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An inexact optimization model for energy-environment systems management in the mixed fuzzy, dual-interval and stochastic environment

G.C. Li [a,b], G.H. Huang [a,*], W. Sun [a], X.W. Ding [b]

[a] Faculty of Engineering and Applied Science, University of Regina, 3737 Wascana Parkway, Regina, SK, Canada S4S0A2
[b] MOE Key Laboratory of Regional Energy Systems Optimization, S&C Resources and Environmental Research Academy, North China Electric Power University, Beijing 102206, China

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ABSTRACT

Greenhouse gas (GHG)-emission mitigation has been a complex issue challenging decision makers in energy systems management. This study presents a fuzzy dual-interval multi-stage stochastic programming (FDMSP) approach for the planning of integrated energy-environment systems under multiple uncertainties. The approach is derived by incorporating the concepts of fuzzy programming, interval-parameter programming and dual-interval programming within a multi-stage stochastic optimization framework. With the FDMSP approach, issues of GHG-emission mitigation can be effectively reflected throughout the process of energy systems planning. The proposed method has advantages in integrating inherent system uncertainties, expressed not only as discrete intervals and dual intervals but also as possibility and probability distributions, into its solution procedure. Moreover, the method can also address the dynamics of system conditions within a multi-stage planning context. Through the application of the FDMSP to a hypothetical case of regional energy-environment system management, it indicated that reasonable solutions could be generated for both binary and continuous variables in deterministic, interval and dual-interval formats; and that interactions among multiple energy related activities could be effectively reflected. Generated decision alternatives from a FDMSP model could help decision makers identify desired strategies related to renewable/non-renewable energy production and allocation, GHG emission mitigation, as well as facility capacity expansion in a mixed multi-uncertain environment. Tradeoffs among system costs, energy utilizations and GHG emission control could be effectively addressed.

1. Introduction

In the past decades, greenhouse gas (GHG) abatements have raised increasing public concerns when facing with disadvantageous changing climate conditions [1–6]. Energy consumption activities are believed to be one of the most important sources of GHG emissions and thus are required to be managed systematically [7–11]. A series of technical and economic measures have been widely adopted in mitigating GHG emissions, such as replacing fossil energy resources with renewable energy resources, improving energy utilization efficiency, charging carbon tax and/or implementing carbon trading. Optimization approaches have been proven effective in dealing with such management issue [12–16]. By introducing optimization methodologies into the management of integrated energy-environment system (IEES), various system interactions and trade-offs among multiple system components could be addressed within the modeling framework [17–19]. However, the quality of information available for system modeling is often not good enough to be presented as deterministic numbers. Instead, some information can only be quantified as certain types of uncertainties, for which a series of corresponding approaches are required [20–22].

The uncertain information in IEES is usually classified into three types (i.e., possibility distributions, probability distributions, or single/dual discrete intervals). In order to address these uncertainties, three corresponding inexact programming techniques (i.e., fuzzy programming, stochastic programming and single/dual interval-parameter programming) have been widely applied [19,23,24]. Consequently, a variety of optimization approaches for energy systems management has been developed based on these

* Corresponding author. Tel.: +1 306 585 4095; fax: +1 306 585 4855.
E-mail address: gordon.huang3@gmail.com (G.H. Huang).

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fundamental methodologies [9,13,22,25,26]. For example, Kanudia et al. developed an inexact Indian MARKAL for energy-environment planning for India based on stochastic programming method [24]; Lin and Huang presented an inexact IPEM model for supporting regional energy systems planning based on interval-parameter programming [23]; Hu et al. developed a feasibility-based inexact fuzzy programming approach (FBIFP) for planning regional electric power generation system [27]; Guo et al. proposed an inexact chance-constrained semi-infinite programming (ICCSIP) method for regional energy system management [18]; Li et al. developed an integrated fuzzy-stochastic optimization model (IFOM) for planning energy-environment systems [12]. These approaches mostly focused on particular type of uncertainty or certain hybrid uncertainties within energy management systems. However, in many real-world problems, multiple uncertainties may coexist in energy management systems, of which the systems complexities may not be adequately reflected through the current approaches. Moreover, system dynamics associated with multi-stage decision makings are frequently confronting decision makers, which also need to be integrated and addressed in the same modeling framework. Thus, it brings about the requirement for an optimization approach that can directly incorporate system uncertainties expressed as fuzzy membership functions, probability density functions, discrete intervals and dual intervals within a multi-stage modeling framework. Fuzzy dual-interval multi-stage stochastic programming (FDMSP) is an efficient planning approach that could not only tackle uncertainties with single/dual interval values and possibility distributions existed in energy and environment systems, but also conduct in-depth analysis of long-term stochastic planning problems within multi-layer scenario trees. Applying the FDMSP approach to the management of IEES will enhance the robustness of the optimization process and thereby generate scientific decision alternatives for energy systems management and GHG emissions control.

Therefore, the objective of this study is to propose a FDMSP approach for the planning of integrated energy-environment systems. In this approach, methodologies of interval-parameter programming (ILP), dual-interval linear programming (DILP) and fuzzy programming (FP) will be incorporated within a multi-stage stochastic programming (MSP) context. Based on the proposed approach, multiple forms of uncertainties expressed as discrete intervals, dual-intervals, possibility and probability distributions can be effectively integrated into system optimization process, dynamics associated with multi-stage random variations can be adequately addressed. Through introducing the FDMSP approach into IEES management systems, insights can be gained into interactions among multiple system components, issues related renewable energy utilization and GHG emissions reduction can be effectively tackled. A case study will then be provided for demonstrating the applicability of the FDMSP-IEES model in supporting energy systems planning and GHG-emission management under multiple uncertainties.

2. Model development

2.1. Formulation of IEES model

In energy-environment management systems, decision makers are responsible for allocating energy resources to multiple departments, planning facility expansions and mitigating GHG emissions over a multi-period planning horizon. This problem can be addressed through formulating an optimization model with the minimized system costs of various energy/environment-related activities. In detail, it covers the expenses for energy-resource allocation, electricity generation, capacity expansion and GHG-emission mitigation. These activities are constrained by a series of economic, technical, and policy requirements. The constraints for GHG-emission mitigations set the allowable limits of GHG emission in each planning period; ensure the declining trend of GHG emission; and keep the supply-demand balance of GHG-emission credits in carbon market. Energy-resource demand constraints ensure the sufficient electricity supplies by domestic productions and external importations to meet the industrial and municipal demands; ensure the sufficient supplies of coal, diesel, gasoline and natural gas to meet the regional demands. Generation capacity constraints ensure the sufficient capacities (including existing and planning capacities) for power generation in the region. Resources availability constraints ensure the relevant energy resources (hydro, wind, solar, nuclear) meet power-generation demands; set the upper bounds for energy-resource supplies (e.g. produced and imported coal, natural gas, diesel and gasoline). Technical constraints define the relevant technical requirements for the decision variables. Thus, the detailed IEES model can be formulated as follows:

$$\begin{aligned}\mathrm{Min}\, f =& \sum_{t=1}^{T}\sum_{j=1}^{J}(\mathrm{Ces}_{t,j}\cdot Z_{t,j}) + \sum_{t=1}^{T}\sum_{k=1}^{K}(\mathrm{Cel}_{t,k}\cdot X_{t,k}) \\ &+ \sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{m=1}^{M}\left(\mathrm{Cex}_{t-1,k,m}\cdot \mathrm{CSopn}_{t,k,m}\cdot Y_{t,k,m}\right) \\ &+ \sum_{t=1}^{T}(\mathrm{Cem}_t\cdot \mathrm{Xem}_t)\end{aligned} \tag{1.0}$$

subject to:

GHG-emission mitigation constraints

$$\sum_{j=1}^{8}(\mathrm{Em}_j\cdot Z_{t,j}) \le \mathrm{EMTGT}_t + S_{t-1} + \mathrm{Xem}_{t-1}, \quad \forall t \tag{1.1a}$$

$$S_t = \mathrm{Xem}_t + S_{t-1} + \mathrm{EMTGT}_t - \sum_{j=1}^{8}(\mathrm{Em}_j\cdot Z_{t,j}), \quad \forall t \tag{1.1b}$$

$$\sum_{j=1}^{8}(\mathrm{Em}_j\cdot Z_{t+1,j}) \le \sum_{j=1}^{8}(\mathrm{Em}_j\cdot Z_{t,j}), \quad \forall t \tag{1.1c}$$

$$\mathrm{Xem}_t \le \mathrm{UPcrdt}_t, \quad \forall t \tag{1.1d}$$

Energy-resource demand constraints

$$\sum_{k=1}^{6} X_{t,k} + Z_{t,9} \ge \mathrm{DIE}_t + \mathrm{DME}_t, \quad \forall t \tag{1.2a}$$

$$\mathrm{CONcp}_t\cdot X_{t,1} \le Z_{t,1} + Z_{t,2}, \quad \forall t \tag{1.2b}$$

$$\mathrm{DTD}_t \le Z_{t,3} + Z_{t,4}, \quad \forall t \tag{1.2c}$$

$$\mathrm{DTG}_t \le Z_{t,5} + Z_{t,6}, \quad \forall t \tag{1.2d}$$

$$\mathrm{DIN}_t + \mathrm{DMN}_t + \mathrm{CONnp}_t\cdot X_{t,2} \le Z_{t,7} + Z_{t,8}, \quad \forall t \tag{1.2e}$$

Generation capacity constraints