Energy 87 (2015) 104–119

Contents lists available at ScienceDirect

Energy

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

Risk analysis for Shanghai's electric power system under multiple uncertainties

M.J. Piao [a, 1], Y.P. Li [a, *], G.H. Huang [a, 2], S. Nie [b]

[a] MOE Key Laboratory of Regional Energy Systems Optimization, S-C Resources and Environmental Research Academy, North China Electric Power University, Beijing 102206, China

[b] Faculty of Applied Science & Engineering, University of Toronto, Toronto, ON M5S 1A4, Canada

ARTICLE INFO

Article history:
Received 6 December 2014
Received in revised form
22 April 2015
Accepted 23 April 2015
Available online 21 May 2015

Keywords:
Electric power systems
Environmental
Fuzzy interval
Risk analysis
Robust optimization
Uncertainty

ABSTRACT

In this study, a RIFP (robust interval-fuzzy programming) approach is developed for risk analysis of EPS (electric power systems) in association with multiple uncertainties expressed as fuzzy-boundary intervals and probability distributions. RIFP can provide an effective linkage between the pre-regulated policies and the associated corrective actions against any infeasibility arising from random outcomes. A RIFP-MEP (RIFP-based municipal-scale electric-power-system planning) model is formulated for the City of Shanghai, China. Various robustness levels and feasibility degrees are incorporated within the modeling formulation for enhancing the RIFP-MEP model capability. Solutions have been generated and are useful for supporting the Shanghai's energy supply, electricity generation, capacity expansion, and air-pollution control. Results can help decision makers to address the challenge generated in the processes of electric power production (such as imbalance between electricity supply and demand, the contradiction between air pollution emission and environmental protection); this allows an increased robustness in controlling system risk in the optimization process, which permits in-depth analyses of various conditions that are associated with different robustness levels of economic penalties when the promised policy targets are violated, and thus help the decision makers to identify desired electricity-generation schemes.

1. Introduction

Management of EPS (electric power systems) has been one of major concerns with regard to electricity-supply security, environmental protection, and resources conservation. Particularly, with the rapid growing population, speedy developing economy and vigorous urban expansion, municipal electricity demand has a dramatic growing rate in recent decades; this tendency has exacerbated the situation of electricity demand-supply and air-pollution control exceedingly [1]. However, in the real-world EPS, there are many complex processes that should be considered by decision makers, such as energy production, conversion, transmission and utilization as well as the resulting GHG (greenhouse gas)/pollutant emissions [2–6]. Moreover, many system parameters (e.g., resource availability, facility capacity, production efficiency, and allocation target as well as their interrelationships) may appear uncertain. These complexities and uncertainties can challenge decision makers to single out optimal alternatives for cost-effective power generation [7]. Therefore, it is desired to develop more robust tools to support EPS management and planning.

As a result, SP (stochastic programming) methods have received extensive attentions since they could directly integrate uncertain information expressed as probability distributions into the modeling formulation. For example, Pereira and Printo [8] proposed a multistage stochastic optimization method for planning energy systems based on the approximation of the expected-cost-to-go functions through the introduction of piecewise linear functions. Dantzig and Infanger [9] introduced a stochastic linear optimization programming into the management of power generation to deal with imprecision in power flow analysis. Bath et al. [10] presented an interactive fuzzy stochastic

* Corresponding author. Tel.: +86 10 6177 3887; fax: +86 10 6177 3889.
E-mail addresses: piaomingjun@163.com (M.J. Piao), yongping.li@iseis.org (Y.P. Li), gordon.huang@uregina.ca (G.H. Huang), nschina01@gmail.com (S. Nie).
[1] Tel.: +86 10 6177 3885; fax: +86 10 6177 3889.
[2] Tel.: +86 10 6177 2108; fax: +86 10 6177 3889.

http://dx.doi.org/10.1016/j.energy.2015.04.059
0360-5442/

method to optimize the power generation by minimize operating cost, NO_x-emission and risk. Spangardt et al. [11] proposed a stochastic programming model for electric-power planning to reduce greenhouse gas emissions under random demand. Beraldi et al. [12] proposed a two-stage stochastic integer programming model for the integrated optimization of power production and trading which included a specific measure accounting for risk management. However, one potential limitation of the conventional SP methods is that they are incapable of considering the variability of the recourse values since they are based on an assumption that the decision maker is risk neutral [13–17]. It may become infeasible when the decision maker is risk averse under high-variability conditions. In fact, EPS are often associated with various system-failure risks (e.g., energy supply risk) due to multiple uncertainties and complexities; the desired energy allocation patterns may vary with time under high-variability conditions, which may result in a high risk of electricity shortage particularly when electricity demand-level is high [18–21].

As an extension of TSP (two-stage stochastic programming) methods, RO (robust optimization) was proposed for penalizing the second-stage costs that were above the expected values, as well as to capture the notion of risk in stochastic programming [22]. RO was effective for incorporating risk aversion into optimization models and finding robust solutions for system management problems [23]. In RO models, uncertain parameters which derived from noisy, incomplete of erroneous data are handled as random variables with discrete distributions [24]. Chen et al. [25] developed a RISO (robust interval-stochastic optimization) method for planning energy systems through incorporating IPP (interval-parameter programming) within the RO framework, such that uncertainties expressed as not only probability distributions but also interval values can be addressed. However, the limitations of RISO were its incapability of both handling uncertainties presented as possibilistic distributions (i.e. fuzzy sets) and reflecting the risk of violating the constraints. Jiménez et al. [26] proposed a FP (fuzzy programming) approach for solving linear problems with fuzzy parameters, which permitted interactive participation of decision makers in all steps of decision process, expressing their preferences in linguistic terms. A set of solutions from the FP model under different feasibility degrees (i.e. constraint-violation risks) are meaningful to support in-depth analyses of tradeoffs between system cost and constraint-violation risk [27–31]. Besides, FP can enable decision makers to identify a compromised solution between two key factors in conflict: feasibility of the constraints and satisfaction degree of the goal [32].

Therefore, the objective of this study is to develop a RIFP (robust interval-fuzzy programming) approach for planning EPS (electric power systems) through IPP (integrating interval-parameter programming) FP (fuzzy programming) into a RO (robust optimization) framework. The detailed tasks entail: (i) handling uncertainties presented in terms of fuzzy-boundary intervals and probability distributions, (ii) analyzing various scenarios that are associated with robustness levels of economic penalties when the promised policy targets are violated, (iii) formulating a RIFP-MEP (RIFP-based municipal-scale electric-power-system planning) model for the City of Shanghai (China), (iv) analyzing results of energy supply, electricity generation, capacity expansion and air-pollution control under a variety of robustness levels and feasibility degrees, and (v) examining the risk of violating the system constraints under multiple uncertainties.

2. Model development

2.1. Robust optimization

RO (robust optimization) could not only penalize the costs that are above the expected values, but also capture the notion of risk under uncertainty [14]. In fact, the RO method is a hybrid of stochastic and goal programs, to balance the tradeoff between the expected recourse costs and the variability of these random values [23]. A general RO model can be formulated as follows [33]:

$$\operatorname{Min} f = C_{T_1}X + \sum_{h=1}^{s} p_h D_{T_2}Y + \rho \sum_{h=1}^{s} p_h \left(D_{T_2}Y - p_h \sum_{h}^{s} D_{T_2}Y + 2\theta_h \right) \tag{1a}$$

subject to

$$D_{T_2}Y - p_h \sum_{h}^{s} D_{T_2}Y + 2\theta_h \geq 0 \tag{1b}$$

$$A_r X \leq B_r, \quad r \in M; \quad M = 1, 2, \ldots, m_1 \tag{1c}$$

$$A_i X + A_i' Y \geq w_{ih}, \quad i \in M; \quad i = 1, 2, \ldots, m_2; \quad h = 1, 2, \ldots, s \tag{1d}$$

$$x_j \geq 0, \quad x_j \in X; \quad j = 1, 2, \ldots, n_1 \tag{1e}$$

$$y_{jh} \geq 0, \quad y_{jh} \in Y; \quad j = 1, 2, \ldots, n_2; \quad h = 1, 2, \ldots, s \tag{1f}$$

In the above modeling formulation, the random variables take discrete values w_{ih} with probability levels p_h, where $h = 1, 2, \ldots, s$ and $\sum p_h = 1$. The x_j and y_{jh} represent the first- and second-stage decision variables, respectively; the term of $(D_{T_2}Y - p_h \sum_h^s D_{T_2}Y + 2\theta_h)$ is a variability measure on the second-stage penalty costs; the nonnegative factor ρ represents a weight coefficient; the θ_h is slack variable used for attaining looser constraints. Depending on the value of ρ, the optimization may favor solutions with a higher expected second-stage cost $\sum_{h=1}^{s} p_h D_{T_2} Y$ in exchanging for a lower variability in the second-stage penalty costs as measured by $(D_{T_2}Y - p_h \sum_h^s D_{T_2}Y + 2\theta_h)$ [34]. When $\rho = 0$, the RO model becomes a conventional TSP one (i.e. the objective is only to minimize the first- and second-stage costs); this also implies that the decision makers possess a risk neutral attitude and would not consider the variability of the uncertain recourse costs. However, when $\rho = 1$, the decision makers can consider the variability of the second-stage cost based on a risk-aversive attitude.

2.2. Interval-fuzzy programming

In many real-world problems, when the subjective judgment of decision makers is influential in the decision-making processes, FP (fuzzy programming) is an effective tool to handle this problem. Consider a linear programming model with fuzzy parameters:

$$\operatorname{Min} f = \sum_{j=1}^{n} \widetilde{C}_j X_j \tag{2a}$$

subject to

$$\sum_{j=1}^{n} \widetilde{A_{ij}} X_j \leq \widetilde{B}_i, \quad i = 1, 2, \ldots, m \tag{2b}$$