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Optimization of electric power systems with cost minimization and environmental-impact mitigation under multiple uncertainties

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HIGHLIGHTS

- A multistage inexact-factorial fuzzy-probability programming method is developed.
- It is capable of uncertainty reflection, policy analysis and interaction recognition.
- Results reveal that uncertainties remarkably affect Qingdao's EPS long-term planning.
- Electricity demand and import-electricity expense have obvious effects on system cost.
- The EPS can be adjusted to a cleaner and safer pattern developing renewable energy.

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ABSTRACT

A multistage inexact-factorial fuzzy-probability programming (MIFP) method is developed for optimizing electric power systems with cost minimization and environmental-impact mitigation. MIFP is capable of addressing parameter uncertainties presented as intervals/fuzzy-probability distributions and their interactions in a systematic manner over a multistage context; it can also quantitatively evaluate the individual and interactive effects on system performance. The proposed MIFP method is then applied to planning electric power system for the City of Qingdao, where multiple scenarios that emission-reduction target is designed as random variable and electricity demand is specified as fuzzy-probability distribution over a long term are analyzed. Results reveal that various uncertainties in system components (e.g., fuel price, electricity-produce cost, emission-mitigation option, and electricity-demand level) have sound effects on the city's future energy systems. High mitigation and high demand correspond to decisions with considerable efforts for developing more renewable energies to reduce pollutants and carbon dioxide emitted from fossil fuels. Results also disclose that the proportion of electricity generated by coal would shrink with time to reduce the environmental negative impacts. The imported electricity would eventually drop as the local renewable energy capacity becomes capable of meeting the city's electricity demand. Through developing renewable energy, the city's electric power system could finally be adjusted towards a cleaner and safer pattern. Results also show that factors of electricity demand and import-electricity expenditure have significant individual and/or joint effects on the system cost. The findings can not only optimize electricity-generation and -supply patterns with a cost-effective manner, but also help decision makers identify desired strategies for enhancing the mitigation of environmental impacts under uncertainty.

1. Introduction

1.1. Motivation

Currently, one of the major aspects is that electric power system (EPS) still relies heavily on fossil fuel that contributes a large proportion in greenhouse gas (GHG) and air pollutant emissions and brings about a number of adverse environmental problems. According to the International Energy Agency (IEA), electricity demand will grow > 70% by 2040 compared to 2013 [1,2]. In 2014, fossil fuels accounted

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Nomenclature

$f^{\pm}$	the expected system cost over the planning horizon ($)
k	electricity-conversion technology, with n = 1 for coal-fired power, 2 for gas-fired power, 3 wind power, 4 for solar power, 5 for biomass power
$p_{t,h}$	probability level of electricity demand (low, medium and high)
pm_f	probability of mitigation level (low and high)
q	pollutant type, 1 for sulfur dioxide (SO_2), 2 for nitrogen oxides (NO_x), and 3 for inhalable particles (PM_{10})
t	planning period, t = 1, 2, 3, 4, 5, 6
$\delta_{k,t}$	emission coefficient of carbon dioxide (CO_2) in electricity-conversion technologies (10^3 tonne/GWh)
$\eta^{\pm}_{t,f,h}$	power loss ratio from transmission line (%)
$VGC^{\pm}_{k,t}$	variable cost for generating electricity ($\$10^3$/GWh)
$VEC^{\pm}_{k,t}$	variable cost for expanding conversion technology k in period t ($\$10^3$/GW)
$CCA^{\pm}_{t}$	CO_2 recapture coefficient
$MC^{\pm}_{k,t}$	allowed capacity expansion amount (GW)
$AMR^{\pm}_{k,t,q}$	pollutant emission coefficients (10^3 tonne/PJ)
$AR^{\pm}_{k,t}$	available resources (TJ)
$CCO^{\pm}_{k,t}$	operation cost for CO_2-treatment ($\$/10^3$ tonne)
$CE^{\pm}_{t,q}$	pollutant emission cost ($\$10^3$/GW)
$CP^{\pm}_{t,q}$	pollutant control cost ($\$10^3$/TJ)
$CU^{\pm}_{k,t}$	electricity transmission cost in period t ($\$10^3$/GWh)
$EC^{\pm}_{k,t,f,h}$	expanded capacity for technology k in period t under mitigation level f and demand level h (GW)
$EDB^{\pm}_{t,h}$	electricity demand (GWh)
$EGA^{\pm}_{k,t,f,h}$	electricity generation amount for technology k, period t, mitigation level f and demand level h (GWh)
$ESC^{\pm}_{t}$	discharge limit of total CO_2 emission (10^3 tonne)
$ES^{\pm}_{t,q}$	allowed amount of pollutant (10^3 tonne)
$FE^{\pm}_{k,t}$	energy consumption rate of electricity-conversion technologies (TJ/GWh)
$FEC^{\pm}_{k,t}$	fixed cost for expanding capacity for electricity-conversion technologies ($\$10^3$)
$FGC^{\pm}_{k,t}$	fixed maintenance cost for generating electricity ($\$10^3$/GW)
$PE^{\pm}_{t,f,h}$	imported electricity amount for period t, mitigation level f and demand level h (GWh)
$PEC^{\pm}_{k,t}$	purchasing electricity resource cost ($\$10^3$/TJ)
$PEJ^{\pm}_{t}$	importing electricity cost ($\$10^3$/GWh)
$RC^{\pm}_{k,t}$	residual capacity for electricity-conversion technologies (GW)
$ST^{\pm}_{k,t}$	service time of electricity-conversion technologies (h)
$SU^{\pm}_{t}$	financial subsidy ($\$10^3$/TJ)
$YC^{\pm}_{k,t,f,h}$	0–1 variable for electricity-generation
$ZL^{\pm}_{k,t,f,h}$	electricity consumption rate of each power plant (%)

for 81.1% of the world primary energy supply; while combustion of such fuels is the primary source of anthropogenic GHG emissions [3]. The amount of carbon dioxide (CO_2) emission was increased from 19.0 billion tons in 1981 to 34.7 billion tons in 2014, which would be expected to further increase by 85% within 2030 [4]. Since 2000, GHG emissions have increased 2.4% a year reaching 49 $GtCO_2eq$ in 2010, out of which 25% came from electricity and heat production [1,2].

As the leading contributor of GHG, electric-power sector is largely driven by thermal technology throughout the world, generating over one-third of the global energy-related CO_2 emissions [5]. China, as one of the developing countries, encountered rapid growths in economy, population and urbanization in the recent decades. All of these have directly led to swift increases in primary energy and electricity demand, with annual growth rates of 8.9% and 11.4% from 2000 to 2012, respectively [6]. Air pollution in many cities caused by energy-related activities becomes more and more serious and poses significant threats to the public health [7]. As the environmental impact of fossil fuel consumption and pollutants/GHG emissions become severe, developing renewable energy to replace the traditional primary energy has risen to the public concern.

Municipal EPS management strategy is therefore desired to establish a resource efficient and low emission mode of urban governance to answer the speedy urbanization, severe environmental pollution, and climate change [8,9]. Many cities and regions design long-term plans to mitigate the environmental impacts of EPS through raising the share of renewable energies and developing efficient technologies. The European Union (EU) Member States have committed themselves to increase the share of renewable energy in the EU's energy mix to 20% and reduce GHG emissions by 20% by 2020 [10]. China has also established the target that CO_2 emission per unit of gross domestic product (GDP) would be decreased by 40–45% of 2005 levels by 2020, and the share of non-fossil energy in the total primary-energy consumption would increase from 15% (by 2020) to 20% (by 2030) [11,12]. Realizing such a target is a considerable challenge because fossil fuels with their high carbon emissions dominate China's energy mix [13]. The growth of renewable energy in recent years has been driven by government-supported programs through subsidies, tax credits, and other incentives.

1.2. Literature review

Energy models, regularly based on simulation and optimization techniques, can support strategic energy systems planning. Karavas et al. [14] designed a multi-agent decentralized energy management system for the autonomous polygeneration microgrid topology based on computational intelligence approaches. Anvari-Moghaddam et al. [15] proposed a multi-agent based energy management system for monitoring and optimal control with various renewable energy resources and controllable loads, where different agents were implemented to cooperate with each other to achieve an optimal operating strategy. Nojavan et al. [16] studied bilateral contracting and selling price determination problems for an electricity retailer in the smart grid environment, where three cases including fixed pricing, time-of-use pricing and real-time pricing with and without demand response program were considered. Nevertheless, energy systems planning is subject to important sources of uncertainty related to different variables (e.g., physical, technical, economic and environmental) and uncertainty is an unavoidable component of such a procedure. There are significant uncertainties in not only how the energy system might develop, but also in how the system is expected to adjust when many system components are altered (e.g., fuel price, emission amount, and conversion efficiency) [17,18]. Renewable energies (particularly solar and wind) are associated with high degree of uncertainty due to climatic conditions; fuzzy and stochastic uncertainties may coexist in energy systems and interact significantly within multiple spatio-temporal dimensions; at the same time, pollutants and GHGs are generated by a variety of energy produce processes and activities, leading to pressure and risk to the environment. A proper modeling and analytical treatment of these uncertainties play a key role in taking operational and financial decisions [19,20]. Effective reflection of these uncertainties and complexities is critical for supporting the formulation of sound management plans and analyzing various policies associated with energy conversion and distribution.

In the past decades, efforts were made in dealing with uncertainties in energy systems management through interval, stochastic and fuzzy programs. Stochastic programming (SP) is an effective measure to address probabilistic uncertainty, and the most commonly used approach