



A fuzzy-stochastic power system planning model: Reflection of dual objectives and dual uncertainties



X.Y. Zhang ^a, G.H. Huang ^{b,*}, H. Zhu ^c, Y.P. Li ^b

^a MOE Key Laboratory of Resources and Environmental Systems Optimization, North China Electric Power University, Beijing 102206, China

^b Center for Energy, Environment and Ecology Research, UR-BNU, Beijing Normal University, Beijing 100875, China

^c S-C Energy and Environmental Research Academy, North China Electric Power University, Beijing 102206, China

ARTICLE INFO

Article history:

Received 24 May 2015

Received in revised form

10 January 2017

Accepted 13 January 2017

Available online 23 January 2017

Keywords:

Electric power system

Carbon dioxide emissions

Dual uncertainties

Fractional programming

Capacity-expansion planning

ABSTRACT

In this study, a fuzzy stochastic dynamic fractional programming (FSDFP) method is proposed for supporting sustainable management of electric power system (EPS) under dual uncertainties. As an improvement upon the mixed-integer linear fractional programming, FSDFP can not only tackle multi-objective issues effectively without setting weights, but also can deal with uncertain parameters which have both stochastic and fuzzy characteristics. Thus, the developed method can help provide valuable information for supporting capacity-expansion planning and in-depth policy analysis of EPS management problems. For demonstrating these advantages, FSDFP has been applied to a case study of a typical regional EPS planning, where the decision makers have to deal with conflicts between economic development that maximizes the system profit and environmental protection that minimizes the carbon dioxide emissions. The obtained results can be analyzed to generate several decision alternatives, and can then help decision makers make suitable decisions under different input scenarios. Furthermore, comparisons of the solution from FSDFP method with that from fuzzy stochastic dynamic linear programming, linear fractional programming and dynamic stochastic fractional programming methods are undertaken. The contrastive analysis reveals that FSDFP is a more effective approach that can better characterize the complexities and uncertainties of real EPS management problems.

© 2017 Elsevier Ltd. All rights reserved.

1. Introduction

Over the past decades, the observed impacts caused by global climate disruption are happening far faster than experts predicted. Many scientists concern about the increased global greenhouse gases (GHGs) emissions [19], which lead to rising temperatures and sea levels as well as changing climate [14]. The increasing utilization of fossil fuels as primary energy resources has been considered as a major contributor to the heightened levels of atmospheric carbon dioxide (CO₂) in a long time [16]. Particularly, about three-quarters of the CO₂ emissions due to human activities resulted from the fossil fuel combustion in electric power systems (EPSs) over the past 20 years [28]. Thus, a number of research works have been undertaken to address the conflicting energy, economic and environmental issues in the EPS management problems [4]. For instance, some effective measures were proposed to reduce CO₂

emissions, such as increasing the efficiency of energy conversion technology, replacing fossil fuels by renewable energy resources (e.g., hydro power, solar energy, wind power and biomass) [18], utilizing carbon capture and storage technologies [17], promoting the development of polygeneration [27] and adopting economic penalties (e.g. carbon tax). Although these effective measures have been developed, the sustainable management of EPSs still faces many difficulties. A significant one is the need to account for multiple conflicting objectives simultaneously [21].

Since the early 1980s, due to the apparent conflicting nature between economic development and environmental protection, many researchers proposed multi-objective programming (MOP) methods for large-scale planning problems of EPS. For example, Quaddus and Goh [24] applied a linear multi-objective model to the EPS planning of Singapore; Rekik et al. [25] proposed a multi-objective control strategy in order to ensure EPS quality improvement. However, conventional MOP methods usually combined multiple conflicting objectives into a single one on the basis of subjective or unrealistic assumptions through introducing weighting factors or economic indicators, whose identification was

* Corresponding author.

E-mail addresses: zhangxiaoyue0301@gmail.com (X.Y. Zhang), huang@iseis.org (G.H. Huang), zhu.marie@gmail.com (H. Zhu), yongping.li33@gmail.com (Y.P. Li).

considered difficult [13]. As an effective method in tackling multi-objective issues, linear fractional programming (LFP) has been employed in a number of management problems [7]. It could address system efficiencies through the optimization of ratios between two quantities (e.g. cost/volume, cost/time, output/input) and compare objectives of different aspects through their original magnitudes without setting weights for each of them [20]. Moreover, LFP is especially helpful to optimize system outputs per unit of inputs (e.g. time, cost, resource) [3], and has been widely used in resources management, public finance, transportation and many other fields. For example, Lara and Stancu-Minasian [13] developed a multi-objective linear fractional programming (MLFP) model for supporting the sustainable management of an agricultural system, the objective of which is to maximize the gross margin and employment levels per unit of water consumption. Gómez et al. [6] applied a conventional linear fractional programming model to a timber harvest scheduling problem and obtained a balanced age class distribution of a forest plantation in Cuba. More recently, LFP was also applied in EPS management problems, which contain various kinds of uncertainties. For instance, Zhu et al. [32,33] proposed a dynamic stochastic fractional programming (DSFP) method and an interval parameter fractional programming (IMIF-EP) method, whose results could provide strong theoretical basis for supporting decisions of EPS planning.

However, these two methods could merely deal with uncertainties described in one single format; they had difficulties in addressing uncertainties existed in multiple levels [29]. In real-world problems, EPS planning are associated with various kinds of uncertainties caused by systematic measurement, parameter estimation, data availability and some other factors. To generate a precise analysis for decision making, multiple uncertainties need to be considered in the processes of problem definition as well as model formulation [30]. For example, the total electricity demand in a certain region has a random feature due to economic development and population fluctuation, and can be described as probability distributions [23]; meanwhile, the statistics of such a random parameter also contains the vagueness of human judgment, which could better be expressed as fuzzy sets [15]. This results in a type of dual uncertainties, which can be represented by the concept of distribution with fuzzy probability [11]. Besides, in some case studies of EPS planning, safety coefficient is introduced to reflect the risk of system failure and can be expressed as a fuzzy set [34]. Therefore, to handle such complexities in real-world problems of EPS planning, an integrated fractional programming approach which is capable of tackling dual uncertainties is desired.

The objective of this study is to propose a fuzzy-stochastic method for supporting sustainable management of EPS under uncertainty. In detail, a fuzzy stochastic dynamic fractional programming (FSDFP) model will be developed for reflecting dual objectives and dual uncertainties in the study system. FSDFP can not only address conflicts among multiple objectives, but also reflect dual uncertainties expressed as combinations of fuzziness and randomness. Effectiveness of the proposed FSDFP approach will be further demonstrated through its application in a typical case study of regional EPS planning.

2. Methodology

A general mixed-integer linear fractional programming (MILFP) problem can be expressed as follows:

$$\text{Max } f(x) = \frac{\sum_{j=1}^n c_j x_j + \beta}{\sum_{j=1}^n d_j x_j + \gamma} \quad (1a)$$

subject to:

$$\sum_{j=1}^n a_{ij} x_j \leq b_i, \quad i = 1, 2, \dots, m \quad (1b)$$

$$x_j \geq 0, \quad j = 1, 2, \dots, n \quad (1c)$$

where x_j ($j = 1, \dots, s$) are non-negative continuous decision variables and x_j ($j = s + 1, \dots, n$) are non-negative integer decision variables, $a_{ij}, b_i, c_j, d_j \in R$; β and γ are scalar constants.

To generate a precise analysis for decision making, multiple uncertainties need to be considered. For example, the total electricity demand in a certain region can be described as probability distributions, and the statistics of such a random parameter could better be expressed as fuzzy sets. This results in a type of dual uncertainties, which can be represented by the concept of distribution with fuzzy probability (DFP). The same representation is also used in fuzzy chance constrained programming (FCCP), and it has already been used in many other research fields to solve practical problems. For example, Rong and Lahdelma [26] used FCCP model for optimizing the scrap charge in steel production; Huang [8] proposed two new FCCP models for addressing capital budgeting issues. When some of parameters in objectives and constraints in model (1) are represented as probability distributions or fuzzy sets as well as their combinations, a fuzzy stochastic dynamic fractional programming (FSDFP) model can be formulated as follows:

$$\text{Max } f(x) = \frac{\sum_{j=1}^n \tilde{c}_j x_j + \beta}{\sum_{j=1}^n \tilde{d}_j x_j + \gamma} \quad (2a)$$

Subject to:

$$\Pr \left[\sum_{j=1}^n \tilde{a}_{ij} x_j \leq b_i(t) \right] \geq 1 - \tilde{p}_i, \quad i = 1, 2, \dots, \eta \quad (2b)$$

$$a_{ij} x_j \leq b_i, \quad i = \eta + 1, \eta + 2, \dots, m \quad (2c)$$

$$x_j \geq 0, \quad j = 1, 2, \dots, n \quad (2d)$$

where $t \in T$, $b_i(t)$ is a random right-hand-side parameter (in constraint i) defined on a probability space T ; \tilde{c}_j and \tilde{d}_j ($j = 1, \dots, n$) are fuzzy coefficients in the objective function; \tilde{a}_{ij} represents the fuzzy coefficient in constraints; \tilde{p}_i ($\tilde{p}_i \in [0, 1]$) is the fuzzy probability of violating constraint i . The results under different \tilde{p}_i levels could reflect the relationships between system objective and reliability, which is very important for the management of EPS [9]. According to the CCP methods [2], when the left-hand-side coefficients $[\tilde{a}_{ij}]$ are deterministic and the right-hand-side coefficients $[b_i(t)]$ are random (for all p_i values), the constraint (2b) can be converted as:

$$\sum_{j=1}^n \tilde{a}_{ij} x_j \leq b_i(t)^{(\tilde{p}_i)}, \quad i = 1, 2, \dots, m \quad (2b')$$

where $b_i(t)^{(\tilde{p}_i)} = F_i^{-1}(\tilde{p}_i)$, $i = 1, 2, \dots, m$, given the cumulative distribution function of b_i [i.e. $F_i(b_i)$] and the fuzzy probability of violating constraint i (\tilde{p}_i). It is apparent that this transformation requires the independent random variables to be continuous.

Comparison of fuzzy numbers is considered one of the most important topics in fuzzy logic theory. Dominance possibility indices is an effective approach for comparing fuzzy numbers,

Download English Version:

<https://daneshyari.com/en/article/5476129>

Download Persian Version:

<https://daneshyari.com/article/5476129>

[Daneshyari.com](https://daneshyari.com)