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Electric power systems planning in association with air pollution control and uncertainty analysis

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ABSTRACT

In this study, a multistage stochastic full-infinite integer programming (MSFIP) method is developed for planning electric-power systems associated with multiple uncertainties presented in terms of crisp intervals, probability distributions, functional intervals and integer variables. Compared with the existing parametric programming method, MSFIP can not only deal with the complex tradeoff between systems cost minimization and pollution-emission mitigation, but also reflect the dynamics through generation of a set of representative scenarios within a multistage context. A case study for regional-scale electric power systems is provided for demonstrating the applicability of the MSFIP, where energy resources, economic concerns, and environmental requirements are integrated into a systematic optimization framework. In the MSFIP model, electricity shortages are exercised with recourse against any infeasibility, which permits in-depth analyses of various policy scenarios that are associated with different levels of economic consequences when the promised electric supply targets are violated. It is indicated that MSFIP model is able to help for lowering the risk of system failure due to potential violation when determining optimal electricity remediation strategies. The modeling results can help to generate a range of alternatives under various system conditions, and thus help decision makers to identify desired policies, including electricity supply, facility capacity expansion and air-pollutant control under multiple uncertainties.

Introduction

Electricity is so basic to the world economy that certain electricity indices are used to express a country's economic strength (such as consumption or production of electricity per capita) [11,13,43,16,21]. Over the past decades, electricity demand and supply have been steadily increasing in response to population growth, economic development and life standard improvement throughout the world [3,30,29,18]. For keeping up with the increase tendency of electricity demand, it is necessary to meet the expense of operation, construction and administration in electric power plants. Additionally, energy activities/services are responsible for relevant infrastructural investments and pollutant/greenhouse gas (GHG) emissions, and conversely have impacts on local environment and ecosystems [7,50,2,46,31]. Likewise, institutional measures and socio-economic activities have effects on electric power systems (EPS) planning through various policies, actions and strategies, which would then have direct/indirect impacts on the components of the region [39,9,22,42,41]. Thus, planning EPS is crucial in accord with the requirement of coordinated development related to society, economy and environment.

In the past decades, to reach the goal of sustainable economic development and effective environmental management, there are a number of comprehensive studies and applications on electric power systems management [4,56,29,9,24,52,8], and many systems analysis techniques on energy models have been employed widely to address the complexities. For example, [35] developed an optimization model using multistage stochastic programming for the weekly cost-optimal generation of electric power in a hydro-thermal generation system under uncertain demands. Sadeghi and Hosseini [40] used fuzzy linear programming approach for planning energy systems in Iran; their study demonstrated that the approach can obviously affect the uncertainties through comparing crisp and fuzzy models, where uncertainties of investment costs in objective function coefficients were taken into account. Li et al. [26] developed an integrated fuzzy-stochastic optimization model for planning energy systems in association with GHG mitigation; in

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this study, multiple uncertainties presented as probability distributions, fuzzy-intervals and their combinations were allowed to be incorporated within an optimization framework. More recently, Piper et al. [38] developed a novel pseudo-stationary model for pollutant measurement prediction from industrial Emissions. Considine and Larson [10] developed an economic model to analyze the underlying economic forces, inducing adjustments in the mix of technologies used in the electric power industry for regulating emissions of GHG emissions, during the first phase of the European Unions Emissions Trading System. Zhao et al. [52] proposed a queue-based interval-fuzzy programming approach for planning of a regional-scale electric-power system under uncertainty. Cacciola et al. [8] presented a representative model of the multivariate relationships that should be able to reproduce local interactions. Lay-Ekuakille et al. [23] provided an experimental IR measurements for hydrocarbon pollutant determination in subterranean waters which could give experience to wastewater treatment in electric power systems.

However, in the EPS, a variety of complexities and uncertainties exist among different electricity activities and their socio-economic and environmental implications. Actually, these uncertainties can be brought from not only parameter measurement and its evaluation [6], but also the cause by all the aspects of energy production, processing, conversion, transportation, utilization. For example, the random characteristics of natural processes (e.g., energy availability and climate change) and supply conditions (e.g., electricity supply, storage capacity, and air-quality requirement), and all the errors in estimated modeling parameters (e.g., benefit and cost parameters) would be possible sources of uncertainties. As illustrated in a World Bank study some of these uncertainties have been more relevant to the decision making process already represented [12]. These complexities have placed many EPS management problems beyond the conventional optimization methods. Thus, it is necessary to inject more and more momentum to the EPS planning, including considerations for diversity of energy activities, structure of electricity generations, variation of system conditions, uncertainty of impact factors, dynamics of capacity expansion, as well as the associated environmental implication [19,33].

A large amount of stochastic mathematical programming (SMP) and interval mathematical programming (IMP) methods were developed to cope with these challenges ([37,44,36,54]. Generally speaking, multistage stochastic programming (MSP) can reflect the dynamic variations of system conditions, especially for sequential structure of large-scale problems; however, the increased data requirements for specifying the parameters' probability distributions can affect their practical applicability [27]. IMP can tackle uncertainties expressed as intervals with known lower and upper bounds, but without known probabilistic and possibilistic distributions. However, in the real-world EPS problems, some parameters may present as functional intervals. For example, energy price may vary with interest rate in various periods, and the cost for facility will change with depreciation rate. The conventional IMP methods have difficulties in tackling functional intervals. Full-infinite programming (FIP) technique can tackle the uncertainties expressed as crisp intervals and functional intervals with infinite objectives and constraints [51,49,17,20,55]. Besides, from a long-term planning point of view, electricity demands will keep increasing due to population increase and economic development. Therefore, the available capacity of electricity-generation facilities may also vary among multiple periods. The related optimization analysis will require the use of integer variables to depict whether a particular facility development or expansion option needs to be undertaken. 0–1 integer programming (IP) technique is a useful tool for this purpose.

Therefore, the objective of this study is to develop a multistage stochastic full-infinite integer programming (MSFIP) method in response to the above challenges. The developed MSFIP will incorporate techniques of multistage stochastic programming (MSP) and full-infinite programming (FIP) within a mixed-integer linear programming (MILP) framework. A case study of regional-scale electric power systems planning will then be provided for demonstrating the application of MSFIP method. The results will be used for generating a range of decision alternatives under various system conditions, and thus helping decision makers to identify desired EPS management policies under uncertainty.

Methodology

Uncertainties can be conceptualized into a scenario tree, with a one-to-one correspondence between the previous random variable and one of the nodes (state of the system) in each stage. Generally, a MSP model can be formulated as follows [27]:

$$\text{Min} \quad f = \sum_{t=1}^{T}\left[\sum_{j=1}^{n_1} c_{jt}x_{jt} + E\left(\sum_{i=1}^{n_2}\sum_{k=1}^{k_t} d_{jtk}y_{jtk}\right)\right] \tag{1a}$$

$$\text{subject to} \quad \sum_{j=1}^{n_1} a_{rjt}x_{jt} \leqslant b_{rt}, \quad r = 1,2,\ldots,m_1;\ t = 1,2,\ldots,T \tag{1b}$$

$$\sum_{j=1}^{n_1} a_{ijt}x_{jt} + \sum_{j=1}^{n_2} a'_{ijt}y_{jtk} \leqslant \widehat{w}_{itk}, \quad i = 1,2,\ldots,m_2; \quad t = 1,2,\ldots,T; \quad k = 1,2,\ldots,K_t \tag{1c}$$

$$x_{jt} \geqslant 0, \quad j = 1,2,\ldots,n_1; \quad t = 1,2,\ldots,T \tag{1d}$$

$$y_{jtk} \geqslant 0, \quad j = 1,2,\ldots,n_2; \quad t = 1,2,\ldots,T; \quad k = 1,2,\ldots,K_t \tag{1e}$$

In model (1), the decision variables are divided into two subsets. x_{jt} represent the first-stage variables; y_{jtk} are related to the recourse actions against any infeasibilities after uncertainties are disclosed; $\widehat{w}_{itk}$ are random variables associated with probability p_{tk}. To solve such a problem, $\widehat{w}_{itk}$ can be approximated by a discrete distribution. Let $\widehat{w}_{itk}$ take values with probability levels of p_{tk}, where p_{tk} is the probability of occurrence for scenario k in period t, with $p_{tk} > 0$ and $\sum_{k=1}^{K_t} p_{tk} = 1$; K_t is the number of scenarios in period t, with the total number of scenarios being $K = \sum_{t=1}^{T} K_t$.

Model (1) can tackle uncertainties expressed as probability distributions and can provide a linkage between the pre-regulated policies and the associated economic implications; however, it can only reflect uncertainties presented as random variables when other coefficients are deterministic. In the real-world energy systems planning problems, deterministic parameters are not suitable for all cases. When parameters expressed as intervals and functional intervals (i.e., lower and upper bounds of intervals are expressed as functions), this leads to a multistage full-infinite stochastic programming (MSFIP) model as follows [53]:

$$\text{Min} \quad f^{\pm} = \sum_{t=1}^{T}\left(\sum_{j=1}^{n_1} c_{jt}^{\pm}(\tau_i)x_{jt}^{\pm} + \sum_{j=1}^{n_2}\sum_{k=1}^{k_t} p_{tk}d_{jtk}^{\pm}(\tau_i)y_{jtk}^{\pm}\right), \quad \text{for all } \tau_i \in [\tau l, \tau u] \tag{2a}$$

$$\text{subject to} \quad \sum_{j=1}^{n_1} a_{rjt}^{\pm}(\tau_i)x_{jt}^{\pm} \leqslant b_{rt}^{\pm}(\tau_i), r = 1,2,\ldots,m_1; \quad t = 1,2,\ldots,T \tag{2b}$$

$$\sum_{j=1}^{n_1} a_{ijt}^{\pm}(\tau_i)x_{ijt}^{\pm} + \sum_{j=1}^{n_2} a'^{\pm}_{ijt}(\tau_i)y_{jtk}^{\pm} \leqslant \widehat{w}_{itk}(\tau_i), i = 1,2,\ldots,m_2; \quad t = 1,2,\ldots,T;\ k = 1,2,\ldots,K_t \tag{2c}$$

$$x_{jt}^{\pm} \geqslant 0, j = 1,2,\ldots,n_1;\ t = 1,2,\ldots,T \tag{2d}$$

$$y_{jtk}^{\pm} \geqslant 0, j = 1,2,\ldots,n_2;\ t = 1,2,\ldots,T; \quad k = 1,2,\ldots,k_t \tag{2e}$$