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A copula-based flexible-stochastic programming method for planning regional energy system under multiple uncertainties: A case study of the urban agglomeration of Beijing and Tianjin

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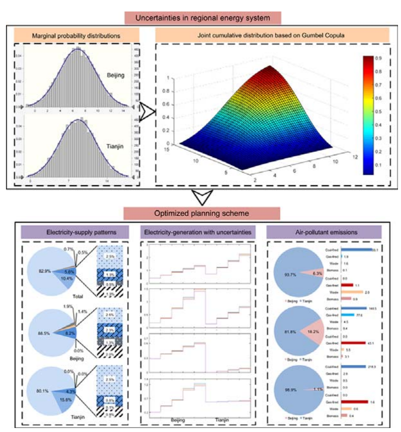
HIGHLIGHTS

- A copula-based flexible-stochastic programming (CFSP) method is proposed.
- CFSP can handle multiple uncertainties and reflect interaction of random variables.
- It is applied to planning RES of the urban agglomeration of Beijing and Tianjin.
- Scenarios of various joint- and individual constraint-violation levels are selected.
- Results can provide in-depth analysis for identifying desired decision schemes.

GRAPHICAL ABSTRACT



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ABSTRACT

In this study, a copula-based flexible-stochastic programming (CFSP) method is developed for planning regional energy system (RES). CFSP can deal with multiple uncertainties expressed as interval values, random variables and fuzzy sets as well as their combinations employed to objective function and soft constraints. It can also reflect uncertain interactions among random variables through using copula functions even having different probability distributions and previously unknown correlations. Then, based on the developed CFSP approach, a CFSP-RES model is formulated for planning RES of the urban agglomeration of Beijing and Tianjin (China). Results disclose that uncertainties existed in the system components have significant effects on the outputs of decision variables and system cost, and the variation of system cost is reached 16.3%. Results also reveal that air pollutant emissions can be mitigated if the urban agglomeration can co-implement renewable energy development plans (REDP) over the planning horizon, with the reductive rates of [3.3, 7.6] % of sulfur dioxide (SO_2), [2.7, 4.1] % of nitrogen oxides (NO_x) and [7.0, 11.5] % of particulate matter (PM_{10}). Compared to joint-probabilistic chance-constrained programming (JCP), the CFSP method is more effective for handling multiple random parameters associated with different probability distributions in which their correlations are unknown. Thus, it is not limited to some unjustified assumptions and can be applied to a wider range of problems than

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previous studies. The findings are helpful to explore the influence of interaction among random variables on modeling outputs and provide in-depth analysis for identifying desired decision schemes for planning RES.

1. Introduction

Over the past decades, the world has undergone rapid economic development and social revolution corresponding to the increasing energy demand. Global energy consumption grew at a rate of 2.3% in 2000–2015, and is projected to slow towards 0.9% in 2035–2050, with more than three-quarters of total energy supplies are still dependent on fossil fuels (i.e. coal, gas and oil) [1]. Meanwhile, the infrastructural investments and pollutant emissions associated with power industry have adverse impacts on environment. For example, according to the International Energy Agency (IEA), around 6.5 million deaths are attributed each year to poor air quality, making this the world's fourth-largest threat to human health, behind high blood pressure, dietary risks and smoking [2]. Air pollution is a major public health crisis, with many of its root causes and cures to be found in the energy sector. Therefore, how to effectively balance the contradiction between energy demand–supply reliability and air quality improvement continues to be great challenges faced by decision makers [3].

Previously, numerous inexact optimization approaches such as Monte Carlo simulation (MCS), chance-constrained programming (CCP), two-stage stochastic programming (TSP) and multistage stochastic programming (MSP) were proposed for dealing with stochastic problems with known probability distributions in the energy system [4–9]. For example, Hemmati et al. [4] used a MCS-based stochastic planning method for congestion management in electric power systems, in which uncertainties of wind and solar resources were handled. Odetayo et al. [6] proposed a CCP approach to integrated planning of distributed power generation and natural gas network in the presence of uncertain real and reactive power demand. Simic [9] developed a multistage interval-stochastic programming model for planning end-of-life vehicles allocation, where uncertainties expressed as probability distributions and discrete intervals were effectively tackled based on a multi-layered scenario tree with a finite set of scenarios. Summarily, these inexact optimization methods are based on MCS and CCP for handling random variables with known probability distributions in the right-hand sides of the constraints, TSP for tackling problems where an analysis of policy scenarios is desired and the right-hand-side coefficients are random with known probability distributions, MSP for permitting revised decisions in each time stage based on the sequentially realized uncertain events; while few of them are employed to analyze interactive relationships among multiple random parameters in the energy system [10,11]. Besides, the conventional joint-probabilistic chance-constrained programming (JCP) methods for reflecting interactive relationships among a set of probabilistic constraints are based on assumptions that all of random variables employed to probabilistic constraints are normally and independently distributed [12,13]. However, in most of real-world regional energy system (RES) planning problems, different random variables may present different probability distributions and the associated correlation may be previously unknown [14]. Thus, the existing JCP methods may encounter difficulty in application to the cases where the random parameters follow different probability distributions and have previously unknown correlations.

Copula-based stochastic programming (CSP) method has advantages of handling JCP problems having different probability distributions and unknown relationship of random variables in the right-hand sides of constraints [15,16]. However, a review of the literature shows no reports on reflecting interactions among multiple random parameters (e.g., electricity demands of different urban cities in the urban agglomeration) having previously unknown probability distributions and unknown correlations in the RES planning models. Additionally, in real-world RES planning problems, some system parameters are not available as deterministic values but can present as discrete intervals or fuzzy sets owing to the incompleteness or impreciseness of observed information [17–19]. Flexible programming (FP) is effective for supporting different kinds of fuzzy numbers as well as various fuzzy ranking methods in soft constraints to defuzzify uncertain parameters [20,21]. Interval-parameter programming (IPP) can deal with uncertainties expressed as interval numbers without distributional information [22,23].

Therefore, the objective of this study devotes to exploiting a copula-based flexible-stochastic programming (CFSP) method for planning the RES management problems. CFSP will be formulated through integrating CSP, FP and IPP within a general mixed-integer linear programming (MILP) framework. Then, based on the developed CFSP approach, a CFSP-RES model is formulated for planning RES of the urban agglomeration of Beijing and Tianjin (China). In the CFSP-RES model, fifteen scenarios under different joint constraint-violation levels and various individual constraint-violation levels are selected to verify the interaction of electricity demands between the urban cities of Beijing and Tianjin. Four satisfaction degrees of flexible constraints on fixed and variable costs are used for dealing with soft constraints and flexibilities on target value of goals. Results will help decision makers: (a) deal with multiple uncertainties existed in the RES; (b) identify optimal energy-supply patterns; (c) reach tradeoffs among energy-supply reliability, system cost and environment mitigation; (d) reflect interactions among random variables and disclose their impacts on modeling outputs.

2. Methodology

2.1. Copula-based stochastic programming

The "copula" approach for modeling multivariate joint distributions was proposed by Sklar in 1959 [24]. This approach shows that a multivariate joint distribution can be completely characterized by its respective marginal distributions and a copula function for binding them together independent of the types of individual marginal distributions [15]. Modeling joint distributions using copulas has effectiveness in allowing researchers to take into account marginal distributions and dependence as two separate but related issues [25–29]. Based on Nelsen [24], Charnes et al. [30] and Infanger and Morton [31], a copula-based stochastic programming (CSP) model can be formulated as follows:

$$\mathrm{Min} E = \sum_{j=1}^{n} c_j x_j \tag{1a}$$

subject to:

$$\Pr\left\{\sum_{j=1}^{n} a_{ij} x_j \leqslant b_i^{rv}, \quad i = 1,2,...,k\right\} \geqslant 1-p \tag{1b}$$

$$\sum_{j=1}^{n} a_{ij} x_j \leqslant b_i, \quad i = k+1, \quad k+2,...,m \tag{1c}$$

$$x_j \geqslant 0, \quad j = 1,2,...,n \tag{1d}$$

where x_j are decision variables; E is a linear objective function; a_{ij} and b_i are constraints' coefficients; $b_i^{rv}(i = 1,2,...,k)$ are random variables with unknown probability distribution; $1-p$ is a prescribed joint probability level at which the entire set of chance constraints are enforced to be satisfied.

Based on Chen et al. [15], the joint chance constraints of (1b) can be converted into the corresponding individual chance constraints as