Engineering Applications of Artificial Intelligence 62 (2017) 252–264

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

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

A hybrid fuzzy-stochastic technique for planning peak electricity management under multiple uncertainties

L. Yu[a], Y.P. Li[b,c,*], G.H. Huang[b,c], B.G. Shan[d]

[a] Sino-Canada Resources and Environmental Research Academy, North China Electric Power University, Beijing 102206, China
[b] Department of Environmental Engineering, Xiamen University of Technology, Xiamen 361024, China
[c] Institute for Energy, Environment and Sustainable Communities, University of Regina, Regina Sask. S4S 7H9, Canada
[d] State Grid Energy Research Institute, Beijing 102209, China

ARTICLE INFO

Keywords:
Chance-constrained
Decision making
Electric power systems
Fuzzy probability
Monte Carlo
Peak electricity

ABSTRACT

In this study, an interval-fuzzy chance-constrained programming (IFCCP) method is developed for reflecting multiple uncertainties expressed as interval-fuzzy-random (integration of interval values, fuzzy sets, and probability distributions). IFCCP has advantages in uncertainty reflection and policy analysis as well as avoiding complicated intermediate models with high computational efficiency. The developed IFCCP method is applied for planning a regional-scale electric power system (EPS) with consideration of peak-electricity demand issue. Results reveal that different peak demands in different seasons lead to changed electricity-generation pattern, pollutant emission and system cost. IFCCP is more reliable for the risk-aversive planners in handling high-variability conditions by considering peak-electricity demand. Results also disclose that fossil-fuels consumption should be cut down in future (i.e. the energy-supply structure would tend to the transition from fossil-dominated into renewable-energy dominated) in order to meet the increased power demand and mitigate the pollutant emissions. Results can help decision makers improve energy supply patterns, facilitate dynamic analysis for capacity expansion, as well as coordinate conflict interactions among system cost, pollutant mitigation and energy-supply security.

1. Introduction

As the foundation for sustaining social and economic development, electricity plays an important role in a variety of human activities throughout the world. Over the past decades, electricity demand and supply have been steadily increasing in response to life standard improvement, economic development and population growth (Han et al., 2015; Kato et al., 2016). The rapid increase of electricity demand and the integration of renewable energy have imposed great stress on the power grid, especially in maintaining grid power balance (IEA, 2014). The power supply and demand of a grid must always balance and such real time balance is a critical system requirement. Any power imbalance/mismatch will affect the reliability and quality of power supply (e.g. power outages, voltage fluctuations), which will cause severe consequences such as widespread blackouts and increased electricity expenses for end-users (OECD, 2005). Therefore, how to solve the power balance issues becomes an utmost attention for decision makers of EPS planning.

Lots of efforts were adopted for planning EPS in response to power balance issues such as power reserve, electricity-generation expansion, renewable energy integration, electricity purchase, electricity prices, load shedding and load shifting control as well as electricity transmission infrastructure upgradation (Chen and Li, 2011; Yoon et al., 2014; Rejc and Čepin, 2014; Gao and Sun, 2016). For example, Fernandez et al. (2013) proposed a novel “Just-for-Peak” buffer inventory methodology to reduce the electricity consumption without compromising system throughput during peak periods, in which 20.1% power demand reduction during peak periods could be achieved. Werminski et al. (2017) used the decentralized active demand response automation for reducing the peak power in the Polish EPS, where about 4% of typically peak power value was reduced. Generally, the above measures were mainly based on demand response controls and they were merely focused on maximizing the benefits of power grid in terms of load profile alterations. The load profiles of end-users sectors were changed into an uncoordinated way and leading to an aggregated load profile, which would greatly impact the normal operation of each sector. Through such uncoordinated control, the overall peak demand of the aggregated load profile could not be effectively and efficiently reduced in a desired way of a grid. Renewable energy integration and electricity purchase are useful tools for satisfying peak electricity demand with an

* Corresponding author.
E-mail addresses: yulei1060220069@sina.com (L. Yu), yongping.li@iseis.org (Y.P. Li), gordon.huang@uregina.ca (G.H. Huang), shanbaoguo@sgeri.sgcc.com.cn (B.G. Shan).

http://dx.doi.org/10.1016/j.engappai.2017.04.014
Received 10 September 2016; Received in revised form 12 February 2017; Accepted 18 April 2017

environment-friendly way, which can effectively reduce the pollutant emissions and can improve the reliability of power demand-supply (Yu et al., 2016).

2. Related work

Over the past decades, many studies were effective for planning EPS by considering peak electricity demand with an environment-friendly way in terms of linear programming (LP), integer programming (IP), dynamic programming (DP) and artificial intelligence (Silva et al., 2012; Moazzami et al., 2013; Cocaña-Fernández et al., 2016; Loganthurai et al., 2016; Dababneh et al., 2016; Pham et al., 2016). For instance, Dudhani et al. (2006) used a linear programming algorithm for peak load demand management in India, in which renewable energy sources were considered to meet the peak load demand at the regional level of India. Burke (2014) used a dynamic programming method to meet the peak demand conditions in summer afternoon, which compares the capital cost of critical peak availability from gas turbines to the capital cost of critical peak availability from distributed solar in the Australian National Electricity Market. However, these linear programming methods were not usually sufficient to model the complexities and nonlinearities of EPS. In addition, these studies narrowed themselves in dealing with peak demand management problems for individual power generation sector (e.g. solar and geothermal), which had difficulties in reflecting the complicated interactions among various power supply technologies. For entire EPS, in fact, the unique energy and environmental and economic features of individual technology could influence each other, which made the whole EPS become more complicated.

Besides, in EPS planning problems, uncertainties can exist in both objective function (e.g., fluctuating electricity price, imprecise fuel cost) and constraints (e.g., peak-electricity demand and pollutant emission) (Zhou et al., 2013). These uncertainties can be brought from not only parameter measurement and its evaluation, but also the cause by all the aspects of energy production, processing, conversion, transportation and utilization. A number of inexact optimization methods were proposed for dealing with such uncertainties and complexities in EPS, such as fuzzy programming (FP), interval-parameter programming (IPP) and chance-constrained programming (CCP) (Mohammad et al., 2013; Elyasi and Salmsi, 2013; Azadeh et al., 2014; Lin and Chen, 2016). In general, although CCP can deal with decision problems whose coefficients (input data) are not certainly known but could be represented as chances or probabilities, the increased data requirements for specifying the parameters' probability distributions may affect their practical applicability (Li and Huang, 2009; Kamjoo et al., 2016). Fuzzy programming methods are effective for dealing with decision problems under fuzzy goal and constraints and handling ambiguous coefficients in the objective function and constraints, where uncertainties are handled in a direct way without a large number of realizations, nevertheless, the main limitations of the FP methods remain in their difficulties in tackling uncertainties expressed as probabilistic distributions (Pishvaee and Khalaf, 2016; Razmi et al., 2016). IPP can handle uncertain parameters that are expressed as intervals with known lower and upper bounds, but unknown membership or distribution functions (Huang, 1996). In fact, in the real-world EPS planning problems, uncertainties can further exist in multiple levels: vagueness and/or impreciseness in the outcomes of a random sample, and randomness and/or fuzziness in the lower and upper bounds of an interval (Li et al., 2010; Yu et al., 2017). These complexities have placed many EPS problems beyond the conventional optimization methods. Therefore, one potential approach for better reflecting multiple uncertainties is to develop an interval-fuzzy chance-constrained programming (IFCCP) method through integrating techniques of IPP, CCP and FP into a general framework.

The objective of this study is to develop such an IFCCP method and apply it to planning a regional-scale EPS with consideration of peak-electricity demand issue. IFCCP can deal with multiple uncertainties expressed as interval-fuzzy-random (integration of intervals, fuzzy sets and probability distributions). The left-hand-side coefficients presented as fuzzy intervals and the right-hand-side coefficients existed in interval-fuzzy-random form can be handled. Besides, IFCCP enhances the traditional fuzzy mathematical programming by choosing different fuzzy dominance indices of constraints, avoiding complicated intermediate models with high computational efficiency. The IFCCP method is applied to planning EPS under uncertainty. Results obtained will be helpful for supporting (a) adjustment of the existing demand and supply patterns of energy resources, (b) facilitation of dynamic analysis for decisions of capacity expansion and/or development planning, and (c) coordination of the conflict interactions among economic cost, system efficiency, pollutant mitigation and energy-supply security.

3. Methodology

3.1. Interval chance-constrained programming

Chance-constrained programming (CCP) is effective for handling decision problems whose coefficients (input data) are not certainly known but could be represented as chances or probabilities (Simic, 2016). A general stochastic linear programming problem can be formulated as follows:

$$\text{Min } f = C(t)X \tag{1a}$$

Subject to:

$$\mathrm{A}(t)\mathrm{X} \le \mathrm{B}(t) \tag{1b}$$

$$x_j \ge 0, \quad x_j \in X, \quad j = 1, 2, \ldots, n \tag{1c}$$

where X is a vector of decision variables, and $\mathrm{A}(t)$, $\mathrm{B}(t)$, and $C(t)$ are sets with random element defined on a probability space T, $t \in T$. To solve model (1), an equivalent deterministic model can be defined. This can be realized by using a CCP approach, which consists of fixing a certain level of probability $p_i \in [0, 1]$ for each constraint i and imposing the condition that the constraint is satisfied with at least a probability of $1-p_i$. The set of feasible solutions is thus restricted by the following constraints (Charnes et al., 1971; Infanger and Morton, 1996):

$$\Pr[\{A_i X \le b_i(t)\}] \ge 1 - p_i, \quad A_i \in A, \quad b_i(t) \in B(t), \quad i = 1, 2, \ldots, m \tag{2}$$

Constraint (2) is generally nonlinear, and the set of feasible constraints is convex only for some particular cases, one of which is when the left-hand-side coefficients (a_{ij}) are deterministic, and the right-hand-side constraints (b_i) are random. This leads to an equivalent linear constraint that has the same size and structure as a deterministic term, and the only required information about the uncertainty is the p_i level for the unconditional distribution of (b_i). Thus, constraint (2) becomes linear (Charnes and Cooper, 1983; Tan et al., 2015):

$$A_i X \le b_i(t)^{(p_i)}, \quad \forall\ i \tag{3}$$

where $b_i(t)^{(p_i)} = F_i^{-1}(p_i)$, given the cumulative distribution function of b_i(i.e.,$F_i(b_i)$), and the probability of violating constraint i (i.e., p_i). IPP is effective for handling uncertainties in objective function and constraints, since interval numbers are acceptable as its uncertain inputs (Li et al., 2008; Nematian, 2016). Thus, an interval chance-constrained programming (ICCP) model can be formulated as follows:

$$\text{Min } f^{\pm} = C^{\pm}X^{\pm} \tag{4a}$$

Subject to:

$$A_i^{\pm}X^{\pm} \le B(t)^{(p)}, \quad A_i^{\pm} \in A^{\pm}, \quad i = 1, 2, \ldots, m \tag{4b}$$

$$x_j^{\pm} \ge 0, \quad x_j^{\pm} \in X^{\pm}, \quad j = 1, 2, \ldots, n \tag{4c}$$

where $B(t)^{(p)} = \{b_i(t)^{(p_i)} | i = 1, 2, \ldots, m\}$.