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An integrated bi-level optimization model for air quality management of Beijing's energy system under uncertainty

S.W. Jin[a,b], Y.P. Li[a,c,*], S. Nie[d]

[a] School of Environment, Beijing Normal University, Beijing 100875, China
[b] Sino-Canada Energy and Environmental Research Center, North China Electric Power University, Beijing 102206, China
[c] Institute for Energy, Environment and Sustainable Communities, University of Regina, Regina, SK S4S 0A2, Canada
[d] Faculty of Applied Science and Engineering, University of Toronto, Toronto, ON, M5S 1A4, Canada

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ABSTRACT

In this study, an interval chance-constrained bi-level programming (ICBP) method is developed for air quality management of municipal energy system under uncertainty. ICBP can deal with uncertainties presented as interval values and probability distributions as well as examine the risk of violating constraints. Besides, a leader-follower decision strategy is incorporated into the optimization process where two decision makers with different goals and preferences are involved. To solve the proposed model, a bi-level interactive algorithm based on satisfactory degree is introduced into the decision-making processes. Then, an ICBP based energy and environmental systems (ICBP-EES) model is formulated for Beijing, in which air quality index (AQI) is used for evaluating the integrated air quality of multiple pollutants. Result analysis can help different stakeholders adjust their tolerances to achieve the overall satisfaction of EES planning for the study city. Results reveal that natural gas is the main source for electricity-generation and heating that could lead to a potentially increment of imported energy for Beijing in future. Results also disclose that PM_{10} is the major contributor to AQI. These findings can help decision makers to identify desired alternatives for EES planning and provide useful information for regional air quality management under uncertainty.

1. Introduction

It is inevitable that, to maintain a comfortable and civilized society, energy is essential for industry, transportation and electricity generation. However, massive consumption of energy sources causes an increasing concentration of atmospheric pollutants (e.g., nitrogen oxides (NOx), particulate matter (PM) and sulfur dioxide (SO_2)) that have been an immense burden for human health and economy development [1,2]. According to the report, air pollution was responsible for 1.6 million deaths in China and 4.2 million deaths throughout the world in 2015 [3,4]. Currently, around 80% of global energy is generated by fossil fuels that have severe impact on the atmospheric environment [5]. Air pollution has been a major environmental concern, because it is related to a variety of human activities and economic implications and, at the same time, it poses serious threats on public health. Particularly for many developing countries and/or regions, they have to produce more energy to meet economy development, such that they are facing double challenge in sustainable development in future: the absence of secure and adequate energy sources at accessible prices and environmental damages caused by excessive energy demand [6]. In response to the above issues, there is an urgent need for a comprehensive and robust technique to optimize regional energy system to maintain the local air quality at a safe level.

Previously, many research works were conducted to manage energy and environmental systems (EES) through mathematical models [7–12]. For the conventional deterministic approaches, since there is a gap between the recognition of uncertainties and its actual incorporation within modeling formulation, they cannot contemplate the different sources of uncertainty in an integrated manner [13]. In the real world, EES is a combination of different components with multilayer energy and information flows, in which multiple formats of uncertainties are involved in the related factors and/or parameters, causing a variety of complexities in the relevant decision-making processes [14]. On the other hand, with the increasing of energy demands, rising concerns over energy security and environmental issue could force decision makers to contemplate comprehensive plans in EES. However, most previous studies mainly focused on a single-decision problem that ignore the hierarchical structure of system and simplify the real-world practical problems.

Bi-level programming (BP) is effective for dealing with the above

* Corresponding author at: School of Environment, Beijing Normal University, Beijing 100875, China.
E-mail addresses: jinshuwei2014@126.com (S.W. Jin), yongping.li@iseis.org (Y.P. Li), shuang.nie@mail.utoronto.ca (S. Nie).

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decision making problems, where each decision maker at two hierarchical levels independently controls a set of decision variables, and their decisions are affected by each other [15,16]. Recently, numerous researchers attempted to use the BP method for planning energy system [17–21]. Although BP can address the tradeoffs between different decision makers in two decision-making levels, it has difficulties in handling uncertainties associated with the economic coefficients and technical factors. For decision makers, uncertain parameters (e.g., random energy supply) as well as the risk of violating constraints need both to be measured. One possible approach to address multiple uncertainties is interval chance-constrained programming (ICCP) that couples interval linear programming (ILP) with chance-constrained programming (CCP) [22].

Therefore, this study aims to develop an interval chance-constrained bi-level programming (ICBP) method for planning energy and environmental systems (EES) in association with multiple uncertainties and multiple decision makers. ICBP will integrate interval chance-constrained programming (ICCP) and bi-level programming (BP) in a general framework. Then, an ICBP-EES model will be built for planning Beijing's energy system, where air quality index (AQI) will be employed to assess the city's integrated air-quality condition under multiple decision makers with different objectives. Interval solutions associated with different risk levels of constraint violation can provide direct support for the city's EES planning and the local air quality management under uncertainty.

The major contribution of this study is the development of ICBP method for EES planning with advantages of uncertainty reflection, risk analysis, and synthetic decision making. Compared with single-level programming techniques, as advanced by Li et al. [23] and Sadri et al. [24], ICBP refers to multiple decision makers with different goals and preferences, where each decision maker at two hierarchical levels independently controls a set of decision variables. In comparison with the conventional multi-objective programming [25,26], the decision making process of ICBP is in a hierarchical order, in which the goal of decision maker who is more important need to be preferably met, then the tradeoffs between decision makers in various decision-making levels can be addressed. Besides, the conventional deterministic frameworks of EES planning could hardly address various responses of energy-related activities, and these responses are simply linked to some parameters instead of integrating into modeling formulation [7–9]. ICBP cannot only deal with uncertainties expressed as interval values and probability distributions, but also reflect the risk of constraint violation. Summarily, three characteristics of ICBP make it superior in comparison to the existing optimization techniques: (i) it can handle uncertainties expressed as probability distributions, interval values, and their combinations, (ii) it can be used for quantitatively analyzing the tradeoffs among multiple decision makers owning different preferences and goals, and (iii) it can provide the information about the risk of constraint violation in the step of solution process.

2. Interval chance-constrained bi-level programming

The general formulation for a bi-level programming (BP) problem is [27]:

$$\underset{x_1}{Min}\, F(x_1, x_2) \tag{1a}$$

where x_2 solves:

$$\underset{x_2}{Min}\, f(x_1, x_2) \tag{1b}$$

subject to:

$$G = \{(x_1, x_2) | g_i(x_1, x_2) \le 0,\ i = 1, 2, \ldots, m,\ x_1, x_2 \ge 0\} \tag{1c}$$

where $x_1 \in R^{n1}$ and $x_2 \in R^{n2}$. The variables are divided into two classes: upper-level ($x_1 \in R^{n1}$) and lower-level ($x_2 \in R^{n2}$) variables; the F: $R^{n1} \times R^{n2} \to R$, f: $R^{n1} \times R^{n2} \to R$ are upper-level and lower-level objective functions, respectively; G is the bi-level constraint sets. In BP problem, upper-level decision maker (ULDM) and lower-level decision maker (LLDM) accept the leader-follower Stackelberg game [28].

Although the BP can effectively handle tradeoffs between decision makers in different decision-making levels, it has limitation in reflecting uncertainties existing in economic coefficients and technical factors. For decision makers, uncertain parameters (e.g., random energy supply) as well as the risk of violating constraints need both to be measured. In order to solve the above problems, an interval chance-constrained programming (ICCP) model can be formulated as follows:

$$Min\, f^{\pm} = C^{\pm} X^{\pm} \tag{2a}$$

subject to:

$$Pr[t | A_i^{\pm}(t) X^{\pm} < b_i^{\pm}(t)] > 1 - p_i \tag{2b}$$

$$A_i^{\pm}(t) \in A(t), \quad i = 1, 2, \ldots, m \tag{2c}$$

$$x_j^{\pm} \ge 0,\ x_j^{\pm} \in X, j = 1, 2, \ldots, n \tag{2d}$$

$$p_i \in [0, 1] \tag{2e}$$

where $X \in \{R\}^{n\times l}$, $C \in \{R^{\pm}\}^{l\times n}$, $A \in \{R\}^{m\times n}$, $B \in \{R\}^{m\times l}$; $A = (a_{ij})_{m\times n}$, $C = (c_1, c_2, \ldots, c_n)$, $B = (b_1, b_2, \ldots, b_m)^T$ and $X = (x_1, x_2, \ldots, x_n)^T$, X are decision variables that can be sorted into two categories: continuous and binary. Through coupling ICCP with BP, an interval chance-constrained bi-level programming (ICBP) model can be formulated as:

Upper level:

$$\underset{x_1^{\pm}}{Min} F^{\pm}(x_1^{\pm}, x_2^{\pm}) \text{ where } x_2^{\pm} \text{ solves:} \tag{3a}$$

Lower level:

$$\underset{x_2^{\pm}}{Min}\, f^{\pm}(x_1^{\pm}, x_2^{\pm}) \tag{3b}$$

subject to:

$$G^{\pm} = \{(x_1^{\pm}, x_2^{\pm}) | Pr[A_i^{\pm}(t) X^{\pm} < b_i^{\pm}(t)] > 1 - p_i,\ i = 1, 2, \ldots, m,\ x_1^{\pm}, x_2^{\pm} \ge 0,\ p_i \in [0, 1]\} \tag{3c}$$

An interactive solution algorithm is proposed for solving model (3) through analyzing the interrelationship between parameters and variables as well as between objective functions and constraints [15]. Since objective functions of ULDM and LLDM are to be minimized, the submodel corresponding to the lower-bound objective-function value can be first formulated:

$$\underset{x_1^-}{Min}\, F^-(x_1^-, x_2^-) \tag{4a}$$

$$\underset{x_2^-}{Min}\, f^-(x_1^-, x_2^-) \tag{4b}$$

subject to:

$$G^- = \{(x_1^-, x_2^-) | A_j^-(t) X < b_j(t)^{(p_j)},\ i = 1, 2, \ldots, m,\ x_1^-, x_2^- \ge 0,\ p_i \in [0, 1]\} \tag{4c}$$

For the lower-bound submodel (4), the ULDM problem can be first solved, and the solution of Eqs. (4a) and (4c) is assumed to be $(x_1^{U-}, x_1^{U-}, f_1^{U-})$; then, the LLDM can be solved independently with the solutions of $(x_2^{L-}, x_2^{L-}, f_2^{L-})$. The range of decision variable x_1^- should be around x_1^{U-} with the maximum tolerance p_1^-. The membership function that specifies x_1^- can be presented as follows:

$$\mu_{x_1^-}(x_1^-) = \begin{cases} \frac{x_1^- - (x_1^{U-} - p_1^-)}{p_1^-}, if\ x_1^{U-} - p_1^- < x_1^- < x_1^{U-} \\ \frac{(x_1^{U-} + p_1^-) - x_1^-}{p_1^-}, if\ x_1^{U-} < x_1^- < x_1^{U-} + p_1^-; \\ 0, \quad , \quad if\ otherwise. \end{cases} \tag{5}$$

where x_1^{U-} is the most preferred decision, $x_1^{U-} + p_1^-$ and $x_1^{U-} - p_1^-$ are the worst acceptable decision; satisfaction degree increases linearly