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Dynamic stochastic fractional programming for sustainable management of electric power systems

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ABSTRACT

A dynamic stochastic fractional programming (DSFP) approach is developed for capacity-expansion planning of electric power systems under uncertainty. The traditional generation expansion planning focused on providing a sufficient energy supply at minimum cost. Different from using least-cost models, a more sustainable management approach is to maximize the ratio between renewable energy generation and system cost. The proposed DSFP method can solve such ratio optimization problems involving issues of capacity expansion and random information. It has advantages in balancing conflicting objectives, handling uncertainty expressed as probability distributions, and generating flexible capacity-expansion strategies under different risk levels. The method is applied to an expansion case study of municipal electric power generation system. The obtained solutions are useful in generating sustainable power generation schemes and capacity-expansion plans. The results indicate that DSFP can support in-depth analysis of the interactions among system efficiency, economic cost and constraint-violation risk.

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1. Introduction

Sustainable management of energy systems plays a significant role in the social and economic development of urban communities. At the present, the major energy sources for electricity generation are non-renewable fossil fuels, which could have serious consequences for the local and global environment [27]. With the growing health and environmental awareness of the people, developing renewable energy sources has gained much attention throughout the world [11,44]. Although numerous optimization methods have been explored, it is still considered difficult to identify sustainable management plans for hybrid electrical systems. The first challenge is to identify a trade-off between conflicting economic and environmental concerns. The second is associated with uncertainties in the input information, such as future electricity demands and resource availabilities. The third is the reflection of dynamic characteristics of facility capacity issues. Therefore, efficient mathematical programming techniques for planning the electric power systems under these complexities are desired.

Previously, many integrated models were proposed in designing environmentally responsible energy management systems [43,28,25,34,38,39]. Classically quite a few models were formulated as single-objective linear programming (LP) problems aiming at the minimization of total cost under specific levels of environmental requirements [23]. For example, Zhu et al. [51] developed a municipal-scale energy model for the City of Beijing, where the objective was to minimize the system cost over the planning horizon, and the constraints included the restrictions for air pollutant emissions. Occasionally environmental concerns were directly quantified by economic indicators and encompassed in the aggregated least-cost objective function. For instance, Li et al. [22] proposed a greenhouse gas (GHG)-mitigation oriented energy system management model, where the trading of GHG-emission credit was represented through an economic measure. However, equating the conventional single-objective least-cost optimization framework to real-world problems involving social and environmental considerations might lead to difficulties in obtaining solutions from a sustainability perspective.

For better reflecting the multi-dimensionality of the sustainability goal, it was increasingly popular to represent the energy management problems within a Multiple Objective Programming (MOP) framework [30,31,18,45,1,33]. Thus environmental impacts were also elected as explicit objective functions in the models

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besides the least-cost desire [20]. Correspondingly, multi-criteria decision making (MCDM) approaches, such as goal programming [36], weighted sum [30,19] and fuzzy multi-objective techniques [33], were widely employed to determine satisfactory compromise solutions. In general, the approaches to deal with multi-objective problems could be classified into two categories: compromise-programming and aspiration-analysis approaches. In compromising programming, the importance of each objective was delineated by weighting factors, and the feasible solution with the shortest overall distance to the ideal values of objectives is considered most desirable [33]. Thus, the solutions determined by compromising programming were highly dependent on the preferences of decision-makers. In contrast, the substance of aspiration approaches was to develop a single objective programming model through optimizing one objective and converting the others into constraints under certain aspiration levels. This manipulation was especially practical for large-scale problems; nevertheless, the trade-offs of multiple objectives were neglected and the system complexities could not be adequately reflected. In general, these MCDM methods had two major limitations. First, they usually combined objectives of multiple aspects into a single measure on the basis of subjective assumptions. The work of setting weighting factors or economic indicators inevitably entailed additional difficulties. Second, they merely focused on system inputs and outputs, and none of them could facilitate analysis of system efficiencies represented as output/input ratios.

For the optimization of system efficiency, Fractional Programming (FP) was used in many management problems [10,41,42,15], in which the optimization of ratio between two quantities (e.g. output/input, cost/time, or cost/volume) was desired. The use of ratio objectives in FP problems assures that only the solutions with better achievements per unit of inputs (e.g. cost, resource, time) would be selected. In addition, the scenarios where FP techniques can be applied are the same as those for LP and MCDM techniques [37,21]. Thus FP can be a natural and powerful tool for studying and analyzing the issues related to sustainability in resources management problems. Although applications of FP were reported in various areas ranging from engineering to economics [32], the method was seldom applied to energy systems planning. Moreover, few studies of FP under uncertainty were reported [7,17].

In real-world problems of energy systems management, renewable energy resources are normally subject to spatial and/or temporal fluctuations; electricity demands are merely imprecisely estimated [29,2]. The type of uncertainty that attracts major attention is "randomness" existing in right-hand-side parameters [14,24,50,49]. For example, the availability of solar and wind energies are uncertain and can be expressed as probability distributions [4]. The chance-constrained programming (CCP) is an attractive tool to deal with problems associated with such uncertainties. Zhu and Huang [48] developed a stochastic linear fractional programming (SLFP) method for supporting sustainable waste management, which incorporated the CCP technique within a FP framework, and could solve ratio optimization problems associated with random information. However, SLFP was not able to deal with the capacity expansion issues in electric power systems. One potential approach to improve SLFP is to integrate the mixed integer linear programming (MILP) technique within its framework.

Therefore, the objective of this study is to develop a dynamic stochastic fractional programming (DSFP) approach for sustainable management of electric power systems. The CCP and MILP techniques will be incorporated into a linear fractional programming (LFP) framework. The integrated DSFP approach can not only deal with ratio objective, but also reflect dynamics of facility expansion under stochastic uncertainties. The developed method will then be applied to a case study to demonstrate its advantages. Desired municipal power system management schemes under different constraint-violation levels will be obtained, which will help decision makers analyze the interrelationships among renewable power generation efficiency, system risk and many related factors.

2. Methodology

2.1. Mixed integer linear fractional programming

A general linear fractional programming (LFP) problem can be formulated as follows:

$$\text{Max} \quad f(x_1, x_2, \ldots, x_n) = \frac{\sum_{j=1}^{n} c_j x_j + \alpha}{\sum_{j=1}^{n} d_j x_j + \beta} \tag{1a}$$

$$\text{s.t.} \sum_{j=1}^{n} a_{ij} x_j \leqslant b_i, \quad i = 1, 2, \ldots, m \tag{1b}$$

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

where a_{ij}, b_i, c_j, $d_j \in R$; α and β are scalar constants. Assume that the solution set of model (1) is nonempty and bounded, and the objective function is continuously differentiable.

Charnes and Cooper [8] showed that if the denominator is constant in sign (assuming that $\sum_{j=1}^{n} d_j x_j + \beta > 0$) for all $X = (x_1, x_2, \ldots, x_n)$ on the feasible region, the LFP model can be transformed to the following linear programming problems under transformation $x_j^* = r \cdot x_j$ $(\forall j)$:

$$\text{Max} \quad g(x_1^*, x_2^*, \ldots, x_n^*, r) = \sum_{j=1}^{n} c_j x_j^* + \alpha \cdot r \tag{2a}$$

$$\text{s.t.} \sum_{j=1}^{n} a_{ij} x_j^* \leqslant b_i \cdot r, \quad i = 1, 2, \ldots, m \tag{2b}$$

$$\sum_{j=1}^{n} d_j x_j^* + \beta \cdot r = 1 \tag{2c}$$

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

$$r \geqslant 0 \tag{2e}$$

Model (2) can be solved through the usual simplex algorithm. Thus the optimal solution of Model (1) can be obtained through transformation $x_j = x_j^*/r$ $(\forall j)$.

In a mixed integer linear fractional programming (MILFP) problem, some decision variables are defined as integers. Thus the problem can be formulated as:

$$\text{Max} \quad f = \frac{\sum_{j=1}^{p} c_j x_j + \sum_{j=p+1}^{n} c_j y_j + \alpha}{\sum_{j=1}^{p} d_j x_j + \sum_{j=p+1}^{n} d_j y_j + \beta} \tag{3a}$$

$$\text{s.t.} \quad \sum_{j=1}^{p} a_{ij} x_j + \sum_{j=p+1}^{n} a_{ij} y_j \leqslant b_i, \quad i = 1, 2, \ldots, m \tag{3b}$$

$$x_j \geqslant 0, \quad j = 1, 2, \ldots, p (p < n) \tag{3c}$$

$$y_j \geqslant 0 \text{ and } y_j = \text{integer variable}, \quad j = p+1, \ldots, n \tag{3d}$$

If the denominator is constant in sign (assuming that $\sum_{j=1}^{p} d_j x_j + \sum_{j=p+1}^{n} d_j y_j + \beta > 0$) on the feasible region, the MILFP model can be transformed to:

$$\text{Max} \quad g = \sum_{j=1}^{p} c_j x_j^* + \sum_{j=p+1}^{n} c_j y_j^* + \alpha \cdot r \tag{4a}$$

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