] tonnes/day under $\lambda = 0.5$, [32.3, 32.5] tonnes/day under $\lambda = 1$, [31.5, 31.7] tonnes/day under $\lambda = 2$, [31, 31.7] tonnes/day under $\lambda = 5$, [30.9, 31.7] tonnes/day under $\lambda = 10$; while for $\lambda = 1$, the amounts of total SO_2 emission mitigated by the OPA technology should be [32.3, 32.5] tonnes/day under $\beta = 0.6$, [31.8, 32.1] tonnes/day under $\beta = 0.8$, [31.4, 31.7] tonnes/day under $\beta = 0.99$. Figure 4 shows the changing trend of the excess SO_2 emissions treated by the OPA, AA, and LWS technologies under different λ and β levels. It is indicated that the excess SO_2 emissions are affected by the risk level as well. For instance, the excess SO_2 emissions to any control technologies would decrease when λ is fixed and β changes from 0.6 to 0.99 (or β is fixed

Table 3 Solution obtained through the ICTP method under $\lambda = 1$ and $\beta = 0.99$

Source	Scenario	OPA (j = 1)		AA (j = 2)		LWS (j = 3)	
		Treated amount of SO_2 emission, $X^{\pm}_{ij,opt}$/(tonne·day^{-1})	Treated amount of excess SO_2 emission, $Y^{\pm}_{ijs,opt}$/(tonne·day^{-1})	Treated amount of SO_2 emission, $X^{\pm}_{ij,opt}$/(tonne·day^{-1})	Treated amount of excess SO_2 emission, $Y^{\pm}_{ijs,opt}$/(tonne·day^{-1})	Treated amount of SO_2 emission, $X^{\pm}_{ij,opt}$/(tonne·day^{-1})	Treated amount of excess SO_2 emission, $Y^{\pm}_{ijs,opt}$/(tonne·day^{-1})
Power plant 1(i = 1)	s = 1	30	0	30	0	24	0
	s = 2	30	0	30	0	24	0
	s = 3	30	0	30	0	24	0
	s = 4	30	0	30	0	24	0
	s = 5	30	0	30	0	24	0
	s = 6	30	0	30	0	24	[0, 2.3]
	s = 7	30	0	30	0	24	[2.3, 5.9]
	s = 8	30	0	30	0	24	[5.9, 9.5]
	s = 9	30	0	30	0	24	[9.5, 13]
	s = 10	30	0	30	0	24	[13, 16.6]
	s = 11	30	0	30	0	24	[16.6, 20.2]
	s = 12	30	0	30	0	24	[20.2, 23.8]
	s = 13	30	[0, 3.4]	30	0	24	[23.8, 24]
	s = 14	30	[5.8, 6.9]	30	0	24	[21.6, 24]
	s = 15	30	12.6	30	0	24	[18.3, 21.9]
	s = 16	30	[13.6, 14.1]	30	0	24	[20.9, 24]
	s = 17	30	[17.4, 17.7]	30	0	24	[20.7, 24]
	s = 18	30	16.1	30	5.2	24	[20.4, 24]
	s = 19	30	13.1	30	12.1	24	[20.1, 23.6]
	s = 20	30	10.3	30	18.7	24	[19.8, 23.4]
Power plant 2(i = 2)	s = 1	30	0	18	0	12	0
	s = 2	30	0	18	0	12	0
	s = 3	30	0	18	0	12	0
	s = 4	30	0	18	0	12	0
	s = 5	30	0	18	0	12	0
	s = 6	30	0	18	0	12	0
	s = 7	30	0	18	0	12	0
	s = 8	30	0	18	0	12	[0, 0.1]
	s = 9	30	0	18	0	12	[0.1, 2.5]
	s = 10	30	0	18	0	12	[2.5, 4.8]
	s = 11	30	0	18	0	12	[4.8, 7.2]
	s = 12	30	0	18	0	12	[7.2, 9.5]
	s = 13	30	0	18	0	12	[9.5, 11.9]
	s = 14	30	[0, 2.2]	18	0	12	[11.9, 12]
	s = 15	30	[2.2, 4.6]	18	0	12	12
	s = 16	30	[4.6, 7]	18	0	12	12
	s = 17	30	[7, 9.3]	18	0	12	12
	s = 18	30	[9.3, 11.7]	18	0	12	12
	s = 19	30	[11.7, 14]	18	0	12	12
	s = 20	30	[14, 16.4]	18	0	12	12

(*Continued*)

Source	Scenario	OPA (j = 1)		AA (j = 2)		LWS (j = 3)	
		Treated amount of SO_2 emission, $X^{\pm}_{ij,opt}$/(tonne·day^{-1})	Treated amount of excess SO_2 emission, $Y^{\pm}_{ijs,opt}$/(tonne·day^{-1})	Treated amount of SO_2 emission, $X^{\pm}_{ij,opt}$/(tonne·day^{-1})	Treated amount of excess SO_2 emission, $Y^{\pm}_{ijs,opt}$/(tonne·day^{-1})	Treated amount of SO_2 emission, $X^{\pm}_{ij,opt}$/(tonne·day^{-1})	Treated amount of excess SO_2 emission, $Y^{\pm}_{ijs,opt}$/(tonne·day^{-1})
Chemical industry plant (i = 3)	s = 1	0	0	0	0	[7.5, 7.7]	0
	s = 2	0	0	0	0	[7.5, 7.7]	0
	s = 3	0	0	0	0	[7.5, 7.7]	0
	s = 4	0	0	0	0	[7.5, 7.7]	0
	s = 5	0	0	0	0	[7.5, 7.7]	0
	s = 6	0	0	0	0	[7.5, 7.7]	0
	s = 7	0	0	0	0	[7.5, 7.7]	0
	s = 8	0	0	0	0	[7.5, 7.7]	0
	s = 9	0	0	0	0	[7.5, 7.7]	0
	s = 10	0	0	0	0	[7.5, 7.7]	0
	s = 11	0	0	0	0	[7.5, 7.7]	0
	s = 12	0	0	0	0	[7.5, 7.7]	0
	s = 13	0	0	0	0	[7.5, 7.7]	[0.2, 0.3]
	s = 14	0	0	0	0	[7.5, 7.7]	[0.5, 0.6]
	s = 15	0	0	0	0	[7.5, 7.7]	[0.8, 0.9]
	s = 16	0	0	0	0	[7.5, 7.7]	1.1
	s = 17	0	0	0	0	[7.5, 7.7]	[1.3, 1.4]
	s = 18	0	0	0	0	[7.5, 7.7]	[1.6, 1.7]
	s = 19	0	0	0	0	[7.5, 7.7]	[1.9, 2]
	s = 20	0	0	0	0	[7.5, 7.7]	2.2
Petroleum refinery (i = 4)	s = 1	8	0	0	0	7.5	0
	s = 2	8	0	0	0	7.5	0
	s = 3	8	0	0	0	7.5	0
	s = 4	8	0	0	0	7.5	0
	s = 5	8	0	0	0	7.5	0
	s = 6	8	0	0	0	7.5	0
	s = 7	8	0	0	0	7.5	0
	s = 8	8	0	0	0	7.5	0
	s = 9	8	0	0	0	7.5	0
	s = 10	8	0	0	0	7.5	[0, 0.6]
	s = 11	8	0	0	0	7.5	[0.6, 1.1]
	s = 12	8	0	0	0	7.5	[1.1, 1.7]
	s = 13	8	1.2	0	0	7.5	[0.5, 1.1]
	s = 14	8	2.3	0	0	7.5	[0, 0.6]
	s = 15	8	0	0	0	7.5	[2.9, 3.4]
	s = 16	8	3.4	0	0	7.5	[0, 0.6]
	s = 17	8	4	0	0	7.5	[0, 0.6]
	s = 18	8	4.6	0	0	7.5	[0, 0.6]
	s = 19	8	5.2	0	0	7.5	[0, 0.5]
	s = 20	8	5.7	0	0	7.5	[0, 0.6]

(*Continued*)

Source	Scenario	OPA (j = 1)		AA (j = 2)		LWS (j = 3)	
		Treated amount of SO_2 emission, $X_{ij,opt}^{\pm}$/(tonne·day^{-1})	Treated amount of excess SO_2 emission, $Y_{ijs,opt}^{\pm}$/(tonne·day^{-1})	Treated amount of SO_2 emission, $X_{ij,opt}^{\pm}$/(tonne·day^{-1})	Treated amount of excess SO_2 emission, $Y_{ijs,opt}^{\pm}$/(tonne·day^{-1})	Treated amount of SO_2 emission, $X_{ij,opt}^{\pm}$/(tonne·day^{-1})	Treated amount of excess SO_2 emission, $Y_{ijs,opt}^{\pm}$/(tonne·day^{-1})
Steel mill (i = 5)	s = 1	2	0	2.7	0	[0, 0.2]	0
	s = 2	2	0	2.7	0	[0, 0.2]	0
	s = 3	2	0	2.7	0	[0, 0.2]	0
	s = 4	2	0	2.7	0	[0, 0.2]	0
	s = 5	2	0	2.7	0	[0, 0.2]	0
	s = 6	2	0	2.7	0	[0, 0.2]	0
	s = 7	2	0	2.7	0	[0, 0.2]	0
	s = 8	2	0	2.7	0	[0, 0.2]	0
	s = 9	2	0	2.7	0	[0, 0.2]	0
	s = 10	2	0.2	2.7	0	[0, 0.2]	0
	s = 11	2	0.4	2.7	0	[0, 0.2]	0
	s = 12	2	0.6	2.7	0	[0, 0.2]	0
	s = 13	2	0.8	2.7	0	[0, 0.2]	0
	s = 14	2	1	2.7	0	[0, 0.2]	0
	s = 15	2	1.1	2.7	0.1	[0, 0.2]	0
	s = 16	2	0.9	2.7	0.5	[0, 0.2]	0
	s = 17	2	0.7	2.7	0.9	[0, 0.2]	0
	s = 18	2	0	2.7	1.8	[0, 0.2]	0
	s = 19	2	0	2.7	2	[0, 0.2]	[0, 0.1]
	s = 20	2	0	2.7	2.3	[0, 0.2]	0

Table 4 Optimal SO_2 emission allocation schemes under different risk parameters

Confidence level	Source	Technology	Risk parameters/(tonne·day^{-1})				
			λ = 0.5	λ = 1	λ = 2	λ = 5	λ = 10
β = 0.6	i = 1	j = 1	[34.2, 34.7]	[32.3, 32.5]	[31.5, 31.7]	[31, 31.7]	[30.9, 31.7]
		j = 2	22	27.3	30.1	30.1	30
		j = 3	[40.5, 43.4]	[37.6, 40.6]	[35.9, 38.8]	[36.4, 38.9]	[36.5, 38.9]
	i = 2	j = 1	[31.4, 32.3]	[31.1, 31.9]	[30.6, 31.1]	[30.3, 30.6]	[30.3, 30.6]
		j = 2	12.3	13.4	15.8	18	18
		j = 3	[19.1, 20.3]	[18.5, 19.7]	[17.2, 18.4]	[16, 17.2]	[16, 17.2]
	i = 3	j = 1	0	0	0	3.3	3.3
		j = 2	0	0	0	0	0
		j = 3	[7.3, 7.5]	[7.6, 7.8]	[8, 8.2]	[5, 5.2]	[5, 5.2]
	i = 4	j = 1	7.9	8.5	8.5	8.3	8.1
		j = 2	0	0	0	0	2.2
		j = 3	[8, 8.4]	[7.8, 8.1]	[7.8, 8.1]	[7.9, 8.3]	[7.5, 7.6]
	i = 5	j = 1	2.4	2.4	2.3	2.1	2.1
		j = 2	2.6	2.6	2.8	3.2	3.3
		j = 3	[0, 0.2]	[0, 0.2]	[0, 0.2]	[0, 0.2]	[0, 0.2]

(*Continued*)

Confidence level	Source	Technology	Risk parameters/(tonne·day^{-1})				
			λ = 0.5	λ = 1	λ = 2	λ = 5	λ = 10
β = 0.8	i = 1	j = 1	[33, 33.3]	[31.8, 32.1]	[31.4, 31.7]	[31, 31.7]	[30.9, 31.7]
		j = 2	25.4	28.9	30.1	30.1	30
		j = 3	[38.5, 41.6]	[36.6, 39.6]	[36, 38.8]	[36.5, 38.9]	[36.5, 38.9]
	i = 2	j = 1	[31.1, 31.9]	[31.1, 31.9]	[30.5, 30.8]	[30.3, 30.6]	[30.3, 30.6]
		j = 2	13.4	13.4	17.1	18	18
		j = 3	[18.5, 19.7]	[18.5, 19.7]	[16.5, 17.7]	[16, 17.2]	[16, 17.2]
	i = 3	j = 1	0	0	0.2	3.3	3.3
		j = 2	0	0	0	0	0
		j = 3	[7.3, 7.5]	[7.6, 7.8]	8.1	[5.3, 5.5]	[5.3, 5.5]
	i = 4	j = 1	7.9	8.5	8.5	8.3	8.1
		j = 2	0	0	0	1	3.1
		j = 3	[8, 8.4]	[7.8, 8.1]	[7.8, 8.1]	[7.6, 7.8]	7.5
	i = 5	j = 1	1.7	2.3	2.1	2.1	2.1
		j = 2	2.8	2.7	3.1	3.3	3.3
		j = 3	[0.5, 0.7]	[0, 0.2]	[0, 0.2]	[0, 0.2]	[0, 0.2]
β = 0.99	i = 1	j = 1	[33, 33.3]	[31.4, 31.7]	[31.3, 31.7]	[30.9, 31.7]	[31, 31.7]
		j = 2	25.4	30.1	30.1	30	30
		j = 3	[38.5, 41.6]	[36.1, 38.8]	[36.1, 38.9]	[36.5, 38.9]	[36.5, 38.9]
	i = 2	j = 1	[31.1, 31.9]	[30.3, 30.6]	[30.3, 30.6]	[30.3, 30.6]	[30.3, 30.6]
		j = 2	13.4	18	18	18	18
		j = 3	[18.5, 19.7]	[16, 17.2]	[16, 17.2]	[16, 17.2]	[16, 17.2]
	i = 3	j = 1	0	0	0.7	3.3	0
		j = 2	0	0	0	0	3.3
		j = 3	[7.3, 7.5]	[7.6, 7.8]	8.1	[6.4, 6.6]	[6.4, 6.6]
	i = 4	j = 1	8	8.4	8.3	8.1	7.4
		j = 2	0	0	1	6.5	7.2
		j = 3	[8, 8.4]	[7.8, 8.1]	[7.6, 7.8]	[6.6, 7.2]	[6.6, 7.2]
	i = 5	j = 1	1.7	2.3	2.1	2.1	2.1
		j = 2	2.8	2.7	3.1	3.3	3.3
		j = 3	[0.5, 0.7]	[0, 0.2]	[0, 0.2]	[0, 0.2]	[0, 0.2]

and λ changes from 0.5 to 10). Therefore, lower λ (and/or β) means a higher level of system risk, which may lead to more excess SO_2 emissions; conversely, higher λ (and/or β) means a lower level of system risk, which may lead to less excess SO_2 emissions.

Figure 5(a) shows the mean-risk function value of $f^{\pm}$ at different risk levels. The result indicated that the optimal value of the mean-risk function would increase when the risk parameters (λ and/or β) increase. For example, the mean-risk function value would increase from \$[14.9, 17.6] $\times 10^3$ to \$[123.8, 145.8] $\times 10^3$ when β is fixed at 0.6 and λ increases from 0.5 to 10. In addition, the mean-risk function value would increase from \$[20.7, 24.3] $\times 10^3$ to \$[23.2, 27.1] $\times 10^3$ when λ is fixed at 1 and β increases from 0.6 to 0.99. Figure 5 (b) illustrates the total expected cost under different λ and β levels. It is indicated that the total expected cost would increase due to higher risk parameters (λ and/or β). This implies that a higher system cost would guarantee a lower system risk; conversely, if the decision maker aims toward an economical plan, a higher expected loss could be confronted. In the real world application, the decision makers may need to choose between a riskier solution with a lower system cost and a more conservative solution with a higher system cost.

Figure 6 presents the recourse cost under different λ and β levels. It is indicated that risk parameters can affect the

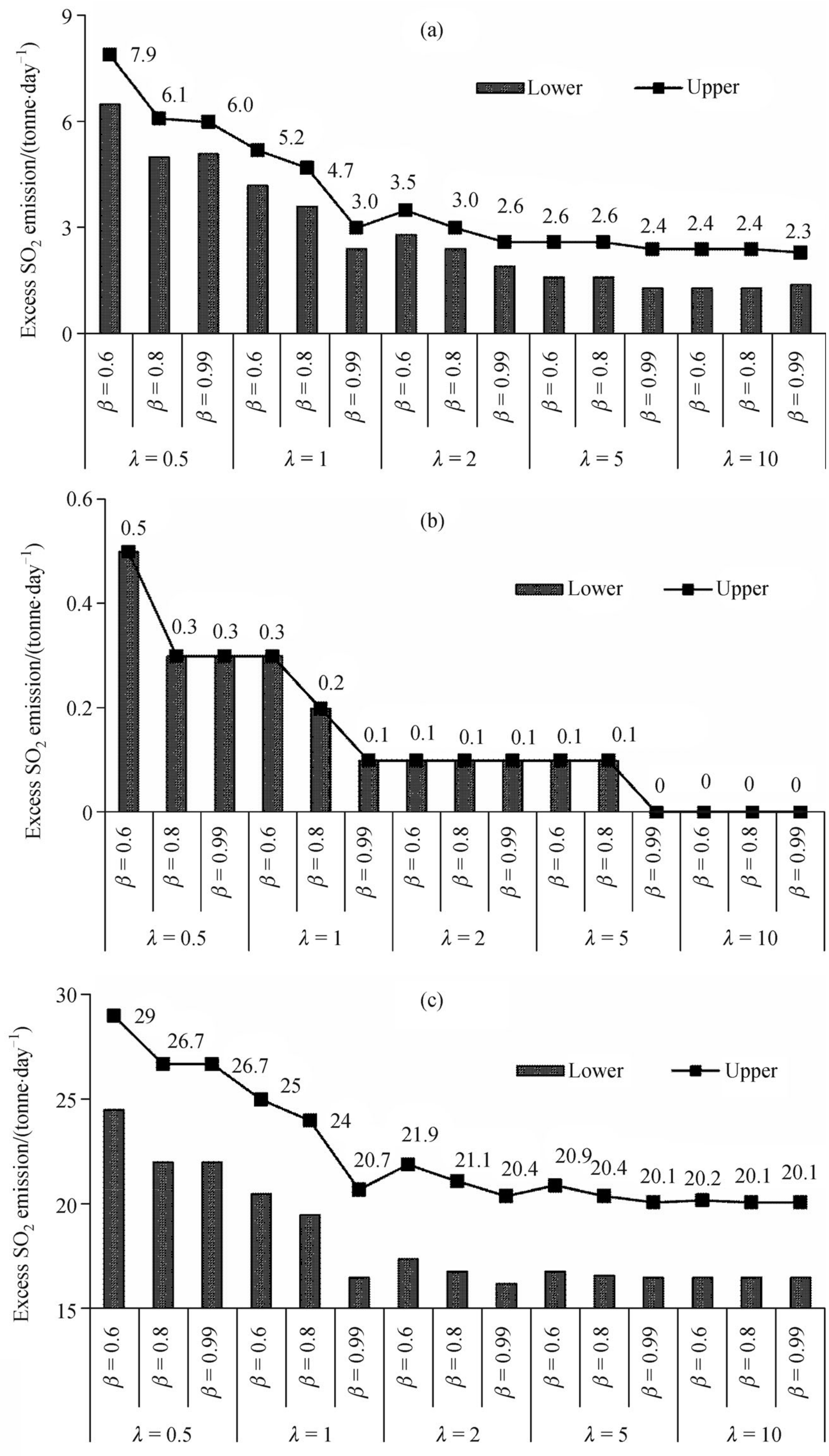

Fig. 4 Excess SO_2 emissions treated by (a) OPA; (b) AA and (c) LWS technologies at different risk levels.

recourse cost. When fixing λ at 0.5 and increasing β from 0.6 to 0.99, the recourse cost would decrease from \$[1.82, 2.51] $\times$ 10^3 to \$[1.57, 2.20] $\times$ 10^3. Besides, the recourse cost would decrease from \$[1.57, 2.20] $\times$ 10^3 to \$[1.00, 1.50] $\times$ 10^3 when β is fixed at 0.8 and λ changes from 0.5 to 10. According to these results, increasing λ may lead to a more risk-averse policy with lower recourse costs in general. Therefore, a more risk-averse policy keeps lower excess SO_2 emissions and results in a lower recourse cost. Figure 7 presents the values of CVaR under different λ and

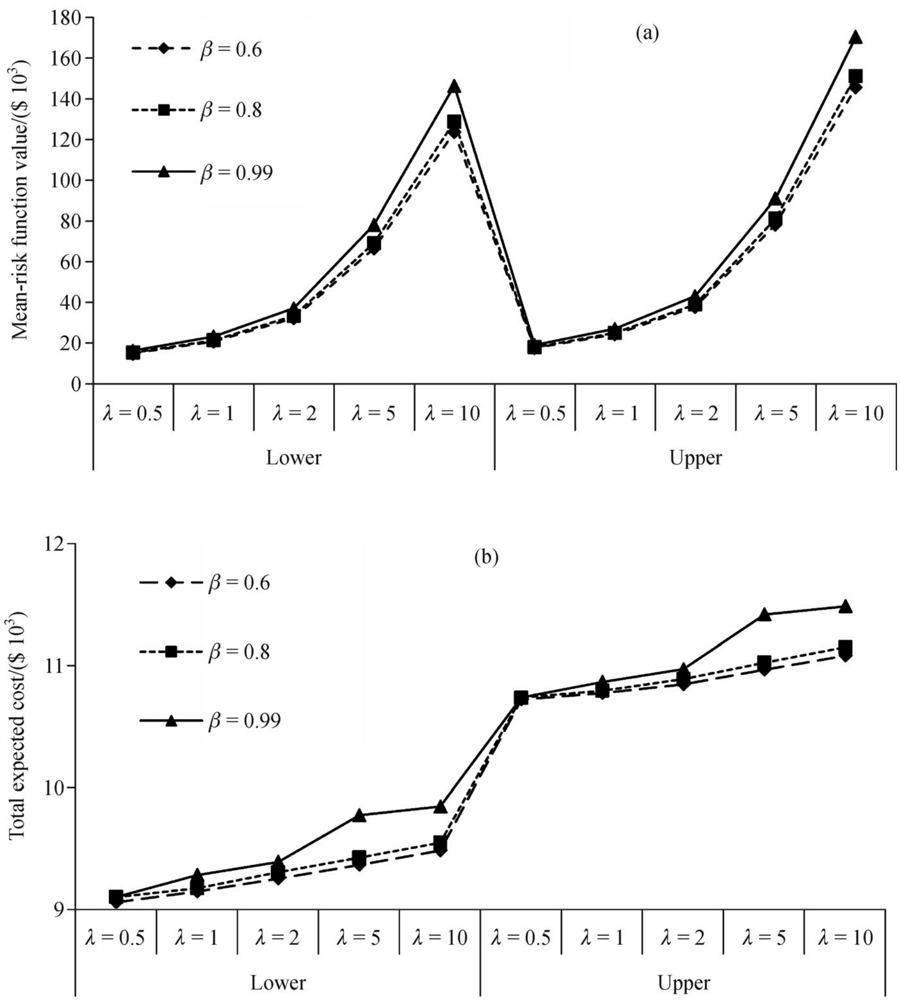

Fig. 5 (a) Mean-risk function value and (b) total expected cost under different risk levels.

β levels. It appears that CVaR increases as β increases due to the definition of CVaR. For example, when λ is fixed at 0.5 and β changes from 0.6 to 0.99, the value of CVaR would increase from \$[11.7, 13.7] $\times$ 10^3 to \$[14.2, 16.4] $\times$ 10^3. $CVaR_\beta$ quantifies the expectation of the worst $(1-\beta)$ % of the total costs, and a specified β level indicates the confidence level in percentage terms. At a larger value of β, the corresponding VaR may increase, and $CVaR_\beta$ would account for the risk of larger realizations. Therefore, larger β values would lead to more conservative policies, which give more weight to worse scenarios. In addition, CVaR decreases as λ increases. For example, when β is fixed at 0.8 and λ changes from 0.5 to 10, the value of CVaR would decrease from \$[12.2, 14.2] $\times$ 10^3 to \$[11.9, 14.0] $\times$ 10^3. This is because of the changing trade-off between the expectation total cost and the CVaR criterion. A higher λ would increase the relative importance of the risk term, leading to more risk-averse policies. Therefore, increasing the parameter λ (and/or β) indicates a higher level of risk aversion.

5 Discussion

To better reflect the advantages of the proposed ICTP method, an interval-parameter TSP (ITSP) model is applied to the study case for comparison purposes. The total expected cost solved by ITSP model is \$[9.1, 10.7] $\times$ 10^3, which is lower than that solved by ICTP method under any risk parameters. However the recourse cost, which equals \$[1.9, 2.6] $\times$ 10^3, solved by ITSP model is higher than those solved by ICTP method under any risk parameters. Table 5 presents the solutions of ITSP for decision variables. Different from the ICTP method, the optimal solution in the ITSP model is to obtain the minimum cost regardless of risk aversion. Consequently, it is incapable of analyzing the trade-off between the system cost and risk of violated environmental standards. For example, the lower levels of allowable SO_2 emission (i.e., $X^{\pm}_{ik,opt}$), higher levels of excess SO_2 emission (i.e., $Y^{\pm}_{isk,opt}$), and the lower system cost would be generated by the ITSP than the ICTP. This implies that the system cost largely

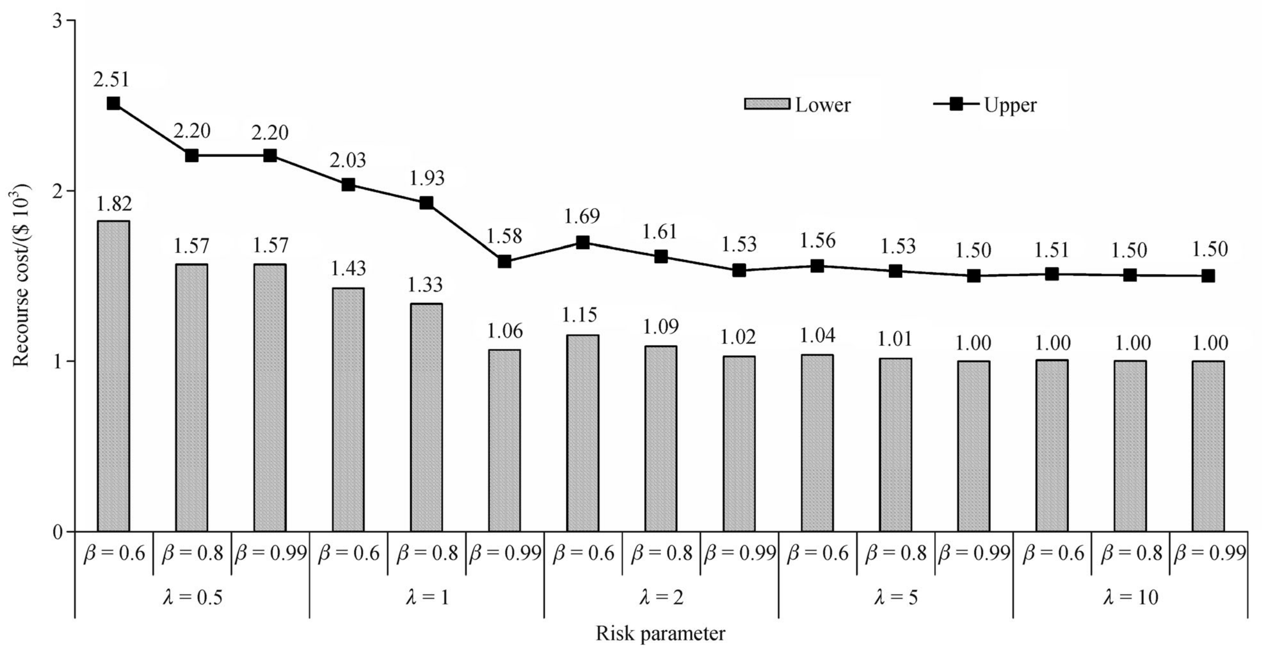

Fig. 6 Recourse cost under different risk levels.

relies on the SO_2 generation condition, and tends to fluctuate more intensively with the change of SO_2 generation rates when the CVaR is preferred with more weight. Furthermore, the solutions in the ITSP seem to be exactly the same as those in ICTP when λ is zero, which indicates that the ITSP can be considered a special or simplified case of the ICTP. Therefore, the risk-averse method (i.e., ICTP) that considers the effects of random variables would provide more robust solutions compared to the risk-neutral approach (i.e., ITSP).

Without consideration of interval-parameter programming, the CVaR-based TSP method can be used to solve the study case through letting all interval parameters be equal to their mid-value. The solution is a set of deterministic values. It represents a decision under an input scenario (mid-values for all parameters), and is actually one of many alternatives from the ICTP. In such a case, the decision alternative would be restricted to a single solution. Thus, the effectiveness and flexibility of the alternative would be reduced since impact of uncertainties is not considered. Although further sensitivity analysis can be undertaken for the CVaR-based TSP solution, a number of possibilities exist when many inputs are uncertain. It can increase the computational burdens. For each possibility, the sensitivity analysis can provide an individual response to variations of the uncertain inputs; however, it can hardly reflect interactions among these uncertainties. In ICTP, the interactive algorithm is used to handle the interval parameters. As a result, the solution corresponding to f^- can be first solved (when the objective is to be minimized), and the relevant solution corresponding to f^+ is to be feasible as one of the two bounds of the interval solution, which leads to a set of optimal and stable interval solutions. In comparison, the best/worst case analysis (Liu et al., 2011), which can also address the interval parameters, would obtain the solution results under two extreme scenarios (i.e., best and worst conditions). It is useful for judging the system's capability to realize the desired goal; but will not necessarily construct a set of stable intervals for decision variables.

The robust risk analysis method (RRAM) was introduced in Chen et al. (2013a, b), which incorporated interval-parameter programming, two-stage stochastic programming, and variance within a general modeling framework. Thus, the main difference between ICTP and RRAM is the quantitative risk measure for the second-stage random variable, where the former uses the CVaR and the latter uses the variance. Moreover, compared with ICTP, the disadvantage of RRAM is that it considers the under-and-over-performances of the probability distribution equally. For example, the high SO_2 generation rate may result in the system risk, while the low waste generation rate is safe to the management system. Therefore, quantitatively evaluating the right tail of distributions of the SO_2 generation rate is necessary. However, consideration of the left tail of distributions must not only waste the expected cost, but also be of no use for the system stability. Moreover, Shao et al. (2011) developed a risk-averse method through incorporating the CVaR into the constraint of the optimization model. This method also can analyze the trade-offs between system cost and risk of violated environmental standard. However, it may have

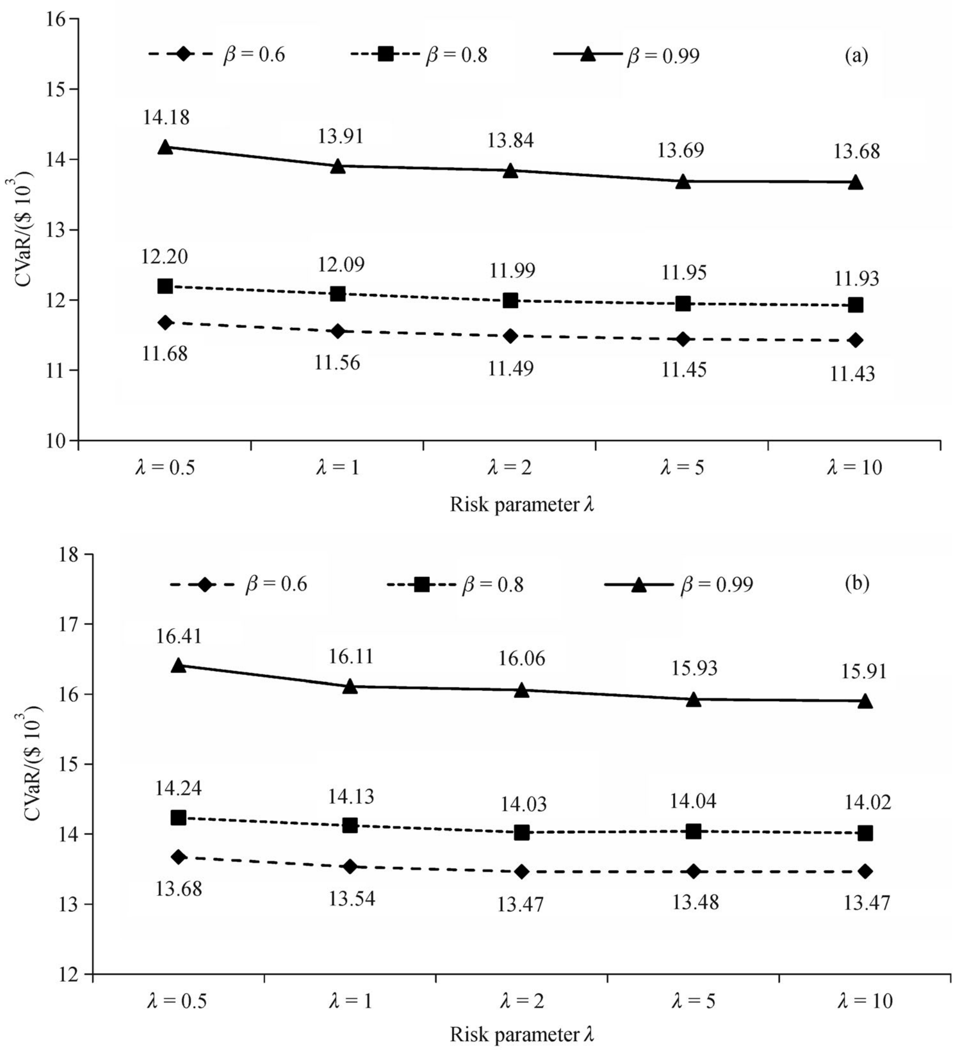

Fig. 7 (a) Lower bound and (b) upper bound of the CVaR under different risk levels.

computational difficulties in estimating the maximum acceptable loss (i.e., the limit value of right hand in the constraint containing CVaR).

6 Conclusions

An interval-parameter CVaR-based two-stage programming (ICTP) method was developed by incorporating the interval-parameter programming, two-stage stochastic programming (TSP) and conditional value at risk (CVaR) within a general optimization framework. In the developed ICTP, uncertainties could be presented as probabilistic distribution functions and discrete intervals. Also, CVaR as a kind of risk measurement method was successfully incorporated within the objective function of ICTP to describe the expected losses under extreme conditions. In general, the proposed ICTP method had several advantages: (i) its objective function simultaneously took expected cost and risk cost into consideration, and also used discrete random variables and discrete intervals to reflect uncertain properties. Therefore, the solution results could possess characteristics of CVaR, interval-parameter programming, and the TSP model; (ii) it quantitatively evaluated the right tail of distributions of random variables, which could better calculate the risk of violated environmental standards compared to the robust risk analysis method; (iii) it was useful for helping decision makers to analyze the trade-offs between cost and risk, and identified desired air quality management strategies under complex uncertainties; and (iv) it was effective to penalize the second-stage costs, as well as to capture the notion of risk in stochastic programming.

An air quality management case was used to demonstrate the applicability of the ICTP method. The obtained decision variables values can be used to reflect decision

Table 5 Solution of the ITSP model

		From power plant 1(i = 1)			From power plant 2(i = 2)			From chemical industry plant(i = 3)			From petroleum refinery(i = 4)			From steel mill(i = 5)		
		j = 1	j = 2	j = 3	j = 1	j = 2	j = 3	j = 1	j = 2	j = 3	j = 1	j = 2	j = 3	j = 1	j = 2	j = 3
Allowable SO_2 emission ($X_{ij,opt}^{\pm}$)/(tonne·day^{-1})		30	21.6	24	30	11.5	12	0	0	[6.6, 6.8]	6.3	0	7.5	1	2.75	[0.5, 0.68]
Excess SO_2 emission ($Y_{ijs,opt}^{\pm}$)/(tonne·day^{-1})	s = 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	s = 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	s = 3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	s = 4	0	0	[0, 3.6]	0	0	0	0	0	0	0	0	0	0	0	0
	s = 5	0	0	[3.6, 7.1]	0	0	0	0	0	0	0	0	0	0	0	0
	s = 6	0	0	[7.1, 10.7]	0	0	[0, 1.9]	0	0	0	0	0	0	0	0	0
	s = 7	0	0	[10.7, 14.3]	0	0	[1.9, 4.3]	0	0	0	0	0	[0, 0.5]	0	0	[0.05, 0.07]
	s = 8	0	0	[14.3, 17.9]	0	0	[4.3, 6.6]	0	0	0	0	0	[0.5, 1.1]	0	0	[0.25, 0.27]
	s = 9	0	0	[17.9, 21.4]	0	0	[6.6, 9]	0	0	[0, 0.1]	0	0	[1.1, 1.7]	0	0	[0.4, 0.5]
	s = 10	[0, 1]	0	[21.4, 24]	0	0	[9, 11.3]	0	0	[0.3, 0.4]	0	0	[1.7, 2.3]	0.15	0	[0.5, 0.52]
	s = 11	[5.3, 5.6]	0	[19.7, 23]	[0, 1.7]	0	[11.3, 12]	0	0	[0.6, 0.7]	0	0	[2.3, 2.8]	0.35	0	[0.5, 0.52]
	s = 12	9.95	0	[18.6, 22.3]	[1.7, 4]	0	12	0	0	0.9	0	0	[2.8, 3.4]	1	0	[0.05, 0.07]
	s = 13	[11.1, 11.8]	0	[21.05, 24]	[4, 6.4]	0	12	0	0	[1.1, 1.2]	3.4	0	[0, 0.6]	1	0	[0.25, 0.27]
	s = 14	[14.8, 15.3]	0	[21, 24]	[6.4, 8.7]	0	12	0	0	[1.4, 1.5]	4	0	[0, 0.6]	1	0.45	[0, 0.02]
	s = 15	23.2	0	[16.1, 19.7]	[8.7, 11.1]	0	12	0	0	[1.7, 1.8]	0	0	[4.6, 5.1]	0.8	0.85	[0, 0.02]
	s = 16	16.5	6	[20.4, 24]	[11.1, 13.5]	0	12	0	0	2	5.1	0	[0, 0.6]	0	1.85	[0, 0.02]
	s = 17	13.5	12.8	[20.2, 23.8]	[13.5, 15.8]	0	12	0	0	[2.2, 2.3]	5.7	0	[0, 0.6]	0	2.05	[0, 0.02]
	s = 18	10.6	19.6	[19.9, 23.5]	[15.8, 18.2]	0	12	0	0	[2.5, 2.6]	6.3	0	[0, 0.6]	0	2.25	[0, 0.02]
	s = 19	19.4	21.6	[12.7, 16.2]	[13.3, 15.6]	4.9	12	0	0	[2.8, 2.9]	0	0	[6.9, 7.4]	0	2.45	[0, 0.12]
	s = 20	17.4	21.6	[18.2, 21.8]	[9, 11.4]	11.5	12	0	0	3.1	6.3	0	[1.1, 1.7]	[0, 0.1]	2.75	0

makers' opinions on the SO_2 abatement planning; and the risk acceptance λ and the percentile β can reflect decision maker's preference toward the system cost and risk control. As multiple scenarios of solutions are normally available, it is suggested that the decision makers should use multi-criteria decision analysis (MCDA) or data envelopment analysis (DEA) technologies for evaluating and ranking various possible alternatives. If the decision makers need only one concrete planning pattern, they should clearly identify their preferences on system economy and risk, and specify the corresponding SO_2 abatement alternative for meeting their requirement. Thus, the ICTP method is valuable for supporting the adjustment or justification of the existing SO_2 emission allocation patterns. On the other hand, to reflect the pollutants dispersion in the atmospheric environment, the Pasquill-Gifford curves were used to calculate the related parameters for the Gaussian dispersion model. Although somewhat simplified, the curves are representative and straightforward to understand. In fact, the variation of the atmosphere stability degree and the dispersion parameters is continuous due to the continuous changes of the atmosphere turbulence. However, the turbulence-related parameters in the Gaussian dispersion model are treated as discrete values, which may lead to the deviations of solutions in the air quality management model. The California puff (CALPUFF) modeling system can predict the ground-level concentration of SO_2 with a higher accuracy, through the comprehensive consideration of boundary layer parameters such as Monin-Obukhov length, convection velocity, boundary height friction velocity, and surface roughness length. However, it requires intensive data inputs. Moreover, incorporating the outputs of CALPUFF into the optimization models is a complex problem and deserves further investigations.

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