Development of an integrated model for energy systems planning and carbon dioxide mitigation under uncertainty – Tradeoffs between two-level decision makers

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A B S T R A C T

A bi-level fuzzy programming (BFLP) method was developed for energy systems planning (ESP) and carbon dioxide (CO\textsubscript{2}) mitigation under uncertainty. BFLP could handle fuzzy information and leader-follower problem in decision-making processes. It could also address the tradeoffs among different decision makers in two decision-making levels through prioritizing the most important goal. Then, a BFLP-ESP model was formulated for planning energy system of Beijing, in which the upper-level objective is to minimize CO\textsubscript{2} emission and the lower-level objective is to minimize the system cost. Results provided a range of decision alternatives that corresponded to a tradeoff between system optimality and reliability under uncertainty. Compared to the single-level model with a target to minimize system cost, the amounts of pollutant/CO\textsubscript{2} emissions from BFLP-ESP were reduced since the study system would prefer more clean energies (i.e. natural gas, LPG and electricity) to replace coal fuel. Decision alternatives from BFLP were more beneficial for supporting Beijing to adjust its energy mix and enact its emission-abatement policy. Results also revealed that the low-carbon policy for power plants (e.g., shutting down all coal-fired power plants) could lead to a potentially increment of imported energy for Beijing, which would increase the risk of energy shortage. The findings could help decision makers analyze the interactions between different stakeholders in ESP and provide useful information for policy design under uncertainty.

1. Introduction

It is well known that economic growth and social development are underpinned by globalization and market liberalization, but we cannot lose sight of the crucial role played by the energy (González-Alcaraz and van Gestel, 2015). Without heat, light and power, people cannot run the factories and cities that provide goods, jobs and homes, nor enjoy the amenities that make life more comfortable and enjoyable. However, energy consumption, mostly from unregulated, poorly regulated or inefficient fuel combustion, is the most important sources of climate change and atmospheric pollutants (Alam et al., 2016; Mirzaei and Bekri, 2017). Throughout the world, almost 96% of carbon dioxide (CO\textsubscript{2}) emissions come from fossil fuels burning (coal, natural gas, and petroleum) associated with economic and other human activities (Pao et al., 2015). The power industry as a typical high energy consumption sector consumes more than 75% of fossil fuels and generates around 40% of the total CO\textsubscript{2} emissions (Zhao et al., 2017). Therefore, how to effectively balance the contradiction between energy consumption and environmental protection to achieve sustainable development continues to be a great challenge faced by decision makers.

In energy and environmental management problems, a variety of issues need to be addressed jointly (e.g., electricity generation, capacity expansion, capital investment, and pollution control), in which various decision makers owning different goals and preferences are often conflicting (Aviso et al., 2010; Chaabouni and Saidi, 2017). For example, some decision makers (e.g., environmental sector) prefer to minimize pollutant/CO\textsubscript{2} emissions generated by energy activities and, at the same time, the other decision makers (e.g., stakeholder) like to minimize the entire economic cost. Under such a situation, the decision makers may have different controlling power over the management objective. However, energy systems planning (ESP) with CO\textsubscript{2} mitigation are mainly focused on either single-objective or multi-objective programs...
The problem is always converted to a single-decision maker with a single composite objective for the whole system through conventional optimization methods (Madani, 2010; Lv et al., 2010). Multi-objective programming methods provide comprehensive strategies depending significantly on weights assigned to multiple objectives that are optimized simultaneously (at the same level) and cannot reflect the leader-follower relationship among different decision makers.

Bi-level programming (BP) with a two-level structure (i.e. upper-level and lower-level) is effective for dealing with different decision-making problems, which is based on a static Stackelberg game with leader-follower strategy (Stackelberg, 1952; Simaan, 1977). Previously, a number of algorithms were developed to solve linear and nonlinear bi-level optimization problems (Bard, 1988; Ben-Ayed and Blair, 1990; Edmunds and Bard, 1991). BP has also been used for planning energy systems (Taha et al., 2014; Škugor and Deur, 2016; Mazidi et al., 2017). Zhou et al. (2011) employed BP to design policies of renewable energy investment in electricity transmission networks, where the lower level was a generation expansion planning problem and the upper level was to minimize the total cost. Baccino et al. (2015) proposed a bi-level optimization framework for electric vehicle fleet charging, where the vehicle charging was optimized in the first level and a power margin related to grid technical constraints was calculated in the second level. BP can provide an effective way for prioritizing the goals of decision makers who are more important in the decision making processes, and addressing the tradeoffs between decision makers in various decision-making levels (Zhang and Vesselino, 2016). Meanwhile, there are various uncertainties in addressing environmental problems caused by energy consumption, especially in context of emerging economy of China. However, a satisfactory solution can be reached by providing tolerances in objective functions and constraints or by defining corresponding degrees of satisfaction through membership functions to indicate the preference of decision makers in a fuzzy environment (Bellman and Zadeh, 1970).

Therefore, the objective of this study is to develop a bi-level fuzzy programming (BFLP) method for providing effective decision-making supports for energy systems planning (ESP). BFLP will couple fuzzy linear programming (FLP) with bi-level programming (BP), such that fuzzy information and leader-follower problem in decision making processes can be effectively tackled. Based on the BFLP approach, a BFLP-ESP model will be formulated for planning Beijing’s energy system, in which two-level decision makers are considered. The objective of the upper level is to minimize CO2 emission and the objective of the lower level is to minimize system cost. Results of energy supply, electricity generation, capacity-expansion as well as pollutant/CO2 emissions will be obtained, which can help decision makers analyze interactions among different objectives and strategies under uncertainty.

The developed BFLP method improves upon the conventional single-level and/or fuzzy optimization methods with advantages in uncertainty reflection, hierarchical analysis and synthetic decision making. Compared with the single-level programming, BFLP refers to different decision makers with different goals and preferences, where each decision maker at two hierarchical levels independently controls a set of decision variables. In multi-objective programming, multiple objectives are optimized simultaneously (at the same level), while the decision making process of BFLP is in a hierarchical order, in which the goal of decision maker who is more important need to be preferably met, then the tradeoffs between decision makers in various decision-making levels can be addressed (Arora and Gupta, 2009). Comparing to the conventional BP, BFLP has an advantage in jointly considering the possible lack of knowledge in technical/economic data and the existing fuzziness. Summarily, three characteristics of BFLP make it superior in comparison to the existing optimization techniques: (i) it can deal with various decision-making problems simultaneously, (ii) it can be used for quantitatively analyzing the tradeoffs between decision makers in different decision-making levels, and (iii) it can jointly consider the possible lack of knowledge in data and existing fuzziness.

2. Methodology

The general formulation of a bi-level programming (BP) problem is (Roghani et al., 2007):

\[
\begin{align*}
\min \quad & F(x_u, x_l) \\
\text{s.t.} \quad & x_l \text{ solves:} \\
\min \quad & f(x_u, x_l) \\
\end{align*}
\]

where \( x_l \) solves:

\[
\begin{align*}
\min \quad & f(x_l) \\
\text{s.t.} \quad & \begin{align*}
x_i & \in \mathbb{R}^n, \quad i = 1, 2, \ldots, m, \quad x_i, x_i \geq 0
\end{align*}
\end{align*}
\]

subject to:

\[
G = \{(x_1, x_2)[g(x_1, x_2) \leq 0, i = 1, 2, \ldots, m, \quad x_1, x_2 \geq 0] \}
\]

where \( x_i \in \mathbb{R}^n \) and \( x_i \in \mathbb{R}^m \). The variables of problem are divided into two classes: upper-level variables (\( x_i \in \mathbb{R}^n \)) and lower-level variables (\( x_i \in \mathbb{R}^m \)), the \( F: \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R} \) are the upper-level and lower-level objective functions respectively; \( G \) is the bi-level constraint set. The decision mechanism of BP problem is that the upper-level decision maker (ULDM) and the lower-level decision maker (LLDM) adopt the leader-follower Stackelberg game, so that we can use fuzzy approach to solve the BP problem (Simaan and Cruz, 1973).

In the decision making processes, both ULDM and LLLDM are interested in minimizing their own objective functions. However, the optimal solution of each decision maker will not be accepted by each other. In order to obtain satisfactory solutions, the ULDM should specify preferred values of his/her control variables and the associated objective value with allowable tolerances through membership functions. The LLLDM then should not only optimize its objective but also try to satisfy the ULDM’s goal and preference as much as possible (Sakawa and Nishizaki, 2001; Pramanik and Roy, 2007). Generally, the following upper-level decision maker problem can be firstly solved:

\[
\begin{align*}
\min \quad & F(x_u, x_l) \\
\text{s.t.} \quad & x \in G
\end{align*}
\]

where the solution of model (2) is assumed to be \((x_u^1, x_l^1, f_l^1)\). Meanwhile, the lower-level decision maker can be solved:

\[
\begin{align*}
\min \quad & f(x_l) \\
\text{s.t.} \quad & x \in G
\end{align*}
\]

where the solution of model (3) is \((x_u^2, x_l^2, f_l^2)\), and the range of decision variable \( x_l \) should be around \( x_l^0 \) with the maximum tolerance \( p_l \). The membership function that can specify \( x_l \) being presented as follows:

\[
\mu_{x_l}(x_l) = \begin{cases} 
\frac{x_l - (x_l^0 - p_l)}{p_l}, & \text{if } x_l^0 - p_l < x_l < x_l^0 \\
\frac{(x_l^0 + p_l) - x_l}{p_l}, & \text{if } x_l^0 < x_l < x_l^0 + p_l \\
0, & \text{if otherwise}
\end{cases}
\]

where \( x_l^0 \) is the most preferred decision; \( x_l^0 + p_l \) and \( x_l^0 - p_l \) are the worst acceptable decisions; satisfaction degree can be increased linearly within the interval of \([x_l^0 - p_l, x_l^0]\), and linearly decreased within \([x_l^0, x_l^0 + p_l]\), even though the result may not necessarily be acceptable to the other decision makers.

For ULDM, the objective function can be considered under all \( f_l \leq f_l^0 \) being acceptable, and \( f_l > f_l^0 = f_l(x_u^1, x_l^2) \) being unacceptable. The LLLDM can obtain the optimum at \((x_u^1, x_l^1)\), which in turn provides the ULDM with the objective value of \( f_l^1 \), leading to \( f_l < f_l^1 \) unattractive in practice. The following membership function can be stated as:
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