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Energy and environmental systems planning under uncertainty—An inexact fuzzy-stochastic programming approach

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ABSTRACT

In this study, an inexact fuzzy-stochastic energy model (IFS-EM) is developed for planning energy and environmental systems (EES) management under multiple uncertainties. In the IFS-EM, methods of interval parameter fuzzy linear programming (IFLP) and multistage stochastic programming with recourse (MSP) are introduced into a mixed-integer linear programming (MILP) framework, such that the developed model can tackle uncertainties described in terms of interval values, fuzzy sets and probability distributions. Moreover, it can reflect dynamic decisions for facility-capacity expansion and energy supply over a multistage context. The developed model is applied to a case of planning regional-scale energy and environmental systems to demonstrate its applicability, where three cases are considered based on different energy and environmental management policies. The results indicate that reasonable solutions have been generated. They are helpful for supporting: (a) adjustment or justification of allocation patterns of regional energy resources and services, (b) formulation of local policies regarding energy consumption, economic development and environmental protection, and (c) in-depth analysis of tradeoffs among system cost, satisfaction degree and environmental requirement under multiple uncertainties.

1. Introduction

Effective management of energy and environmental systems (EES) is a priority for many regions throughout the world. In the past decades, rising energy demands and fossil fuel prices, increasing environmental- and health-impact concerns, as well as shrinking energy reserves and environmental capacities have forced decision makers to contemplate and propose comprehensive and ambitious plans for EES management [1–7]. However, such planning efforts are complicated with a variety of processes that should be considered by decision makers, including the diversity of supply and mitigation technology options available (influencing model size and complexity), the temporal and/or spatial evolutions of parameters over medium- to long-term time horizons, the dynamic variation of system's conditions, the environmental and social arguments, as well as the various uncertainties during the planning process [9,10]. Therefore, in response to these uncertainties and complexities, more robust systems analysis techniques are desired for effectively managing EES within a multi-sector, multi-period, and multi-option context.

Previously, a number of inexact optimization techniques were developed to deal with such uncertainties and complexities in the EES, such as fuzzy, interval and stochastic mathematical programming methods (abbreviated as FMP, IMP and SMP) [11–30]. For example, Liu et al. [13] developed an interval-parameter chance-constrained method for nonrenewable energy resources management, which could deal with uncertainties expressed as discrete intervals and probability distributions. Mavrotas et al. [14] developed a fuzzy linear programming model to handle uncertainties in energy costs presented as fuzzy sets. Sadeghi and Hosseini [15] used fuzzy linear programming approach for optimization of supply energy system in Iran, where uncertainties of investment costs in the objective function coefficients were considered; the study indicated that uncertainties would significantly affect the results of energy model when compared crisp and fuzzy models. Muela et al. [17] developed a fuzzy possibilistic model for power generation planning, in which environmental criteria was considered and uncertainties in various energy demands were presented as fuzzy sets. Liu et al. [18] developed an integrated fuzzy-possibilistic joint-probabilistic mixed-integer programming model and applied it to the expansion planning of power generation under uncertainty. Lin and Huang [19] developed an energy systems planning model through using interval-parameter integer programming for the optimization problem of energy allocation and capacity expansion within a regional jurisdiction, where interval solutions allow for detailed interpretation of the trade-offs between environmental pollution risks and economic objectives. In

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general, fuzzy programming methods were effective in dealing with decision problems under fuzzy goal and constraints and handling ambiguous coefficients in the objective function and constraints; chance-constrained programming method could reflect the reliability of satisfying system constraints under uncertainty; interval-parameter programming method could handle uncertain parameters that are expressed as intervals with known lower and upper bounds, but unknown membership or distribution functions. However, they had difficulties in facilitating the analysis of various energy and environmental policy scenarios that were associated with different levels of economic penalties when the pre-regulated targets (e.g., electricity generation targets) were violated.

Stochastic programming with recourse was effective for problems where an analysis of policy scenarios is desired and coefficients are random with known probability distributions [31–36]. In this method, decision variables were divided into two subsets: those that had to be determined before the random uncertainties were disclosed and those (recourse variables) that could be determined after the uncertainties were disclosed [37–40]. Previously, a number of two-stage and multistage stochastic programming with recourse (TSP and MSP) were developed for tackling the above uncertainties and complexities in the planning EES. For example, Pereira and Pinto [11] proposed a multistage stochastic optimization approach for the planning of a multi-reservoir hydroelectric system under uncertainty, through associating a given probability to each of a range of inputs that occurred at different stages of an optimization horizon. Takriti et al. [41] proposed a MSP-based model for the problem of generating electric power when demands were uncertain; numerical results indicated significant savings in the cost of operating power generating systems when the stochastic model was used instead of the deterministic model. Nürnberg and Römisch [42] developed a TSP model for the short- or mid-term cost-optimal electric power production planning, where random uncertainties in electricity load demand were considered. Recently, Lin et al. [20] developed a hybrid interval-fuzzy two-stage stochastic energy systems planning model to deal with uncertainties that can be expressed as fuzzy numbers, probability distributions, and discrete intervals.

In general, TSP had advantages in reflecting complexities of system uncertainties as well as analyzing policy scenarios when the pre-regulated targets were violated; however, it had difficulties in reflecting the dynamic variations of system conditions, especially for sequential structure of large-scale problems. In comparison, as an extension of dynamic stochastic programming methods, MSP was effective in reflecting such a dynamic feature. MSP improved upon the conventional TSP methods by permitting revised decisions in each time stage based on the uncertainty realized so far [31]. The uncertain information in a MSP was often modeled through a multilayer scenario tree. The primary advantage of scenario-based stochastic programming was the flexibility it offered in modeling the decision process and defining the scenarios, particularly if the state dimension was high [31,32].

Therefore, as an extension of the previous efforts, an inexact fuzzy-stochastic energy model (IFS-EM) will be developed for supporting regional-scale energy and environmental systems (EES) planning under uncertainty. The IFS-EM will incorporate techniques of interval-parameter fuzzy linear programming (IFLP), multistage stochastic programming (MSP) and mixed-integer linear programming (MILP) within a general optimization framework. Uncertainties existing in the model stipulations and coefficients, expressed as interval values, fuzzy sets and probability distributions, can be directly included in the model and communicated into the optimization process, such that the solutions reflecting the inherent uncertainties can be generated. Moreover, it will be used for reflecting dynamics in terms of decisions for electricity generation schemes and air pollution mitigation plans through transactions at discrete points of a complete scenario set over a multistage context. It can also be used for analyzing multiple policy scenarios that are associated with economic penalties when the promised targets are violated. A case study will then be provided for demonstrating applicability of the developed method. Three cases will be considered based on varied energy and environmental management policies. The results can help decision makers not only discern optimal energy-allocation patterns and air pollution mitigation plans, but also gain in-depth insights into the tradeoffs among system cost, satisfaction degree and environmental requirement under multiple uncertainties.

2. Methodology

2.1. Interval-parameter fuzzy linear programming

Consider an interval-parameter fuzzy linear programming (IFLP) problem [43] as follows:

$$\text{Min} \quad f^{\pm} \underset{\sim}{=} C^{\pm}X^{\pm} \tag{1a}$$

$$\text{s.t.} \quad A^{\pm}X^{\pm} \underset{\sim}{<} B^{\pm} \tag{1b}$$

$$X^{\pm} \geqslant 0 \tag{1c}$$

where $A^{\pm} \in \{R^{\pm}\}^{m\times n}$, $B^{\pm} \in \{R^{\pm}\}^{m\times 1}$, $C^{\pm} \in \{R^{\pm}\}^{1\times n}$ and $\{R^{\pm}\}$ denote a set of interval numbers, and m and n are real numbers ($m \geqslant 1$ and $n \geqslant 1$); $X^{\pm}$ represent a set of decision variables; the '−' and '+' superscripts denote the lower and upper bounds of parameters/variables, respectively; and symbols $\underset{\sim}{=}$ and $\underset{\sim}{<}$ represent fuzzy equality and inequality, respectively. In fact, a decision in a fuzzy environment can be defined as the intersection of membership functions corresponding to fuzzy objective and constraints [44,46,47]. Given a fuzzy goal (G) and a fuzzy constraint (E) in a space of decision alternatives ($X^{\pm}$), a fuzzy decision set (D) can then be formed in the intersection of G and E. In a symbolic form, we have $D = G \cap E$, and correspondingly:

$$\mu_D = \text{Min}\{\mu_G, \mu_E\} \tag{2a}$$

where μ_D, μ_D and μ_D denote membership functions of fuzzy decision D, fuzzy goal G, and fuzzy constraint E, respectively [38]. Let $\mu_{E_i}(X^{\pm})$ be membership functions of constraints E_i ($i = 1,2,\ldots,m$), and $\mu_{G_j}(X^{\pm})$ be those of goals G_j ($j = 1,2,\ldots,n$). A decision can then be defined by the following membership function [47,48]:

$$\mu_D(X^{\pm}) = \mu_{E_i}(X^{\pm}) * \mu_{G_j}(X^{\pm}) \tag{3a}$$

$$\mu_D(X^{\pm}) = \text{Min}\{\mu_i(X^{\pm}) | i = 1,2,\ldots,m+1\} \tag{3b}$$

where "*" denotes an appropriate and possibly context-dependent "aggregator"; $\mu_i(X^{\pm})$ can be interpreted as the degree to which $X^{\pm}$ satisfies fuzzy inequality in the objective and constraints. A desired decision is thus the one with the highest $\mu_D(X^{\pm})$ value:

$$\text{Max} \quad \mu_D(X^{\pm}) = \text{Max Min}[\mu_i(X^{\pm})], \quad X^{\pm} \geqslant 0 \tag{4}$$

where $\mu_i(X^{\pm})$ should be zero if the objective and constraints are violated, and 1 if they are totally satisfied. Consequently, the IFLP problem can be converted into an ordinary linear programming model by introducing a new variable of $\lambda = \mu_D(X^{\pm})$, which corresponds to the membership function of the fuzzy decision [38,46–48]. Specifically, the flexibility in the constraints and fuzziness in the objective (which are represented by fuzzy sets and denoted as "fuzzy constraints" and "fuzzy goal", respectively) can be expressed as membership grades (λ) corresponding to the degrees of overall satisfaction for the constraints and objective. Thus, model (1) can be converted into:

$$\text{Max} \quad \lambda^{\pm} \tag{5a}$$

$$\text{s.t.} \quad C^{\pm}X^{\pm} \leqslant f^{+} - \lambda^{\pm}(f^{+} - f^{-}) \tag{5b}$$

$$A^{\pm}X^{\pm} \leqslant B^{+} - \lambda^{\pm}(B^{+} - B^{-}) \tag{5c}$$

$$X^{\pm} \geqslant 0 \tag{5d}$$

$$0 \leqslant \lambda^{\pm} \leqslant 1 \tag{5e}$$

where f^{-} and f^{+} are the lower and upper bounds of the objective's aspiration level, respectively; $\lambda^{\pm}$ is the control variable corresponding to the degree (membership grade) of satisfaction for the fuzzy decision. An interactive two-step algorithm is developed to solve the above problem through analyzing the detailed interrelationships between the parameters and the variables and between the objective function and the constraints [44]. The submodel for λ^{+} corresponding to f^{-} can be formulated in the first step when the system objective is to be minimized; the other submodel for λ^{-} can then be formulated based on the solution of the first submodel. The IFLP can directly handle uncertainties presented as interval numbers and/or fuzzy sets. However, it has difficulties in tackling uncertainties expressed as random variables in a non-fuzzy decision space and in providing a linkage between the pre-regulated policies and the associated implications.

2.2. Multistage stochastic programming with recourse

In many real-world problems, uncertainties may be expressed as random variables, and the related study systems are of dynamic feature. Thus the relevant decisions must be made at each time stage under varying probability levels. Such a problem can be formulated as a scenario-based multistage stochastic programming (MSP) model with recourse as follows [47]:

$$\text{Min} \quad f = \sum_{t=1}^{T} C_t X_t + \sum_{t=1}^{T} \sum_{k=1}^{K_t} p_{tk} D_{tk} Y_{tk} \tag{6a}$$

$$\text{s.t.} \quad A_{rt} X_t \leqslant B_{rt}, \quad r = 1,2,\ldots,m_1;\ t = 1,2,\ldots,T \tag{6b}$$

$$A_{it} X_t + A'_{itk} Y_{tk} \leqslant w_{itk}, \quad i = 1,2,\ldots,m_2;\ t = 1,2,\ldots,T;\ k = 1,2,\ldots,k_t \tag{6c}$$

$$x_{jt} \geqslant 0,\ x_{jt} \in X_t, \quad j = 1,2,\ldots,n_1;\ t = 1,2,\ldots,T \tag{6d}$$

$$y_{jtk} \geqslant 0,\ y_{jtk} \in Y_{tk}, \quad j = 1,2,\ldots,n_2;\ t = 1,2,\ldots,T;\ k = 1,2,\ldots,k_t \tag{6e}$$

where p_{tk} is the probability of occurrence for scenario k in period t, with $p_{tk} \leqslant 1$ and $\sum_{k=1}^{K_t} p_{tk} = 1$; and K_t is the number of scenarios in period t, with the total number of scenarios being $K = \sum_{t=1}^{T} K_t$. In model (6), the decision variables are divided into two subsets: the first-stage decision variables (x_{jt}) that must be determined before the random variables are disclosed, and recourse variables (y_{jtk}) that can be determined after the random variables are disclosed.

2.3. Interval-fuzzy multistage linear programming

Obviously, model (6) can address uncertainties in the right-hand sides of the constraints to be presented as random variables. Therefore, one potential approach that can deal with multiple uncertainties presented in terms of fuzzy sets, interval values, and random variables is to couple MSP and IFLP into a general framework; this leads to an interval-fuzzy multistage linear programming (IFMP) model as follows [40,47]:

$$\text{Max} \quad \lambda^{\pm} \tag{7a}$$

$$\text{s.t.} \quad \sum_{t=1}^{T} C_t^{\pm} X_t^{\pm} + \sum_{t=1}^{T} \sum_{k=1}^{K_t} p_{tk} D_{tk}^{\pm} Y_{tk}^{\pm} \leqslant f^{+} - \lambda^{\pm}(f^{+} - f^{-}) \tag{7b}$$

$$A_{rt}^{\pm} X_t^{\pm} \leqslant B_{rt}^{+} - \lambda^{\pm}(B_{rt}^{+} - B_{rt}^{-}), \quad r = 1,2,\ldots,\ m_1;\ t = 1,2,\ldots,T \tag{7c}$$

$$A_{it}^{\pm} X_t^{\pm} + (A'_{itk})^{\pm} Y_{tk}^{\pm} \leqslant w_{itk}^{+} - \lambda^{\pm} \Delta w_{itk}^{\pm}, \quad i = 1,2,\ldots,m_2;\ t = 1,2,\ldots,T;\ k = 1,2,\ldots,K_t \tag{7d}$$

$$x_{jt}^{\pm} \geqslant 0,\ x_{jt}^{\pm} \in X_t^{\pm}, \quad j = 1,2,\ldots,n_1;\ t = 1,2,\ldots,T \tag{7e}$$

$$y_{jtk}^{\pm} \geqslant 0,\ y_{jtk}^{\pm} \in Y_{tk}^{\pm}, \quad j = 1,2,\ldots,n_2;\ t = 1,2,\ldots,T;\ k = 1,2,\ldots,k_t \tag{7f}$$

$$0 \leqslant \lambda^{\pm} \leqslant 1 \tag{7g}$$

In model (7), a $\lambda^{\pm}$ level close to 1 would correspond to a high possibility of satisfying the constraints/objective under advantageous conditions; conversely, a $\lambda^{\pm}$ value near 0 would be related to a solution that has a low possibility of satisfying the constraints/objective under demanding conditions. The detailed solution method for the IFMP model is presented in Appendix A to this paper.

3. Application

3.1. Statement of problems

In a typical regional-scale energy and environmental system, four main components are considered. They are (i) the energy resources supply sector, which provides energy resources with different availability including diverse renewable and nonrenewable resources to the system; (ii) the energy conversion sector, which contains various electricity conversion technology and air pollution mitigation technology options with varied economic, environmental and technological performance; (iii) the electricity-demand sector, which involves kinds of demand side technologies that drive energy consumptions by numerous end-users and is characterized by varying socio-economic, geographical, demography, technology advancement and environmental conditions; (iv) the environmental protection sector, which regulates energy-related environmental protection policies [23]. A decision maker is often responsible for allocating energy resources/services from multiple facilities to multiple end-users through multiple technologies under multiple demand-levels and environmental constraints within a multi-period horizon. The study problem can be formulated as minimizing the expected value of net system cost with optimized energy resources allocation patterns, pollution mitigation plans and capacity expansion planning schemes over the planning horizon. In addition, in the energy conversion sector, every power conversion technology has a pre-regulated electricity generation target and each pollution mitigation technology also has a pre-defined pollution mitigation target. If the target is not exceeded, the system will be encountered the regular cost; otherwise, the system will be subject to penalties resulted from the extra labor, management, operation and maintenance costs, or capacity expansion and higher costs for imported energy.

In the EES problems, potential energy demand from a long-term perspective may be expressed as random variable with a given probability level in one case and the other uncertain parameters may be expressed as intervals and/or fuzzy sets; besides, the relevant electricity-generation plan would be of dynamic features and a link to a pre-regulated policy is desired. The relevant decisions must be made at each time stage under various uncertainties in order to select the most appropriate power conversion technology and type of fuel to meet the random electricity demand and the most suitable pollution mitigation technology to satisfy the environmental constraints, according to the availability, economic, environmental and technological characteristics of different fuels and technologies. Therefore, the developed IFMP method is considered to be feasible for giving such a decision support.

3.2. Overview of the study system

A hypothetical but representative study system is developed for illustrating applicability of the proposed inexact fuzzy-stochastic programming approach based on representative cost and technical data from EES management literatures. Three time periods are considered, with each having a time interval of five years (this can be adjusted based on the decision makers' interests while planning real-world cases). In the theoretical energy and environmental system (Fig. 1), multiple conventional and renewable energy resources/technologies need to be allocated to multiple end-users (i.e., industrial, commercial, agricultural, residential sectors), while various air pollution mitigation technology options are to be adopted to control air pollutants emissions in a region.

In detail, coal, natural gas, nuclear fuel and renewable energy resources (hydropower, wind and solar) are mainly employed for power generation. Power conversion technologies include those for large-scale electricity generation, as well as those for small-scale renewable resources utilization. Generally, large-scale technologies are mostly used for generating electricity from conventional energy resources such as coal and natural gas. At the same time, small-scale technologies are based on local availabilities of renewable energy resources except hydropower [8,49]. The end-user's random electricity demands and electricity generation targets of each power conversion technology are presented in Table 1. In the region, if electricity supply cannot sufficiently meet the end-users' demands, decision makers will face a dilemma of either investing more funds in capacity expansions of the existing facilities or turning to other electricity production options or putting extra funds into electricity imports at raised prices [8,49]. No matter which way would be adopted in response to the deficiencies of electricity productions, economic penalties would be incurred. The peak load demands (V_t) are [1.5,3.0], [2.0,3.5] and [2.5,4.0] GW in periods 1, 2 and 3, respectively. Table 2 provides the economic and technological datum of each power conversion technology. The initial installed capacity of coal-fired power, natural gas-fired power, hydropower, wind power, solar power and nuclear power conversion technologies are 1.00, 0.28, 0.26, 0, 0, and 0 GW, respectively. Sulfur dioxide (SO_2), nitrogen oxides (NO_x) and particulate matter (PM) are the main pollutants emitted from power plants. There are many removal technologies that have been used for controlling these pollutants. In this study system, soda ash scrubber (SAS), wet limestone scrubber (WLS) and lime spray dryer (LSD) are used to reduce the amount of SO_2 emission, with the average removal efficiencies being 92.0%, 83.0% and 77.5%, respectively. Selective catalytic reduction (SCR) and selective non-catalytic reduction (SNCR) are selected to control the amount of NO_x emission, with the average removal efficiencies being 85.0% and 70.0%, respectively. Fabric filiter/baghouse (BH), electrostatic precipitator (ESP) and wet collector (WC) are used to mitigate the amount of PM emission, with the average removal efficiencies being 99.0%, 95.0% and 90.0%, respectively. The regular costs (including the capital and operating costs for mitigating pollutant emissions) of different pollution control measures as well as the penalties for handling the excess emission and paying the fine

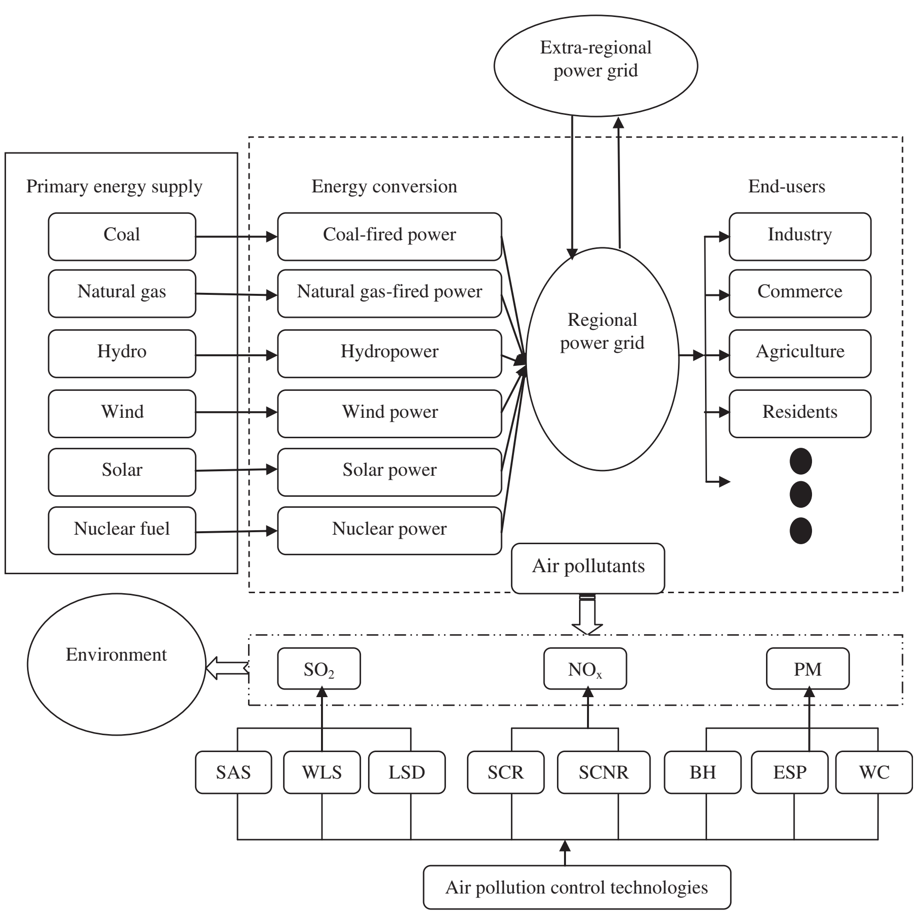

Fig. 1. The schematic of regional energy and environmental system.

Table 1
End-user's total electricity demands and electricity generation targets.

Time period	$t = 1$		$t = 2$		$t = 3$	
Demand level	Probability (%)	Electricity demand	Probability (%)	Electricity demand	Probability (%)	Electricity demand
End-user's total electricity demand (10^3 GW h)						
Low (L)	25	[50,65]	20	[85,105]	15	[135,150]
Medium (M)	50	[65,81]	60	[105,127]	55	[150,175]
High (H)	25	[81,96]	20	[127,147]	30	[175,200]
Electricity generation targets of each power conversion technology (10^3 GW h)						
Coal-fired power, $W_{1t}^{\pm}$	[27.5,50.0]		[25.0,60.0]		[22.5,70.0]	
Gas-fired power, $W_{2t}^{\pm}$	[6.0,20.0]		[7.0,25.0]		[8.0,30.0]	
Hydropower, $W_{3t}^{\pm}$	[5.0,10.0]		[5.5,15.0]		[6.0,20.0]	
Wind power, $W_{4t}^{\pm}$	[0,5.0]		[0,5.0]		[0,5.0]	
Solar power, $W_{5t}^{\pm}$	[0,5.0]		[0,5.0]		[0,5.0]	
Nuclear power, $W_{6t}^{\pm}$	[0,10.0]		[0,15.0]		[0,20.0]	

Table 2
Economic and technological datum of each power conversion technology.

Conversion technology		Time period		
		$t = 1$	$t = 2$	$t = 3$
Regular and surplus costs for power generation by each power conversion technology ($\$10^3$/GW h)				
Coal-fired power	Regular cost, $PV_{1t}^{\pm}$	[5.0,7.0]	[5.5,7.5]	[6.0,8.0]
	Surplus cost, $PP_{1t}^{\pm}$	[3.0,5.0]	[3.5,5.5]	[4.0,6.0]
Gas-fired power	Regular cost, $PV_{2t}^{\pm}$	[4.5,6.5]	[5.0,7.0]	[5.5,7.5]
	Surplus cost, $PP_{2t}^{\pm}$	[2.5,4.5]	[3.0,5.0]	[3.5,5.5]
Hydropower	Regular cost, $PV_{3t}^{\pm}$	[4.0,6.0]	[4.5,6.5]	[5.0,7.0]
	Surplus cost, $PP_{3t}^{\pm}$	[3.5,5.5]	[4.0,6.0]	[4.5,6.5]
Wind power	Regular cost, $PV_{4t}^{\pm}$	[2.5,3.5]	[3.0,4.0]	[3.5,4.5]
	Surplus cost, $PP_{4t}^{\pm}$	[1.5,2.5]	[2.0,3.0]	[2.5,3.5]
Solar power	Regular cost, $PV_{5t}^{\pm}$	[2.0,3.0]	[2.5,3.5]	[3.0,4.0]
	Surplus cost, $PP_{5t}^{\pm}$	[1.0,2.0]	[1.5,2.5]	[2.0,3.0]
Nuclear power	Regular cost, $PV_{6t}^{\pm}$	[10.0,14.0]	[11.0,15.0]	[12.0,16.0]
	Surplus cost, $PP_{6t}^{\pm}$	[6.0,9.0]	[6.5,9.5]	[7.0,10.0]
Fixed ($\$10^6$) and variable ($\$10^6$/GW) costs for capacity expansion				
Coal-fired power	Fixed cost, $A_{1t}^{\pm}$	[325,395]	[385,455]	[445,515]
	Variable cost, $B_{1t}^{\pm}$	[700,850]	[750,900]	[800,950]
Gas-fired power	Fixed cost, $A_{2t}^{\pm}$	[300,375]	[350,425]	[400,475]
	Variable cost, $B_{2t}^{\pm}$	[650,800]	[700,850]	[750,900]
Hydropower	Fixed cost, $A_{3t}^{\pm}$	[700,900]	[770,970]	[840,1040]
	Variable cost, $B_{3t}^{\pm}$	[1800,2300]	[1900,2400]	[2000,2500]
Wind power	Fixed cost, $A_{4t}^{\pm}$	[800,1000]	[880,1080]	[960,1160]
	Variable cost, $B_{4t}^{\pm}$	[1900,2450]	[1950,2500]	[2000,2550]
Solar power	Fixed cost, $A_{5t}^{\pm}$	[900,1150]	[990,1240]	[1080,1330]
	Variable cost, $B_{5t}^{\pm}$	[2000,2400]	[2100,2500]	[2200,2600]
Nuclear power	Fixed cost, $A_{6t}^{\pm}$	[1000,1300]	[1100,1400]	[1200,1500]
	Variable cost, $B_{6t}^{\pm}$	[1950,2350]	[2100,2500]	[2250,2650]
Variable upper bounds for capacity expansion of each power conversion technology (GW)				
Coal-fired power, M_{1t}		0.7	0.5	0.3
Gas-fired power, M_{2t}		0.5	0.6	0.7
Hydropower, M_{3t}		0.3	0.4	0.5
Wind power, M_{4t}		0.1	0.2	0.3
Solar power, M_{5t}		0.2	0.3	0.4
Nuclear power, M_{6t}		0.3	0.4	0.5

are listed in Table 3. Normally, the penalties are significantly higher than the regular costs, and the measure with higher pollutant removal efficiency often has a relatively higher operating cost (due to the high reagent cost). Thus, decision makers need to identify desired energy-flow allocation, facility-expansion and air pollutants mitigation schemes with a minimized system cost and a maximize satisfaction degree.

The representative costs and technical data in Tables 2 and 3 were investigated based on governmental reports and other related Refs. [7,8,31,50–56]. The deterministic parameters (e.g., variable upper bounds for capacity expansion of each power conversion technology) are based on the assumption that they can be definitely determined by decision makers or that their uncertainties are small enough to be ignored. The intervals indicate that

Table 3
Regular and penalty costs of pollution control techniques.

Pollution control technique	Time period		
	$t = 1$	$t = 2$	$t = 3$
Regular cost for treating pre-regulated SO_2 emission ($/tonne)			
SAS, CS_{1t}	[55,75]	[57,77]	[59,79]
WLS, CS_{2t}	[45,60]	[48,63]	[51,66]
LSD, CS_{3t}	[30,40]	[33,43]	[35,45]
Penalty cost for treating excess SO_2 emission ($/tonne)			
SAS, DS_{1t}	[90,110]	[95,115]	[100,120]
WLS, DS_{2t}	[125,150]	[130,155]	[135,160]
LSD, DS_{3t}	[110,140]	[115,145]	[120,150]
Regular cost for treating pre-regulated NO_x emission ($/tonne)			
SCR, CN_{1t}	[55,75]	[59,79]	[62,82]
SNCR, CN_{3t}	[35,50]	[38,53]	[40,55]
Penalty cost for treating excess NO_x emission ($/tonne)			
SCR, DN_{1t}	[95,115]	[100,120]	[105,125]
SNCR, DN_{3t}	[110,130]	[115,135]	[120,140]
Regular cost for treating pre-regulated PM emission ($/tonne)			
BH, CP_{1t}	[135,160]	[140,165]	[145,170]
ESP, CP_{2t}	[125,150]	[133,158]	[140,165]
WC, CP_{3t}	[115,140]	[125,150]	[135,160]
Penalty cost for treating excess PM emission ($/tonne)			
BH, DP_{1t}	[185,215]	[193,223]	[200,230]
ESP, DP_{2t}	[195,225]	[203,233]	[210,240]
WC, DP_{3t}	[205,235]	[213,243]	[220,250]

the specified values of parameters are unknown, but the lower and upper bounds can be provided. For example, many factors may affect the system cost, the emission loads of air pollutants, and the operating cost in real-world cases. The cost for the study system may change according to the fuel quality, the prices of fuels, the labor fee, and the levels of regional economic development; the values of emission loadings are affected by the types of fuels, the combustion conditions, the amount of electricity generation; the operating cost is estimated based on the types of power conversion technologies and mitigation measures to be adopted. Correspondingly, the system cost, the emission loads of air pollutants, and the operating cost would be sensitive variables which could be defined as intervals with known upper and lower bounds but unknown distribution information.

Based on the regional environmental protection policy, the gross of air-pollutant emissions are interpreted as constraints in the developed model. Correspondingly, different environmental management policies may lead to varied power generation plans and changed capacity expansion schemes. In this study, three different cases are considered in order to make in-depth analysis of interactions among energy-supply security, economic cost, and environmental requirement. These cases can be described as follow:

- In *Case 1*, the totaling amount of air pollutants emitted are confined with a certain level over the planning horizon, being $[45.0, 60.0] \times 10^3$ tonnes for SO_2, $[25.0, 40.0] \times 10^3$ tonnes for NO_x and $[0.5, 1.0] \times 10^3$ tonnes for PM in periods 1, 2 and 3, respectively. Therefore, this case corresponds to decisions with efforts for allocation and management of energy resources, services, activities and investment under stabilized environmental management policies in order to pose as a baseline case in this study system.
- *Case 2* is based on current status of the regional-scale energy and environmental system without any particular regulatory, economic or political barriers, targets or strategies; under this case, the developed model is run without any exterior constraints (e.g., without air pollution emission control constraints). Given a range of energy resources and technology alternatives, it will automatically choose the lowest-cost set of options to meet the random electricity demand in the region.
- *Case 3* provides an analysis of varied environmental management policies for SO_2, NO_x and PM emissions allowances under an aggressive environmental protection goal over the planning horizon. Based on case 1, the gross of region's air-pollutants emissions are to be mitigated by 10%, 20% and 30% along with the time period, namely, [40.5,54.0], [36.0,48.0] and $[31.5, 42.0] \times 10^3$ tonnes for SO_2, [22.5,36.0], [20.0,32.0] and $[17.5, 28.0] \times 10^3$ tonnes for NO_x, [0.45,0.90], [0.40,0.80] and $[0.35, 0.70] \times 10^3$ tonnes for PM in periods 1, 2 and 3, respectively.

3.3. Modeling formulation

Therefore, the problems under consideration are: (a) how to effectively assign the power demand to the six power conversion technologies and minimize the system cost and risk of penalties under uncertainty, (b) how to incorporate energy and environmental policies within the study problem with a low risk of system failure, and (c) how to generate an optimized capacity expansion scheme with sound timing and sizing consideration.

In this case, since random variables (potential electricity demand) with knowing probability (p_{th}) exist, three scenario trees with a branching structure of 1–3–3–3 can be constructed. All of the scenario trees have the same structure with one initial node at time 0 and three succeeding ones in period 1; each node in period 1 has three succeeding nodes in period 2, and so on for each node in period 3. These result in 27 nodes (scenarios) in period 3. Moreover, mixed-integer linear programming (MILP) technique is used for facilitating dynamics analysis of the timing, sizing and siting in terms of energy-supply capacity expansions. In the MILP, binary variables will be employed to help decide whether or not particular supply technology development or expansion options will be undertaken; fixed-charge cost functions will be introduced in the developed model to reflect the economies of scale in capacity expansion [37,39]. It is assumed that, if the system requires capacity expansion at the beginning of a particular period, this expansion project has to be completed by the end of the previous period. Therefore, through introducing MILP into the IFMP framework, an IFS-EM for regional-scale EES planning can be formulated as follows:

$$\text{Max} \quad \lambda^{\pm} \tag{8a}$$

s.t.

(1) Constraints for system cost:

$$\begin{aligned}
&\sum_{t=1}^{T}(PEC_t^{\pm}Z1_t^{\pm} + PEN_t^{\pm}Z2_t^{\pm}) + \sum_{t=1}^{T}\sum_{h=1}^{H_t} p_{th}PIE_t^{\pm}Z3_{th}^{\pm} \\
&+ \sum_{i=1}^{I}\sum_{t=1}^{T} PV_{it}^{\pm}W_{it}^{\pm} + \sum_{i=1}^{I}\sum_{t=1}^{T}\sum_{h=1}^{H_t} p_{th}(PV_{it}^{\pm} + PP_{it}^{\pm})Q_{ith}^{\pm} \\
&+ \sum_{i=1}^{I}\sum_{t=1}^{T}\sum_{h=1}^{H_t} p_{th}(A_{it}^{\pm}Y_{ith}^{\pm} + B_{it}^{\pm}X_{ith}^{\pm}) \\
&+ \sum_{i=1}^{I}\sum_{j_s=1}^{n_s}\sum_{t=1}^{T} CS_{j_st}^{\pm}XS_{ij_st}^{\pm} + \sum_{i=1}^{I}\sum_{j_n=1}^{n_n}\sum_{t=1}^{T} CN_{j_nt}^{\pm}XN_{ij_nt}^{\pm} + \sum_{i=1}^{I}\sum_{j_p=1}^{n_p}\sum_{t=1}^{T} CP_{j_pt}^{\pm}XP_{ij_pt}^{\pm} \\
&+ \sum_{i=1}^{I}\sum_{j_s=1}^{n_s}\sum_{t=1}^{T}\sum_{h=1}^{H_t} p_{th}DS_{j_st}^{\pm}YS_{ij_sth}^{\pm} + \sum_{i=1}^{I}\sum_{j_n=1}^{n_n}\sum_{t=1}^{T}\sum_{h=1}^{H_t} p_{th}DN_{j_nt}^{\pm}YN_{ij_nth}^{\pm} \\
&+ \sum_{i=1}^{I}\sum_{j_p=1}^{n_p}\sum_{t=1}^{T}\sum_{h=1}^{H_t} p_{th}DP_{j_pt}^{\pm}YP_{ij_pth}^{\pm} \\
&\leqslant f_{1\text{opt}}^{+} - \lambda^{\pm}\left(f_{1\text{opt}}^{+} - f_{1\text{opt}}^{-}\right)
\end{aligned} \tag{8b}$$

(2) Constraints for mass balance of fossil fuels:

$$(W_{1t}^{\pm} + Q_{1th}^{\pm})FE_{1t}^{\pm} \leqslant Z1_t^{\pm}, \quad \forall t; \;\; h = 1, 2, \ldots, H_t \tag{8c}$$

$$(W_{2t}^{\pm} + Q_{2th}^{\pm})FE_{2t}^{\pm} \leqslant Z2_t^{\pm}, \quad \forall t; \;\; h = 1, 2, \ldots, H_t \tag{8d}$$

(3) Constraints for availabilities of energy resources:

$$(W_{3t}^{\pm} + Q_{3th}^{\pm})FE_{3t}^{\pm} \leqslant UPH_t^{+} - \lambda^{\pm}(UPH_t^{+} - UPH_t^{-}), \quad \forall t; \;\; h = 1, 2, \ldots, H_t \tag{8e}$$

$$(W_{4t}^{\pm} + Q_{4th}^{\pm})FE_{4t}^{\pm} \leqslant UPW_t^{+} - \lambda^{\pm}(UPW_t^{+} - UPW_t^{-}), \quad \forall t; \;\; h = 1, 2, \ldots, H_t \tag{8f}$$

$$(W_{5t}^{\pm} + Q_{5th}^{\pm})FE_{5t}^{\pm} \leqslant UPS_t^{+} - \lambda^{\pm}(UPS_t^{+} - UPS_t^{-}), \quad \forall t; \;\; h = 1, 2, \ldots, H_t \tag{8g}$$

$$(W_{6t}^{\pm} + Q_{6th}^{\pm})FE_{6t}^{\pm} \leqslant UPU_t^{+} - \lambda^{\pm}(UPU_t^{+} - UPU_t^{-}), \quad \forall t; \;\; h = 1, 2, \ldots, H_t \tag{8h}$$

(4) Constraints for electricity supply and demand balance:

$$\sum_{i=1}^{I} (W_{it}^{\pm} + Q_{ith}^{\pm} + Z3_{th}^{\pm}) = d_{th}^{+} - \lambda^{\pm}(d_{th}^{+} - d_{th}^{-}), \quad \forall t; \;\; h = 1, 2, \ldots, H_t \tag{8i}$$

(5) Constraints for electricity generation of every power conversion technology:

$$W_{it}^{\pm} + Q_{ith}^{\pm} - \sum_{t'=1}^{t} X_{ith}^{\pm} ST_{it}^{\pm} \leqslant RC_i[ST_{it}^{+} - \lambda^{\pm}(ST_{it}^{+} - ST_{it}^{-})], \;\; \forall i; \; t; \; h = 1, 2, \ldots, H_t \tag{8j}$$

$$W_{it}^{\pm} \geqslant Q_{ith}^{\pm} \geqslant 0, \;\; \forall i; \; t; \; h = 1, 2, \ldots, H_t \tag{8k}$$

(6) Constraints for electricity peak load demand:

$$\sum_{i=1}^{I} \left(RC_i + \sum_{t'=1}^{t} X_{ith}^{\pm} \right) \geqslant [V_t^{-} + \lambda^{\pm}(V_t^{+} - V_t^{-})], \quad \forall t; \;\; h = 1, 2, \ldots, H_t \tag{8l}$$

(7) Constraints for capacity expansion of electricity-generation facilities:

$$Y_{ith}^{\pm} \begin{cases} = 1, \text{if capacity expansion is undertaken} \\ = 0, \text{if otherwise} \end{cases}, \;\; \forall i; \; t; \; h = 1, 2, \ldots, H_t \tag{8m}$$

$$N_{it} \leqslant X_{ith}^{\pm} \leqslant M_{it} Y_{ith}^{\pm}, \;\; \forall i; \; t; \; h = 1, 2, \ldots, H_t \tag{8n}$$

(8) Constraints for air-pollution control demand:

$$\sum_{j_s}^{n_s} XS_{ij_s t}^{\pm} = W_{it}^{\pm} INS_{it}^{\pm}, \;\; \forall i; \; t \tag{8o}$$

$$\sum_{j_n}^{n_n} XN_{ij_n t}^{\pm} = W_{it}^{\pm} INN_{it}^{\pm}, \;\; \forall i; \; t \tag{8p}$$

$$\sum_{j_p}^{n_p} XP_{ij_p t}^{\pm} = W_{it}^{\pm} INP_{it}^{\pm}, \;\; \forall i; \; t \tag{8q}$$

$$\sum_{j_s}^{n_s} YS_{ij_s th}^{\pm} = Q_{ith}^{\pm} INS_{it}^{\pm}, \quad \forall i; \; t; \;\; h = 1, 2, \ldots, H_t \tag{8r}$$

$$\sum_{j_n}^{n_n} YN_{ij_n th}^{\pm} = Q_{ith}^{\pm} INN_{it}^{\pm}, \quad \forall i; \; t; \;\; h = 1, 2, \ldots, H_t \tag{8s}$$

$$\sum_{j_p}^{n_p} YP_{ij_p th}^{\pm} = Q_{ith}^{\pm} INP_{it}^{\pm}, \quad \forall i; \; t; \;\; h = 1, 2, \ldots, H_t \tag{8t}$$

(9) Constraints for air-pollutants emissions:

$$\sum_{i=1}^{I} \sum_{j_s=1}^{n_s} \left(1 - \eta_{j_s}^{\pm}\right)\left(XS_{ij_s t}^{\pm} + YS_{ij_s th}^{\pm}\right) \leqslant ES_t^{+} - \lambda^{\pm}(ES_t^{+} - ES_t^{-}), \quad \forall t; \;\; h = 1, 2, \ldots, H_t \tag{8u}$$

$$\sum_{i=1}^{I} \sum_{j_n=1}^{n_n} \left(1 - \eta_{j_n}^{\pm}\right)\left(XN_{ij_n t}^{\pm} + YN_{ij_n th}^{\pm}\right) \leqslant EN_t^{+} - \lambda^{\pm}(EN_t^{+} - EN_t^{-}), \quad \forall t; \;\; h = 1, 2, \ldots, H_t \tag{8v}$$

$$\sum_{i=1}^{I} \sum_{j_p=1}^{n_p} \left(1 - \eta_{j_p}^{\pm}\right)\left(XP_{ij_p t}^{\pm} + YP_{ij_p th}^{\pm}\right) \leqslant EP_t^{+} - \lambda^{\pm}(EP_t^{+} - EP_t^{-}), \quad \forall t; \;\; h = 1, 2, \ldots, H_t \tag{8w}$$

(10) Non-negative constraints:

$$Z1_t^{\pm}, Z2_t^{\pm}, Z3_{th}^{\pm}, W_{it}^{\pm}, Q_{ith}^{\pm} \geqslant 0, \quad \forall i; \; t; \;\; h = 1, 2, \ldots, H_t \tag{8x}$$

The detailed nomenclatures for the variables and parameters are provided in Appendix B. The $f_{1\text{opt}}^{-}$ and $f_{1\text{opt}}^{+}$ are the lower and upper bounds of objective function values obtained from corresponding interval multistage stochastic integer programming (IMSIP) model [39,40]. The objective is to maximize the satisfaction degree for system objective and constraints under uncertainty. Higher $\lambda^{\pm}$ levels correspond to less strict system constraints, which represent a higher satisfaction degree for the objective/constraints under advantageous conditions; meanwhile, a higher $\lambda^{\pm}$ level is associated with a lower system cost. Conversely, a lower $\lambda^{\pm}$ level (a lower satisfaction degree) corresponds to more strict constraints under demanding conditions, resulting in a higher system cost.

The complexities associated with electricity generation targets $W_{kt}^{\pm}$ (i.e. the first-stage decision variables) are expressed as interval numbers. In this study, an optimized set of target values will be identified by letting u_{kt} be decision variables. This optimized set will correspond to the lowest possible system cost under the uncertain electricity generation targets. Accordingly, let $W_{it}^{\pm} = W_{it}^{-} + \Delta W_{it} u_{it}$, where $\Delta W_{it} = W_{it}^{+} - W_{it}^{-}$ and $u_{it} \in [0, \; 1]$ [40,45]. Thus, when $W_{kt}^{\pm}$ approach their lower bounds (i.e. when $u_{it} = 0$), a relatively low cost would be obtained; however, a higher penalty may have to be paid when the electricity demand is not satisfied. Conversely, when $W_{it}^{\pm}$ reach their upper bounds (i.e. when $u_{it} = 1$), a higher cost would be generated but, at the same time, a lower risk of violating the promised targets (and thus lower penalty). Based on the solution method described in Appendix A, the IFMIP model can be converted into two deterministic submodels. Interval solutions can then be obtained by solving the two submodels sequentially. The detailed solution process can be summarized as follows:

Step 1: Formulate the IFS-EM [i.e. model (8)].

Step 2: Reformulate model (8) by introducing $W_{kt}^{\pm} = W_{kt}^{-} + \Delta W_{kt} u_{kt}$, where $\Delta W_{kt} = W_{kt}^{+} - W_{kt}^{-}$ and $u_{kt} \in [0, \; 1]$.

Step 3: Transform the developed model in step 2 into two submodels, where f^{-} is desired since the objective is to minimize $f^{\pm}$; formulate the first submodel which corresponds to f^{-}.

Step 4: Solve the f^{-} submodel and obtain solutions of λ_{opt}^{+}, $u_{kt\text{opt}}$, $Z1_{t\text{opt}}^{-}$, $Z2_{t\text{opt}}^{-}$, $Z3_{th\text{opt}}^{-}$, $Q_{kth\text{opt}}^{-}$, $X_{kth\text{opt}}^{-}$, $Y_{kth\text{opt}}^{-}$, $XS_{ij_s t\text{opt}}^{-}$, $YS_{ij_s th\text{opt}}^{-}$, $XN_{ij_n t\text{opt}}^{-}$, $YN_{ij_n th\text{opt}}^{-}$, $XP_{ij_p t\text{opt}}^{-}$, $YP_{ij_p th\text{opt}}^{-}$ and f_{opt}^{-}.

Step 5: Calculate $W_{kt\text{opt}}^{\pm} = W_{kt}^{-} + \Delta W_{kt} u_{kt\text{opt}}$.

Step 6: Formulate the second submodel which corresponds to f^{+}.

Step 7: Solve the f^{+} submodel and obtain solutions of λ_{opt}^{-}, $Z1_{t\text{opt}}^{+}$, $Z2_{t\text{opt}}^{+}$, $Z3_{th\text{opt}}^{+}$, $Q_{kth\text{opt}}^{+}$, $X_{kth\text{opt}}^{+}$, $Y_{kth\text{opt}}^{+}$,

$XS^{+}_{ij_s topt}$, $YS^{+}_{ij_s thopt}$, $XN^{+}_{ij_n topt}$, $YN^{+}_{ij_n thopt}$, $XP^{+}_{ij_p topt}$, $YP^{+}_{ij_p thopt}$ and f^{+}_{opt}.

Step 8: Combine the two submodels' solutions to obtain the solution of model (8), including:

(a) Optimized decision maker's satisfaction degree:

$$\lambda^{\pm}_{opt} = [\lambda^{-}_{opt},\ \lambda^{+}{}_{opt}]$$

(b) Optimized energy resources supply schemes:

$$Z1^{\pm}_{topt} = \left[Z1^{-}_{topt},\ Z1^{+}_{topt}\right],\ \forall t$$
$$Z2^{\pm}_{topt} = \left[Z2^{-}_{topt},\ Z2^{+}_{topt}\right],\ \forall t$$
$$Z3^{\pm}_{thopt} = \left[Z3^{-}_{thopt},\ Z3^{+}_{thopt}\right],\quad \forall t;\ h = 1,2,\ldots,H_t$$

(c) Optimized excess electricity-generation plans:

$$Q^{\pm}_{ithopt} = \left[Q^{-}_{ithopt},\ Q^{+}_{ithopt}\right],\ \forall i;\ t;\ h = 1,2,\ldots,H_t$$

(d) Optimized capacity expansion schemes:

$$X^{\pm}_{ithopt} = \left[X^{-}_{ithopt},\ X^{+}_{ithopt}\right],\quad \forall i;\ t;\ h = 1,2,\ldots,H_t$$
$$Y^{\pm}_{ithopt} = \left[Y^{-}_{ithopt},\ Y^{+}_{ithopt}\right],\quad \forall i;\ t;\ h = 1,2,\ldots,H_t$$

(e) Optimized air pollution mitigation targets:

$$XS^{\pm}_{ij_s topt} = \left[XS^{-}_{ij_s topt},\ XS^{+}_{ij_s topt}\right],\quad \forall i;\ j_s;\ t$$
$$XN^{\pm}_{ij_n topt} = \left[XN^{-}_{ij_n topt},\ XN^{+}_{ij_n topt}\right],\quad \forall i;\ j_n;\ t$$
$$XP^{\pm}_{ij_p topt} = \left[XP^{-}_{ij_p topt},\ XP^{+}_{ij_p topt}\right],\quad \forall i;\ j_p;\ t$$

(f) Optimized excess air-pollution control plans:

$$YS^{\pm}_{ij_s thopt} = \left[YS^{-}_{ij_s thopt},\ YS^{+}_{ij_s thopt}\right],\ \forall i;\ j_s;\ t;\ h=1,2,\ldots,H_t$$
$$YN^{\pm}_{ij_n thopt} = \left[YN^{-}_{ij_n thopt},\ YN^{+}_{ij_n thopt}\right],\ \forall i;\ j_n;\ t;\ h=1,2,\ldots,H_t$$
$$YP^{\pm}_{ij_p thopt} = \left[YP^{-}_{ij_p thopt},\ YP^{+}_{ij_p thopt}\right],\ \forall i;\ j_p;\ t;\ h=1,2,\ldots,H_t$$

(g) Optimized system cost:

$$f^{\pm}_{opt} = \left[f^{-}_{opt},\ f^{+}_{opt}\right]$$

Step 9: Obtain the optimal electricity generation schemes and air pollution mitigation plans under each scenario; Optimal electricity generation schemes of every power conversion technology:

$$A^{\pm}_{ithopt} = W^{\pm}_{itopt} + Q^{\pm}_{ithopt},\quad \forall i;\ t;\ h = 1,2,\ldots,H_t$$

Optimal air pollution mitigation plans of each air-pollution control technique:

$$S^{\pm}_{ij_s thopt} = XS^{\pm}_{ij_s topt} + YS^{\pm}_{ij_s thopt},\quad \forall i;\ j_s;\ t;\ h = 1,\ldots,H_t$$
$$N^{\pm}_{ij_n thopt} = XN^{\pm}_{ij_n topt} + YN^{\pm}_{ij_n thopt},\quad \forall i;\ j_n;\ t;\ h = 1,\ldots,H_t$$
$$P^{\pm}_{ij_p thopt} = XP^{\pm}_{ij_p topt} + YP^{\pm}_{ij_p thopt},\quad \forall i;\ j_p;\ t;\ h = 1,\ldots,H_t$$

Step 10: Stop.

4. Results and discussion

4.1. Energy resources supply scheme

Figs. 2 and 3 show the energy resources supply schemes under cases 1–3. In this study, coal and natural gas would be supplied based on the results of the worst scenario (i.e. related to a maximum electricity deficit level); this is to guarantee the security of energy supplies under uncertainty. Under case 1, as shown in the Fig. 2a, the amount of coal supply would almost be stabilized at a certain level over the planning horizon, being [490.7,730.1], [489.7,648.9] and $[490.3,699.9] \times 10^3$ TJ in periods 1–3, respectively. This is because the totaling amount of air pollutants emitted would be confined with a certain level during the planning periods, while coal-fired power conversion technology corresponds to a higher air pollution-emission rate, compared with other power conversion technologies. In comparison, the amount of natural gas supply would be raised with the increasing electricity demand, being [54.0,86.4], [420.6,538.7] and $[528.0,678.0] \times 10^3$ TJ in periods 1–3, respectively (Fig. 2b). It is demonstrated that significant increase would occur in periods 2 and 3. This is because capacities of gas-fired power would be expanded to meet the random electricity demands in these periods. For the imported electricity, there would be no need to import electricity from other regions in periods 1 and 2 in spite of how the electricity demand-level is (Fig. 3); in period 3, the imported electricity would be 3.34 and 28.34×10^3 GW h when the demand-levels are medium and high. This implies that, as one of the recourse actions to be chosen, imported electricity would play an important part in period 3 under case 1, especially when the demand-levels are high.

Compared with the results under case 1, the amount of coal supply would significantly increase under case 2, being [511.1,772.2], [849.7,1124.6] and $[955.8,1268.6] \times 10^3$ TJ in periods 1–3, respectively (Fig. 2a). Coal would play the most important role in the energy supply activities under this case. This is due to the following two facts: (i) there are no exterior constraints (e.g., without air pollution emission control constraints) under this case and (ii) coal-fired power conversion technology has the lowest operating and penalty cost of all the power conversion technologies. Natural gas supply would be reduced, being [54.0,69.0], [151.4,293.6] and $[466.7,656.1] \times 10^3$ TJ in periods 1–3, respectively (Fig. 2b). In addition, for the imported electricity, there would be no need to import electricity from other regions in period 1; in period 2, the supply would be $[0,0.99] \times 10^3$ GW h when the electricity demand-levels are low, medium and high in period 1 and high in period 2 with joint probabilities of 5%, 10% and 5%, respectively; the supply would be $[0,3.58] \times 10^3$ GW h when the demand-level is high in the period 3 (Fig. 3). The results indicate that, as one of the recourse actions to be chosen, imported electricity would not be the first selection under this case.

Under case 3, the role of coal supply would be ever decreasing in the energy supply activities compared with the results under cases 1 and 2 as shown in Fig. 2a. This is because, under this case, strict environmental policies for air quality management would be adopted. Thus, electricity generated from coal-fired power conversion technology would significantly decrease natural gas supply amount would increase under case 3, being [54.0,86.4], [420.6,538.7] and $[528.0,678.0] \times 10^3$ TJ in periods 1–3, respectively (Fig. 2b). This indicates more and more gas-fired power conversion technology would be adopted, compared with cases 1 and 2. In comparison with cases 1 and 2, more electricity would be imported from other regions to meet the increasing electricity demand (Fig. 3). In period 2, the supply amount would be 8.98×10^3 GW h when the electricity demand-levels are low, medium and high in period 1 and high in period 2 with joint probabilities being 5%, 10% and 5%, respectively. In period 3, the variant would be more complicated than those in cases 1 and 2. For example, if the demand-levels are both medium in the previous two periods but are potentially low, medium and high in period 3 (with joint probabilities of 4.5%, 16.5% and 9%, respectively), the supply amount would be [5.89,6.69], 21.07 and 46.07×10^3 GW h. Whereas, if the demand-levels are both high in the previous two periods but are potentially low, medium and high in period 3 (joint probabilities are 0.75%, 2.75% and 1.5%, respectively), the supply amount would be 5.89, 21.07 and 46.07×10^3 GW h. This indicates

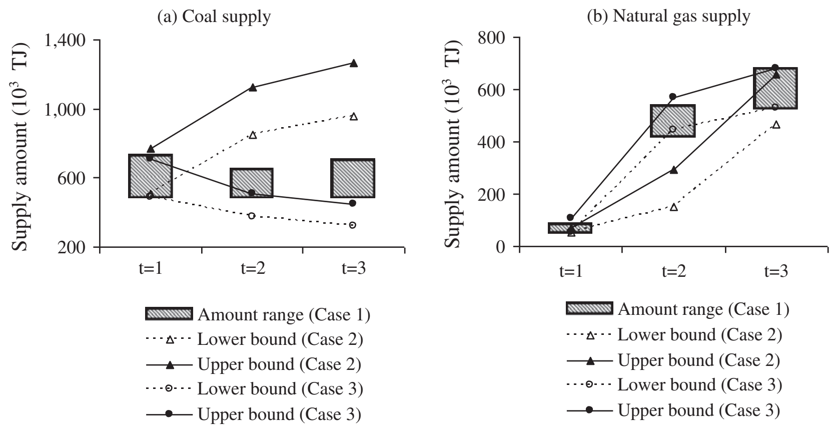

Fig. 2. Coal and natural gas supply under cases 1–3.

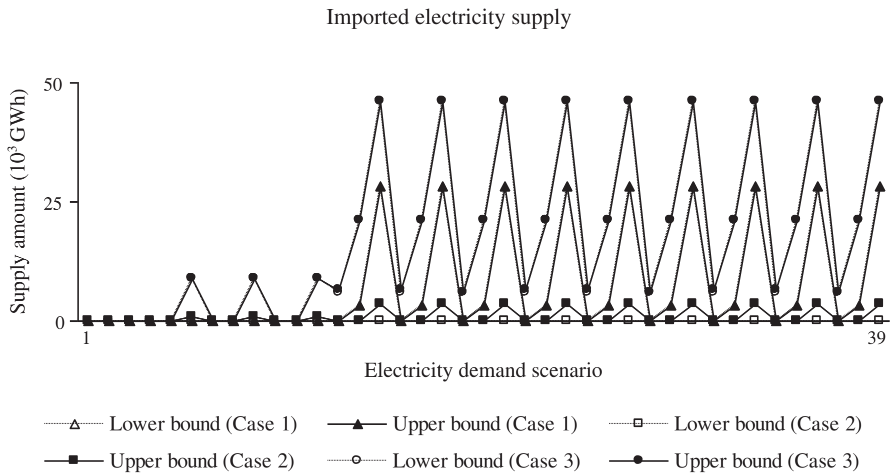

Fig. 3. Imported electricity supply under cases 1–3.

that, under case 3, imported electricity would be one of the most important recourses, especially when the electricity demand-levels are medium and/or high in periods 2 and 3.

4.2. Electricity-generation plan

Figs. 4–9 present the optimized electricity generation schemes of every power conversion technology under all possible 39 scenarios over the planning horizon for the three cases. Under case 1, as constraints for gross control of air-pollutants emission are added, generation quantity of coal-fired power would not significantly increase, due to its high SO_2-,No_x- and PM-emission rates. Meanwhile, generation quantities of gas-fired power and hydropower would markedly increase and clean power conversion technologies (associated with low pollutants-emission rates) would be adopted. Under this case, coal-fired power would play the most important part in the electricity generation activities, whose optimized generation targets would be 29.20, 35.12 and 50.03×10^3 GW h in periods 1–3, respectively (Fig. 4a). For the gas-fired power, its optimized generation targets would be 6.00, 25.00 and 30.00×10^3 GW h in the three planning periods (Fig. 5a), respectively, which would reach its upper target level in periods 2 and 3 (as shown in Table 1). For the hydropower, its optimized generation targets would fluctuate and increase during the three periods, being 10.00, 15.00 and 16.69×10^3 GW h (Fig. 6a). This is attributable to its relatively low operating cost and no pollutant emission in the power conversion process. The optimized generation targets of nuclear would be 3.85, 3.91 and 7.95×10^3 GW h in the three planning periods, respectively (Fig. 7a). The optimized generation targets of the wind and solar power would be 0, 4.00, 5.00×10^3 GW h (Fig. 8a) and 1.00, 2.05, 2.09×10^3 GW h in periods 1–3 (Fig. 9a), respectively.

Deficits would occur if the available generation targets cannot meet the random electricity demand, especially when the demand-level is high. In general, different power conversion technology has varied excess generation quantities under changed possible scenarios. For example, under case 1, the excess generation quantities would be $[19.87, 29.20] \times 10^3$ GW h for the coal-fired power, $[0, 1.52] \times 10^3$ GW h for the gas-fired power, $[6.28, 10.00] \times 10^3$ GW h for the hydropower, 3.85×10^3 GW h for the nuclear power and 1.00×10^3 GW h for the solar power when the demand-level is high in period 1 (probability is 25%). When the demand-levels are medium in period 1 and low, medium and high in period 2 (joint probabilities are 10%, 30%, and 10%, respectively), the excess generation quantities would be 0, [0, 11.08] and $[14.35, 17.21] \times 10^3$ GW h for the coal-fired power, [0, 16.39], [20.01, 22.26] and 22.26×10^3 GW h for the gas-fired power, 0, [0, 5.00] and $[1.48, 15.00] \times 10^3$ GW h for the hydropower, 0, 0 and 3.91×10^3 GW h for the nuclear power, [0, 1.00], [0, 1.00] and $[0, 1.00] \times 10^3$ GW h for the wind power and [0, 2.05], [0, 2.05] and $[0, 2.05] \times 10^3$ GW h for the solar power. When the demand-levels are both medium in periods 1 and 2 and low, medium and

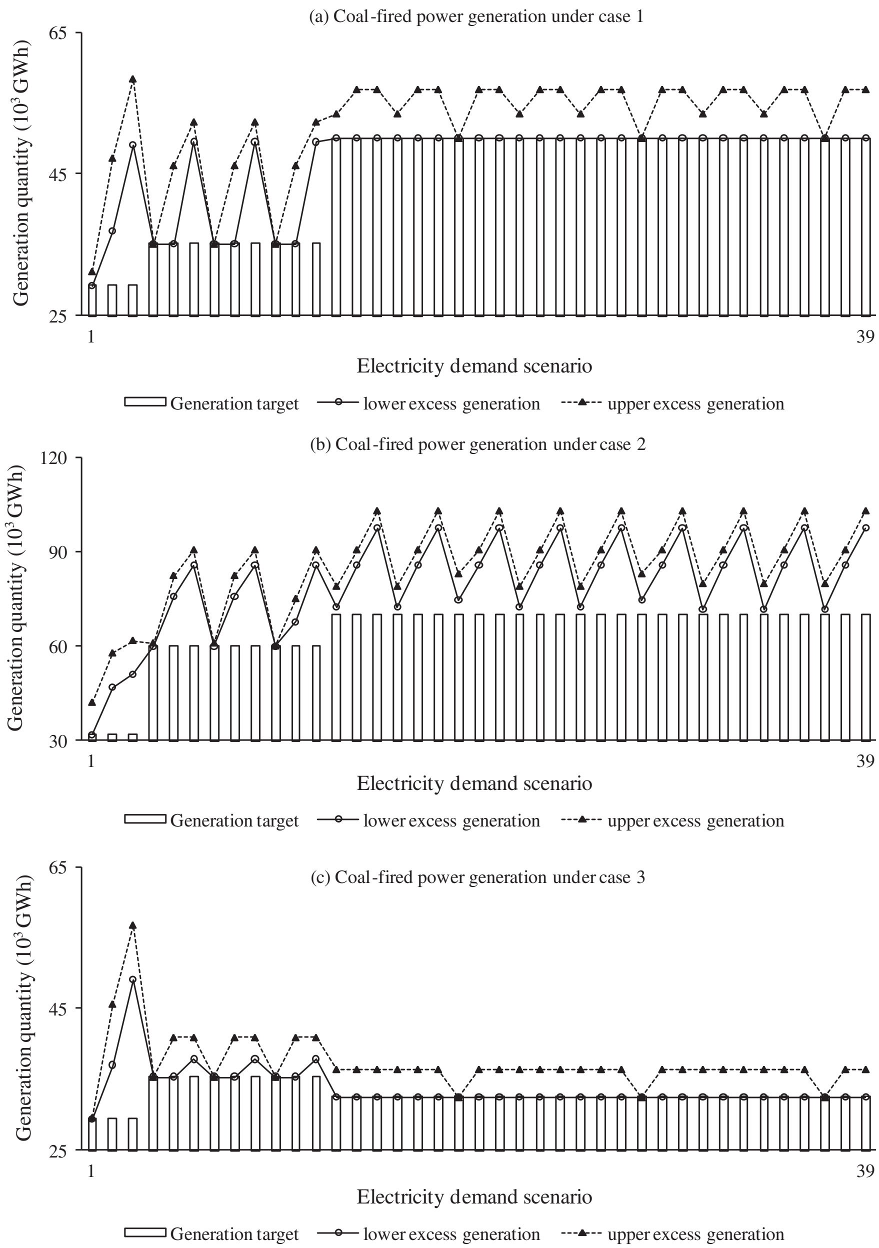

Fig. 4. Generation plans of coal-fired power under cases 1–3.

high in period 3 (joint probabilities are 4.5%, 16.5%, and 9.0%, respectively), the excess generation quantities would be [50.03, 53.48], [50.03, 56.91] and [50.03, 56.91] $\times$ 10^3 GW h for the coal-fired power, [50.16, 54.10], 60.00 and 60.00 $\times$ 10^3 GW h for the gas-fired power, [16.69, 20.00], [16.69, 30.83] and [16.69, 30.83]$\times$ 10^3 GW h for the hydropower, 7.95, [7.95, 9.22] and [7.95, 9.22] $\times$ 10^3 GW h for the nuclear power, [8.13, 10.00], 10.00 and 10.00 $\times$ 10^3 GW h for the wind power and [2.09, 4.10], [2.09, 4.10] and [2.09, 4.10] $\times$ 10^3 GW h for the solar power. In case of insufficient electricity supply, coal-fired power would first be chosen as the recourse action to compensate the deficits in period 1; but in periods 2 and 3, gas-fired power and hydropower generation would be the major recourse actions.

In comparison with the results under case 1, coal-fired power conversion technology would play the most important part in the electricity generation activities under case 2 (Fig. 4b). Gas-fired power would be the secondary important electricity supply source, while hydropower and nuclear power would be the supplement (Figs. 5b–7b). The optimized generation targets of coal-fired power would reach its upper target level in periods 2 and 3 (as shown in Table 3). This is because coal-fired power conversion technology has relatively low operating and penalty costs and comparatively low capital cost for capacity expansion. Although hydropower has lower operating cost compared with coal-fired and gas-fired power, its optimized generation targets would only be stabilized at 8.42$\times$ 10^3 GW h during the planning horizon; this is due to the relatively high capital cost for its capacity expansion, which limits the development of hydropower. Nuclear would enhance the diversity of power generation, and thus increase the stability and security of the study system. The excess generation quantities of every power conversion technology would be different from those under case 1 as shown in Figs. 4b–7b. In case of insufficient electricity supply, coal-fired power would be vital important as the recourse action to compensate the deficits over the planning horizon, while the other power conversion technologies would only be supplements.

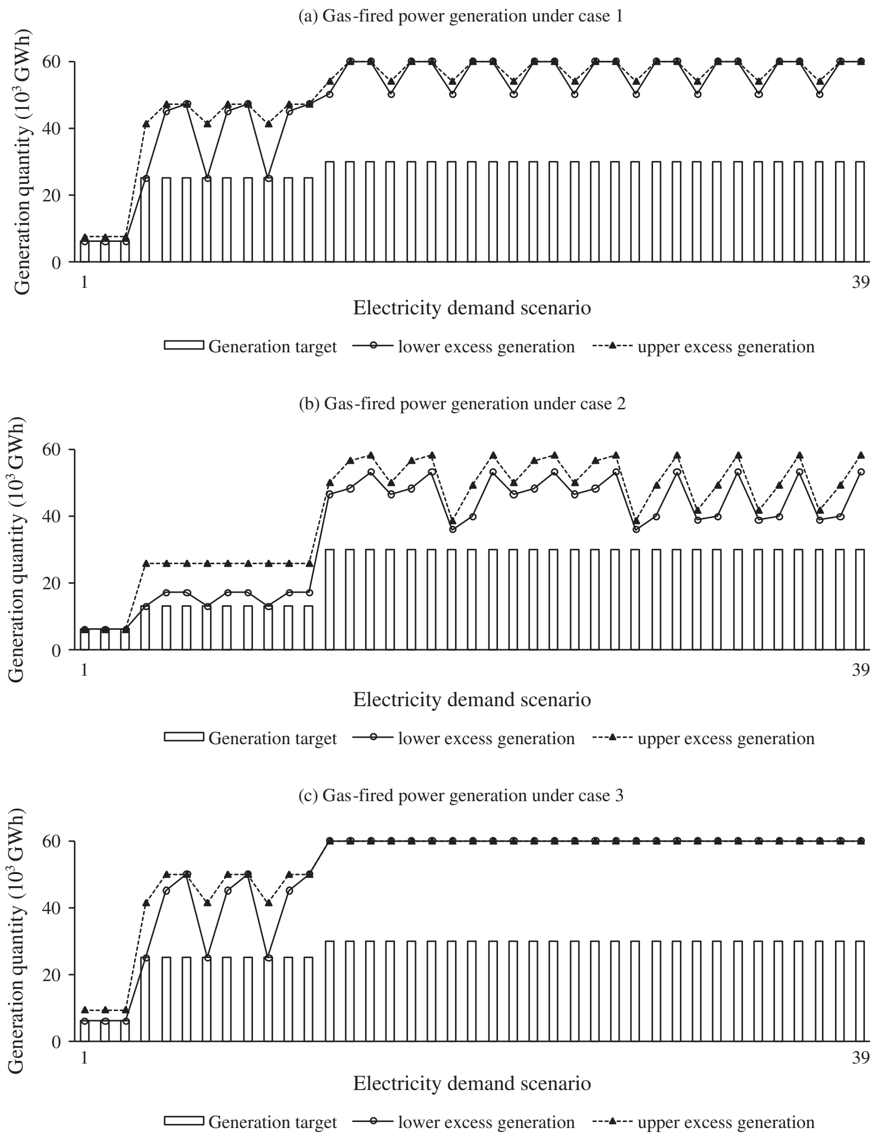

Fig. 5. Generation plans of gas-fired power under cases 1–3.

Under case 3, as more strict environmental protection objectives must be achieved than those under cases 1 and 2, the dominant role of coal-fired power would completely be replaced by other conversion technologies. The optimized generation targets of coal-fired power would decrease to 29.37, 35.34 and 32.47×10^3 GW h in periods 1–3, respectively (Fig. 4c). For the gas-fired power, hydropower and wind power, their optimized generation targets would be the same as those under case 1 (Figs. 5c, 6c and 8b). However, the optimized generation targets of nuclear power and solar power would have slight increase as shown in Figs. 7c and 9b, respectively. The excess generation quantities of every power conversion technology would also be different from those under cases 1 and 2. In period 1, the coal-fired power generation would still be an important recourse action in compensating the electricity shortage. But from period 2, the gas-fired power and the hydropower would play an increasingly important role. This is because an aggressive environmental protection policy would be adopted over the planning horizon under case 3. Therefore, more and more environment-friendly power conversion technologies would be chosen for electricity generation to satisfy the ever increasing electricity demands and enhancing air-quality requirements.

4.3. Capacity expansion

Fig. 10 displays the solutions of capacity expansion schemes of each conversion technology under all possible 39 scenarios in the whole planning horizon for the three cases. Generally, shortages would occur if the electricity demand-levels are continuously high, and a capacity expansion project would be undertaken to avoid insufficient electricity supply. Under case 1 (as shown in Fig. 10a), the results demonstrate that only 0.41 GW would be expanded for coal-fired power conversion technology in period 1 despite of the electricity demand scenarios. There would be 0.5 GW to be expanded in period 1 and 0.6 GW in period 2 for gas-fired power conversion technology, which would achieve its upper bounds of capacity expansion in these two periods. When the demand-levels are medium and high in period 3, 0.26 GW would be expanded for gas-fired power. For hydropower conversion technology, the conditions would be completely different under varied electricity demand scenarios. For example, [0.28, 0.29] GW would be expanded in period 1; in period 2, [0, 0.31] GW would be expanded only when the demand-level is high in this period with joint probabilities being 5%, 10% and 5%. When the demand-levels are low in period 1 and high in period 2 but are potentially low,

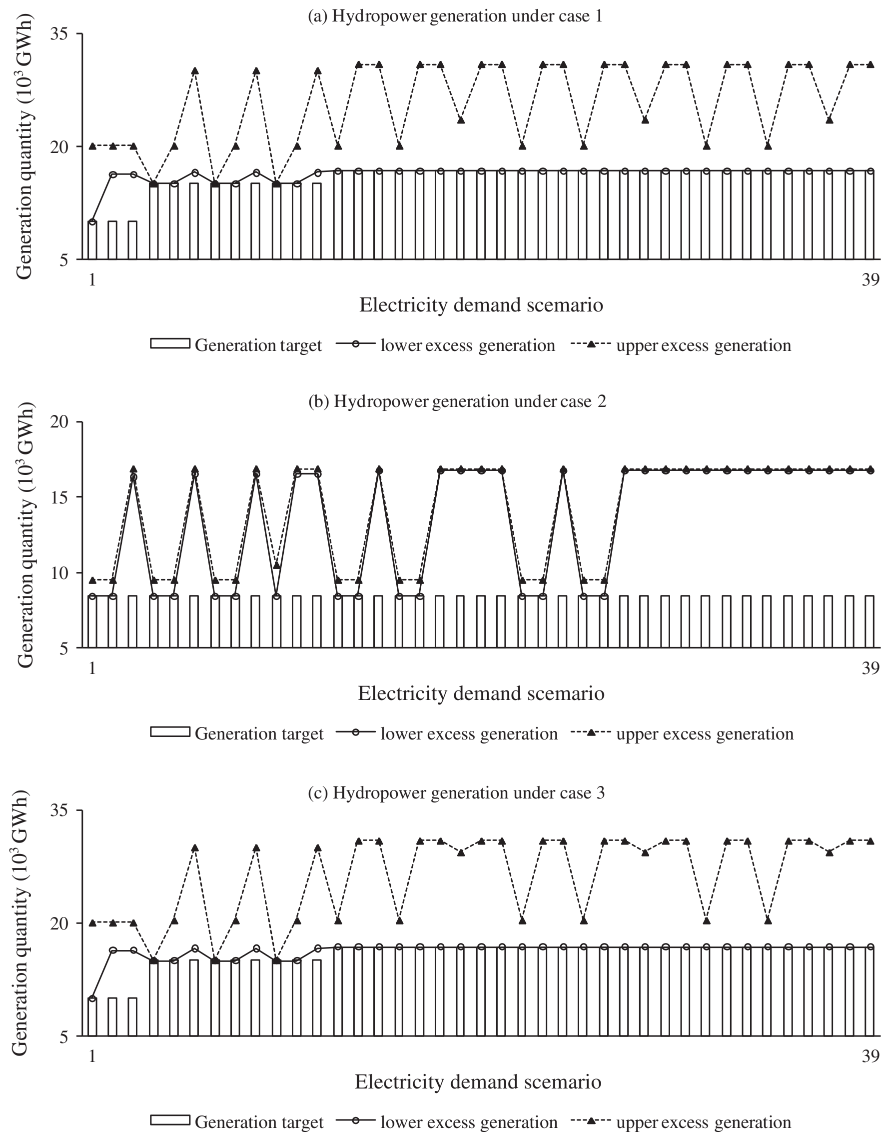

Fig. 6. Generation plans of hydropower under cases 1–3.

medium and high in period 3 (joint probabilities are 0.75%, 2.75%, and 1.5%, respectively), there would be no necessary for expansion. Nevertheless when the demand-levels are high in period 1 and low in period 2 but are potentially low, medium and high in period 3 (joint probabilities are 0.75%, 2.75%, and 1.5%, respectively), there would be 0, [0, 0.31] and [0, 0.31] GW to be expanded. For nuclear power conversion technology, capacity expansion project would only occur in period 1, being [0.21, 0.22] GW no matter how the demand scenarios are. For wind power conversion technology, 0.20 GW would be expanded in period 2 and 0.21, 0.30 and 0.30 GW would be expanded in period 3 when the demand-levels are potentially low, medium and high, respectively. This indicates that wind power would reach its upper bound of capacity expansion when the demand-levels are high. For solar-power conversion technology, [0.10, 0.16] GW would be expanded only in period 1.

Under case 2 (as shown in Fig. 10b), the results indicate that more coal-fired power conversion technology would be expanded over the planning horizon, especially when the demand-levels are high. Accordingly, the expansion quantities would be decreased for the other power conversion technologies. For gas-fired power conversion technology, the expansion quantity would be 0.5 GW in period 1 and 0 in period 2; in period 3, the expansion scheme would be fundamentally different under varied electricity demand-levels. For hydropower conversion technology, the expansion quantity would be stabilized at 0.28 GW, while the expansion decision would be made only when the demand-levels are continuously high in the three planning periods. For nuclear power conversion technology, capacity expansion project would only be undertaken once in period 1, being [0.28, 0.30], [0.28, 0.30] and [0.21, 0.30] GW when the demand-levels are low, medium and high, respectively. Wind- and solar-power conversion technologies would not be developed under case 2.

In comparison, under case 3, more imported electricity would be purchased from other regions as a recourse action to compensate the electricity shortage than those under cases 1 and 2 as shown in Fig. 10c. Therefore, the expansion scheme would be changed accordingly. For coal-fired power, 0.38 GW would be installed only in periods 1. Gas-fired power would be expanded during the whole planning horizon, being 0.5, 0.6 and 0.26 GW in periods 1, 2 and 3, respectively. For hydropower, [0.28, 0.30] GW would be expanded in period 1; 0.30 GW would be expanded in periods 2 and 3 when the demand-levels are high in these periods. For nuclear power conversion

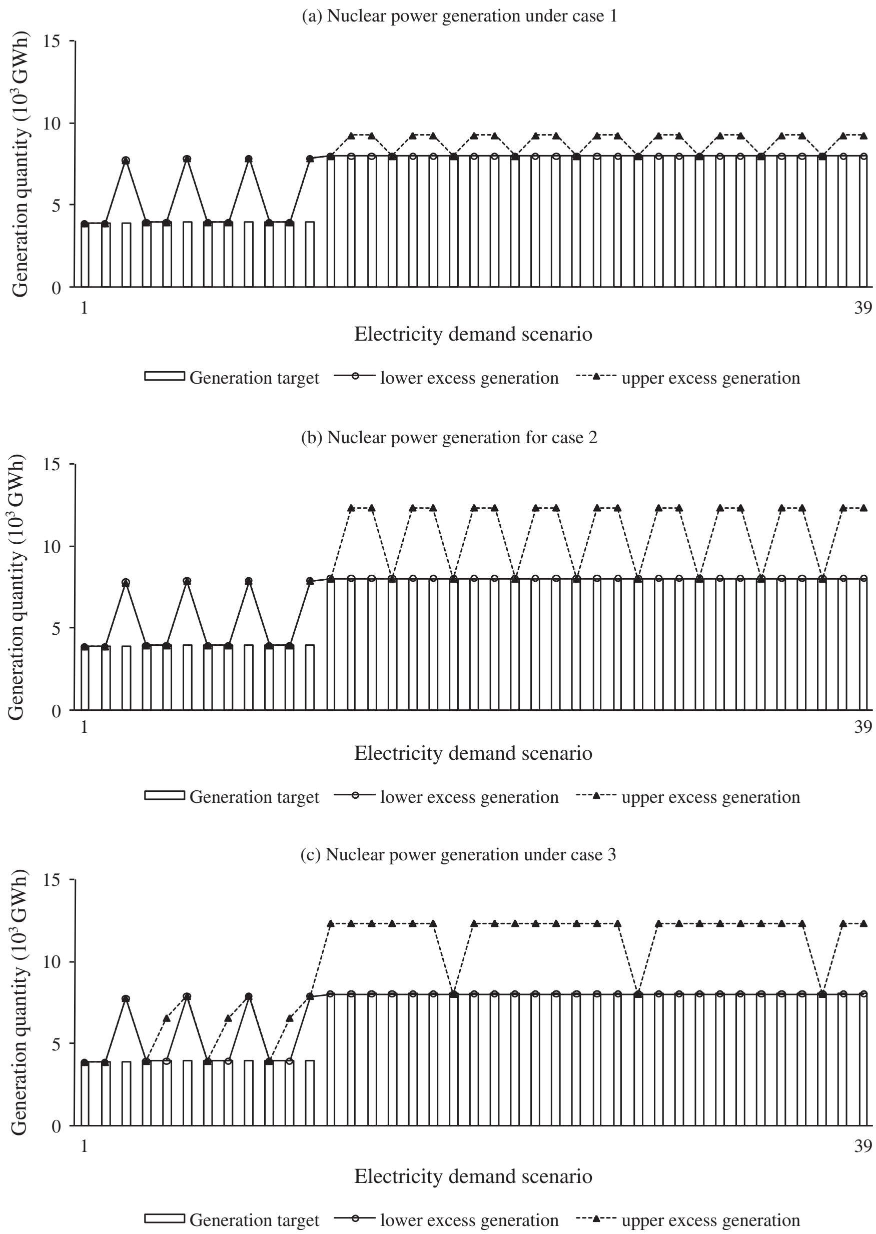

Fig. 7. Generation plans of nuclear power under cases 1–3.

technology, capacity expansion project would also only be conducted in period 1, being [0.21, 0.30]. For wind power conversion technology, 0.20 GW would be expanded in period 2 and 0.30 GW would be expanded in period 3 despite of the demand scenarios. For solar power conversion technology, [0.11, 0.17] GW would be expanded in period 1 no matter how the demand-level is.

4.4. Air pollution emission control

In this study, a project of air-pollution control was considered, in order to satisfy the ambient air-quality requirement and to reduce the penalty towards excess emission. Figs. 11–13 show the optimized mitigation schemes for SO_2, NO_x and PM under the three cases, respectively. Under case 1, the target amounts of treated SO_2 would be [239.77, 292.35], [285.58, 349.30] and [401.41, 492.06] $\times 10^3$ tonnes in periods 1, 2 and 3 (Fig. 11a), respectively. For coal-fired power conversion technology, [88.60, 88.77], [88.54, 123.76] and [88.64, 101.61] $\times 10^3$ tonnes of SO_2 would be treated by LSD, [150.86, 203.26], [195.92, 223.91] and [311.58, 388.65] $\times 10^3$ tonnes of SO_2 would be treated by SAS. For gas-fired power conversion technology, [0.30, 0.42], [1.13, 1.63] and [1.20, 1.80] $\times 10^3$ tonnes of SO_2 would be treated by SAS. The target amounts of treated NO_x would be [89.45, 119.29], [114.34, 156.46] and [153.58, 214.10] $\times 10^3$ tonnes in periods 1–3 (Fig. 12a), respectively. For coal-fired power conversion technology, [67.13, 84.18], [101.84, 112.60] and [140.08, 190.10] $\times 10^3$ tonnes of NO_x would be treated by SCR, [19.02, 29.71], [0, 22.61] and 0×10^3 tonnes of NO_x would be treated by SCNR. For gas-fired power conversion technology, [3.30, 5.40], [12.50, 21.25] and [13.50, 24.00] $\times 10^3$ tonnes of NO_x would be treated by SCR. The target amounts of treated PM would be [26.28, 39.42], [29.85, 45.65] and [40.02, 62.53] $\times 10^3$ tonnes in periods 1–3 (Fig. 13a), respectively. For coal-fired power conversion technology, [24.77, 34.44], [27.81, 37.96] and [37.48, 55.62] $\times 10^3$ tonnes of PM would be treated by BH, [1.51, 4.99], [2.04, 7.69] and [2.55, 6.92] $\times 10^3$ tonnes of PM would

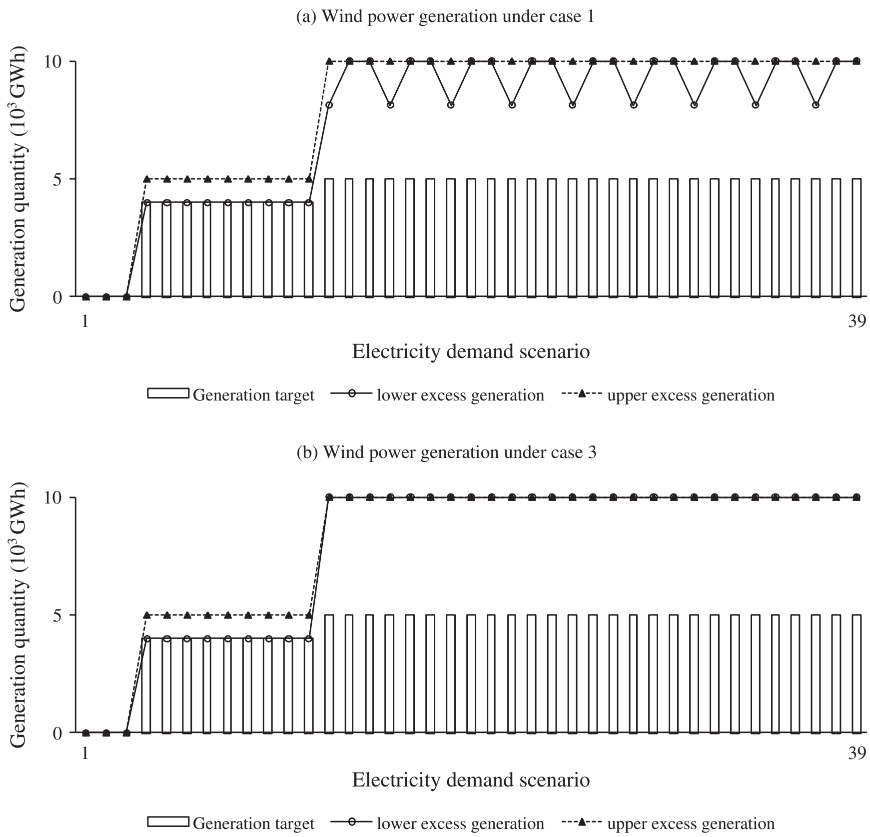

Fig. 8. Generation plans of wind power under cases 2 and 3.

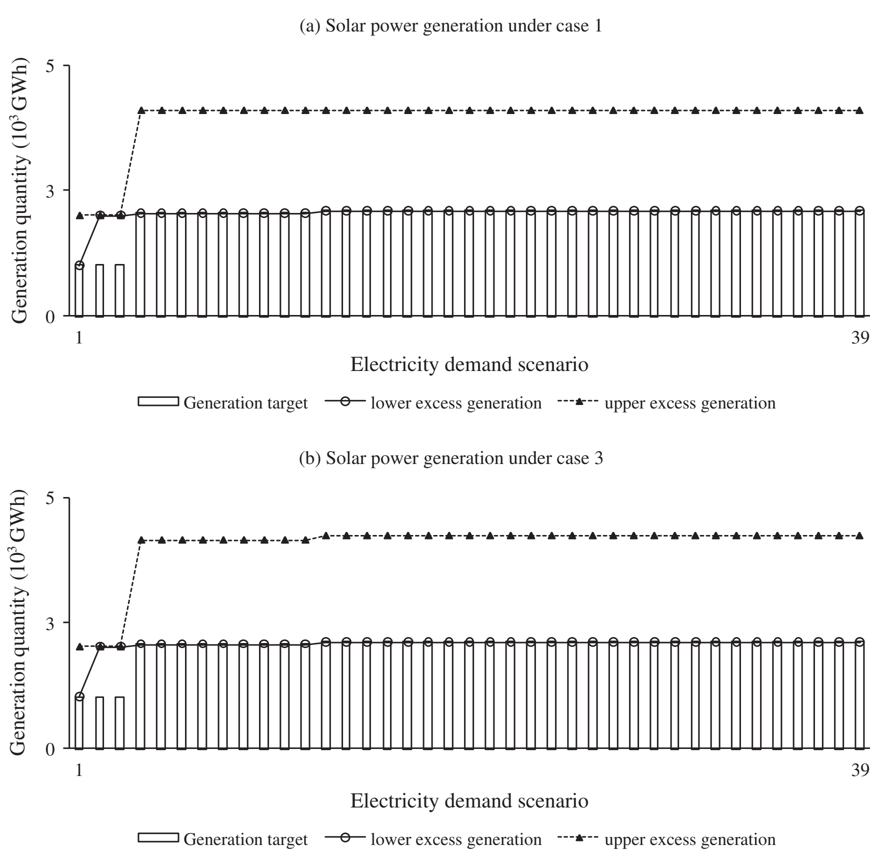

Fig. 9. Generation plans of solar power under cases 2 and 3.

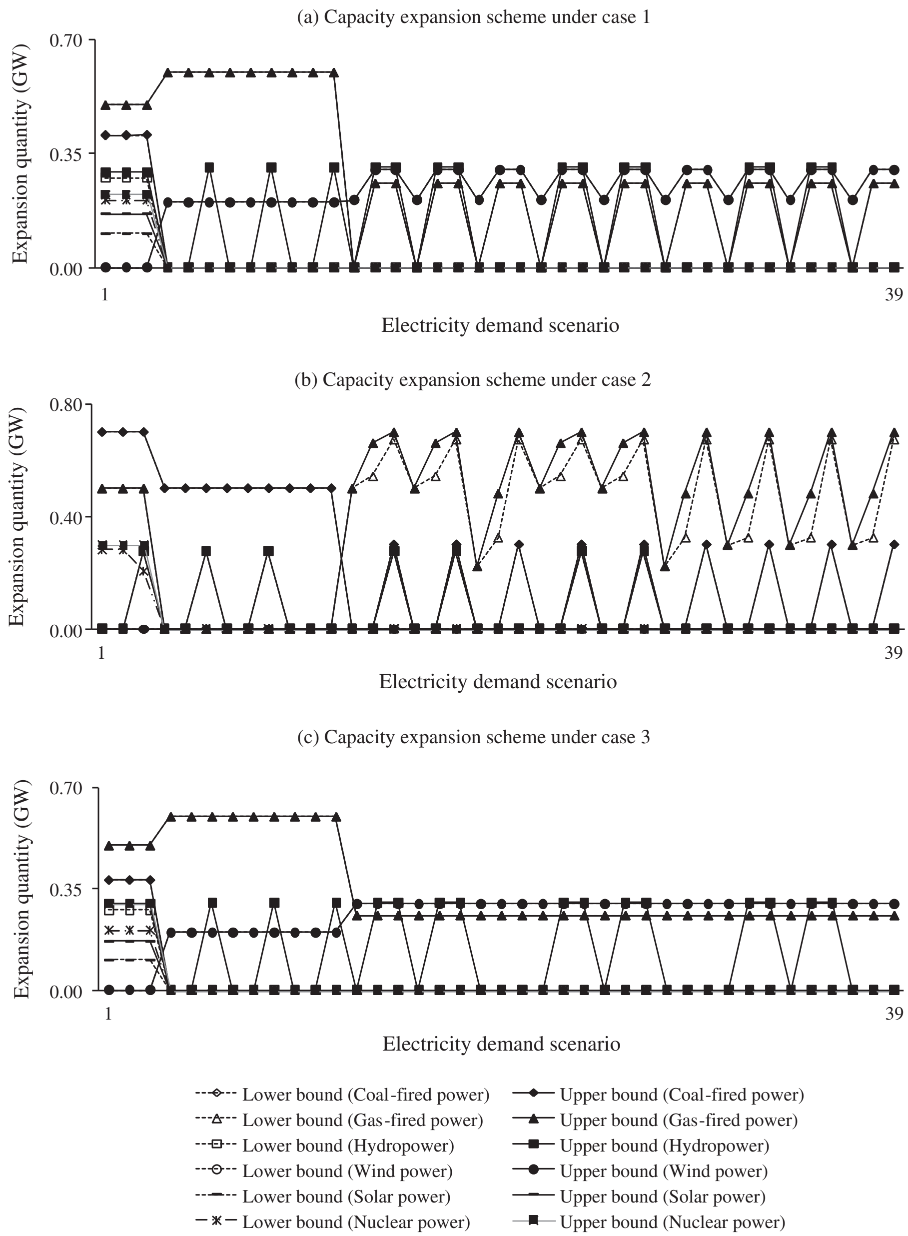

Fig. 10. Capacity expansion schemes under cases 1–3.

be treated by ESP. This implies that, when environmental constraints are added, high-efficiency mitigation measures must be installed to reduce the pollutant emissions and to satisfy the environmental requirements. Thus, the results would provide useful bases for generating decision alternatives with a desired technology combination that would lead to a satisfied environmental quality as well as a minimized abatement cost.

In addition, there would be some excess emissions of SO_2, NO_x and PM, due to the excess electricity generation of coal-fired and gas-fired power conversion technologies. Take excess SO_2 emission for example. There would be [0, 20.68], [63.34, 180.44] and [162.90, 292.14] $\times 10^3$ tonnes mitigated by SAS in period 1, when the electricity demand-levels are low, medium and high (probabilities are 25%, 50% and 25%), respectively. When the demand-levels are medium in period 1 but are potentially low, medium and high in period 2 (joint probabilities are 10%, 30%, and 10%, respectively), there would be [0, 1.07], [0.90, 111.15] and [117.20, 171.87] $\times 10^3$ tonnes of SO_2 mitigated by SAS. When the demand-levels are medium in period 1 and low in period 2 but are potentially low, medium and high in period 3 (joint probabilities are 0.75%, 2.75%, and 1.50%, respectively), there would be [0.81, 1.45], [1.20, 69.25] and [1.20, 69.25] $\times 10^3$ tonnes of SO_2 mitigated by SAS. For this case, no excess emission was allotted to WLS or LSD as well. This is attributable to two facts: (i) the SAS has the highest efficiency and lowest penalty in treating the excess SO_2 emission and (ii) when the SO_2 generation rate is high, a mitigation measure with a high efficiency must be installed to reduce the excess emission and to satisfy the ambient air quality standard. As the main source of SO_2 emission, coal-fired power generation would be reduced for this case, thus the mitigation amount of SO_2 would also decrease.

Under case 2, the target amounts of treated SO_2, NO_x and PM would be significantly increased along with the ever increasing electricity demand-levels as shown in Figs. 11b–13b. This is attributed to the fact that the developed model is run without any exterior constraints (e.g., without air pollution emission control constraints) under case 2. In order to make comparison with case

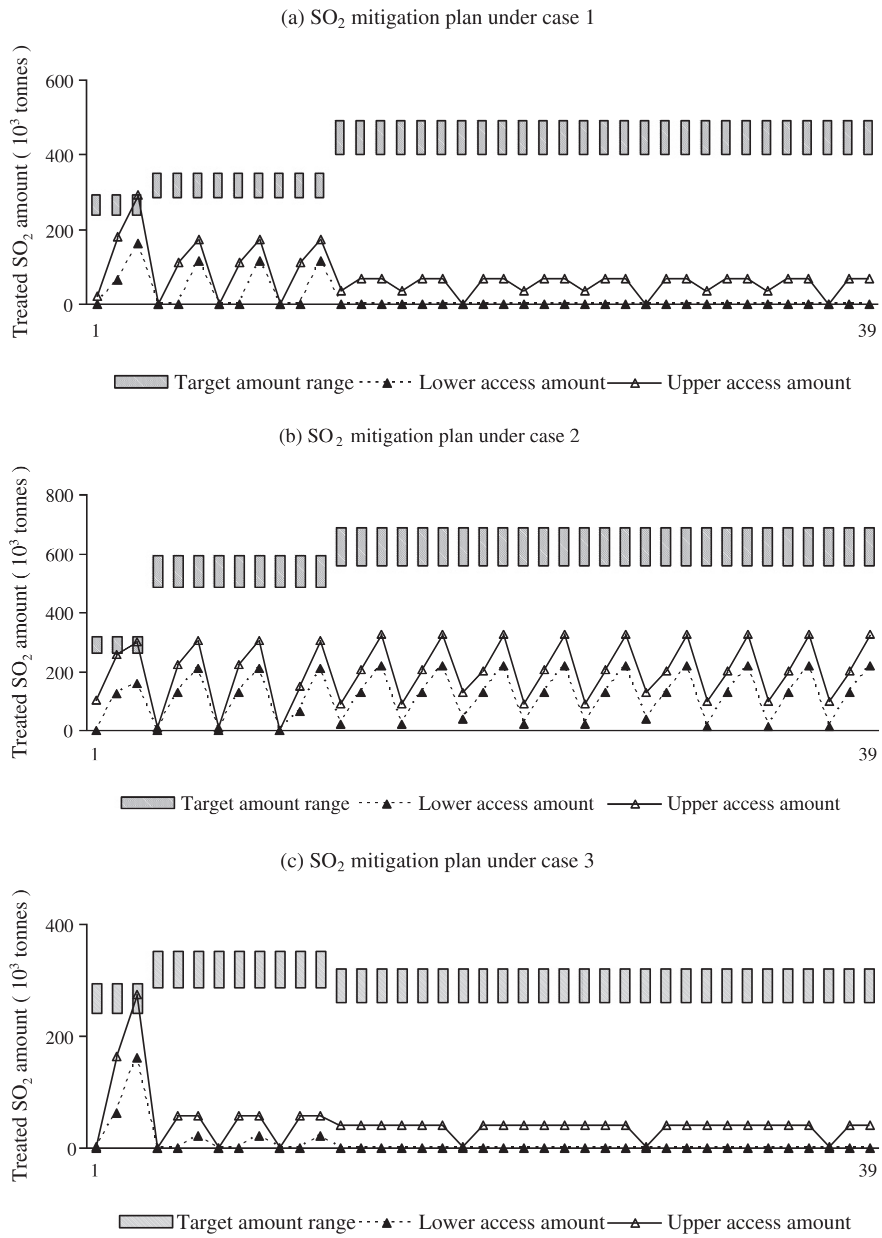

Fig. 11. SO_2 mitigation plans under cases 1–3.

1, excess SO_2 control plans would also be taken as an example to illustrate the excess mitigation schemes. There would be [0, 101.37], [123.09, 258.93] and [157.69, 298.98] $\times 10^3$ tonnes of SO_2 mitigated by SAS in period 1, when the electricity demand-levels are low, medium and high (probabilities are 25%, 50% and 25%), respectively. When the demand-levels are medium in period 1 but are potentially low, medium and high in period 2 (joint probabilities are 10%, 30%, and 10%, respectively), there would be [0, 10.62], [128.87, 223.59] and [209.39, 304.68] $\times 10^3$ tonnes of SO_2 mitigated by SAS. When the demand-levels are medium in period 1 and low in period 2 but are potentially low, medium and high in period 3 (joint probabilities are 0.75%, 2.75%, and 1.50%, respectively), there would be [37.20, 128.37], [127.01, 203.91] and [221.14, 326.46] $\times 10^3$ tonnes of SO_2 mitigated by SAS. No excess emission would be allotted to WLS or LSD despite of SO_2 generation rate. This is because SAS has the lowest penalty cost in treating the excess SO_2 emission. Similar interpretations can also be made for the other mitigation techniques.

Under case 3, the target amounts of treated SO_2, NO_x and PM would be significantly decreased along with the time periods as shown in Figs. 11c–13c. This is because an aggressive environmental protection goal must be achieved under this case. Therefore, electricity generated from coal-fired and gas-fired power conversion technologies would be reduced accordingly. And thus, mitigation measures with higher efficiency must be installed to reduce the pollution emissions and to satisfy the stricter environmental requirements. In comparison with cases 1 and 2, excess SO_2 would also be mitigated by SAS only but the mitigation amount would significantly be decreased. There would be [0, 2.82], [62.63, 162.78] and [161.87, 274.01] $\times 10^3$ tonnes of SO_2 mitigated by SAS in period 1, when the electricity demand-levels are low, medium and high (probabilities are 25%, 50% and 25%), respectively. When the demand-levels are medium in period 1 but are potentially low, medium and high in period 2 (joint probabilities are 10%, 30%, and 10%, respectively), there would be [0, 1.07], [0.90, 56.80] and [21.46, 56.80] $\times 10^3$ tonnes of SO_2 mitigated by

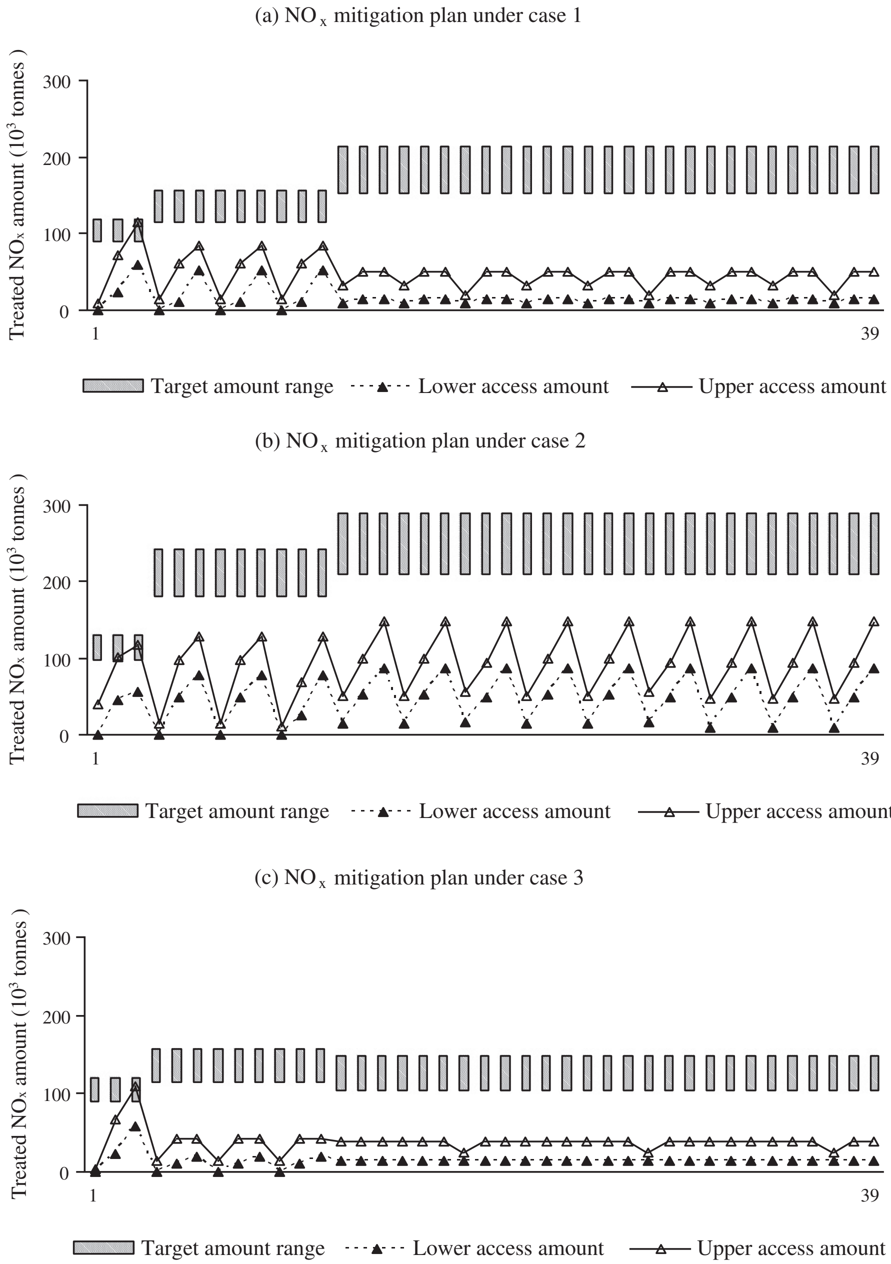

Fig. 12. NO_x mitigation plans under cases 1–3.

SAS. When the demand-levels are low in period 1 and high in period 2 but are potentially low, medium and high in period 3 (joint probabilities are 0.75%, 2.75%, and 1.50%, respectively), there would be [1.20, 1.80], [1.20, 40.56] and [1.20, 40.56] $\times 10^3$ tonnes of SO_2 mitigated by SAS.

4.5. System cost and satisfaction degree

The IFS-EM is to achieve a maximized satisfaction degree for system objective and constraints under uncertainty. Under case 1, the expected system cost is \$[26.39, 44.14] $\times 10^9$, with the degree of satisfaction $\left(\lambda_{\text{opt}}^{\pm}\right)$ being [0.024, 0.996]. The lower system cost value represents as an alternative with a lower energy demand-level, whereas the higher one corresponds to an alternative with a higher energy demand-level. As a result, planning with a higher system cost would guarantee that the energy requirements and environmental regulations are met; in comparison, as the plan aims toward a lower system cost, these requirements may not be met. The $\lambda^{\pm}$ level corresponds to the decision makers' preference regarding environmental and economic tradeoffs. In detail, λ_{opt}^{-} = 0.024 corresponds to a higher system cost (f_{opt}^{+} = \$44.14 billion), representing a maximum degree of satisfaction under demanding conditions. In comparison, λ_{opt}^{+} = 0.996 corresponds to a lower system cost (f_{opt}^{-} = \$26.39 million), representing a maximum degree of satisfaction under advantageous conditions. Thus, the solution of $\lambda_{\text{opt}}^{\pm}$ denotes the degree of satisfying the system objective/constraints under uncertainty. Similar analysis can also be conducted under the other two cases. Under case 2, the expected system cost is \$[18.80, 34.96] $\times 10^9$, with the degree of satisfaction $\left(\lambda_{\text{opt}}^{\pm}\right)$ being [0.244, 0.989]. The system cost and the upper bound of satisfaction degree $\left(\lambda_{\text{opt}}^{+}\right)$ is lower than those under case 1, while the lower

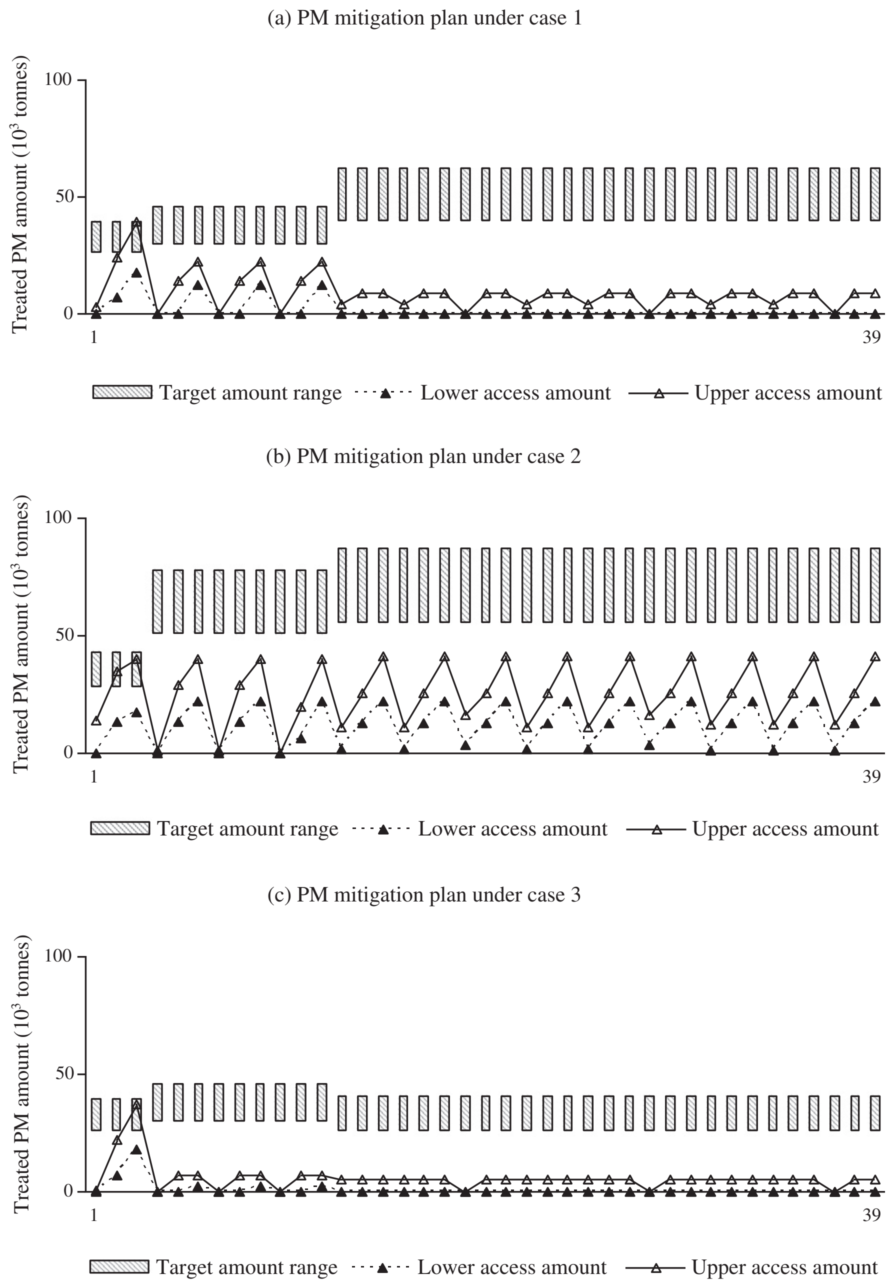

Fig. 13. PM mitigation plans under cases 1–3.

bound of satisfaction degree $\left(\lambda_{\text{opt}}^{-}\right)$ is higher than that under case 1. This is due to the removal of environmental protection constraints, which would change the constraint condition of the model and thus decrease the cost of energy supply and air pollution emission control. Under case 3, the expected system cost is $[34.27,54.21] $\times 10^9$, with the degree of satisfaction $\left(\lambda_{\text{opt}}^{\pm}\right)$ being [0.004,0.982]. In comparison, under case 3, the system cost is higher and the satisfaction degree is lower than those under case 1. This is because the raised strictness both on the lower and upper boundary and/or the admissible violation of the uncertain emissions allowances (i.e. shrunk fuzzy intervals) was conducted. Tightened limitations of emission allowances (i.e. aggressive environmental management policies) would then be associated with lower constraint-violation risks. Decisions with lower constraint-violation risks would be associated with a higher system cost but an increased system reliability; a desire for lower cost could result in raised risks of violating the system constraints.

The system cost includes expenses for energy resources supply, operating costs and capacity expansion costs for power conversion technologies, and operating costs for air-pollution control techniques. Fig. 14 presents the detailed systems cost under different cases. The costs for energy resources supply are $[15.33,27.43] $\times 10^9$ (or [58.08,62.15]% of the total system cost) under case 1, $[11.07,24.25] $\times 10^9$ (or [58.90,69.37]% of the total system cost) under case 2, and $[23.21,37.31] $\times 10^9$ (or [67.73,68.83]% of the total system cost) under case 3. This indicates that the strict environmental policies would lead to an increased energy resources supply cost. The operating costs for power conversion are $[1.95,3.46] $\times 10^9$ (or [7.38,7.83]% of the total system

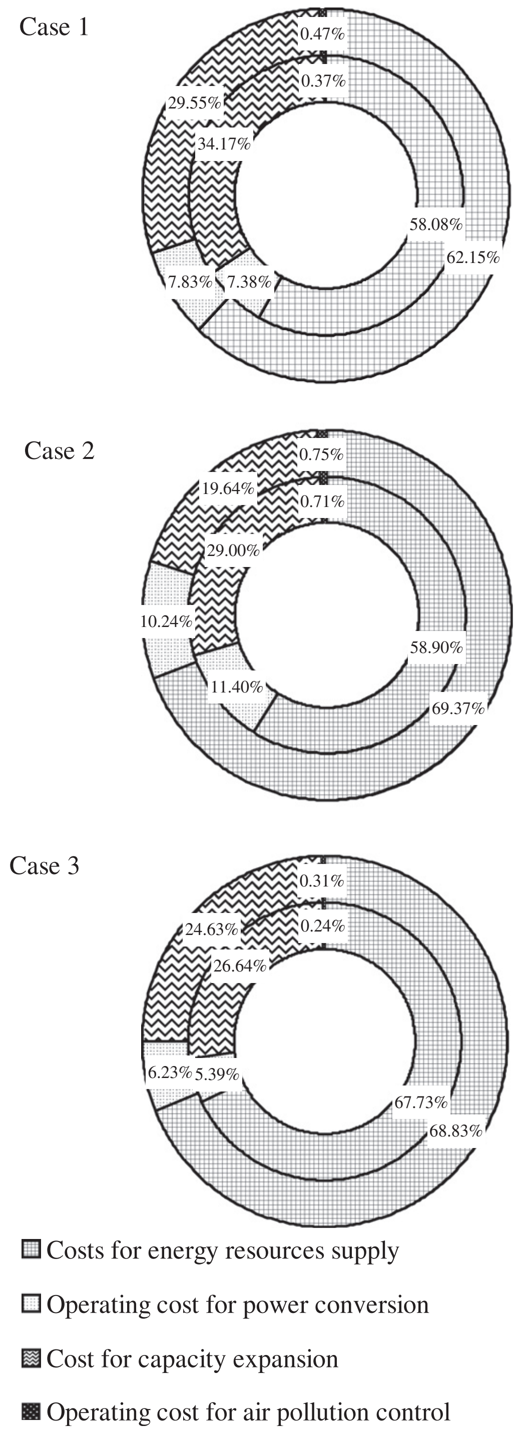

Fig. 14. Detailed system cost under cases 1–3.

cost) under case 1, \$[2.14,3.58] $\times 10^9$ (or [10.24,11.40]% of the total system cost) under case 2, and \$[1.85,3.37] $\times 10^9$ (or [67.73,68.83]% of the total system cost) under case 3. This demonstrates that the strict environmental policies would lead to reduced operating costs for power conversion. The expenses for capacity expansion of power conversion technologies are \$[9.02,13.04] $\times 10^9$ (or [29.55,34.17]% of the total system cost) under case 1, \$[5.45,6.87] $\times 10^9$ (or [19.64,29.00]% of the total system cost) under case 2, and \$[9.13, 13.35] $\times 10^9$ (or [24.63,26.64]% of the total system cost) under case 3. This is due to more power conversion technologies with high price but low pollutant emission rates would be adopted in cases 2 and 3 compared with those in case 1. The operating costs for air-pollution control techniques are \$[0.09,0.21] $\times 10^9$ (or [0.37,0.47]% of the total system cost) under case 1, \$[0.13,0.26] $\times 10^9$ (or [0.71,0.75]% of the total system cost) under case 2, \$[0.08,0.17] $\times 10^9$ (or [0.24,0.31]% of the total system cost) under case 3, this implies that aggressive environmental management policies would lead to reduced operating costs for air-pollution control techniques. Therefore, decisions with stricter environmental constraints would lead to a higher system cost but a cleaner environment; conversely, a desire for reducing the system cost would result in increased risk of violating the environmental criteria.

4.6. Discussion

Solutions of the IFS-EM provide an effective linkage between the pre-regulated energy and environmental policies and the associated economic implications (e.g., losses and penalties caused by improper policies) within a multistage context. The solutions contain a combination of deterministic, interval and distributional information, and can thus facilitate the reflection for different forms of uncertainties. The interval solutions can help decision makers obtain multiple decision alternatives, as well as provide bases for further analyses of tradeoffs between system cost and decision makers' satisfaction degree; the binary-variable solutions represent the decisions of facility expansion, where several alternatives are generated; the continuous-variable solutions are related to decisions of energy supply schemes and air-pollution control plans. In general, the results obtained could help support (a) adjustment or justification of allocation patterns of regional energy resources and services, (b) formulation of local policies regarding energy consumption, economic development and energy structure, and (c) analysis of interactions among economic cost, environmental requirement, and energy-supply security.

Besides, techniques of post-optimality analysis (e.g., multicriteria decision analysis, analytical hierarchy process technique, dual programming, and parametric programming) could be used for further supporting fine adjustments of the modeling results and thus for enhancing their applicability to practical situations. Furthermore, intelligent decision support system (IDSS) could be developed based on an integration of optimization modeling, scenario development, user interaction, policy analysis and visual display into a general framework. Uncertainties in energy and environmental systems could be effectively reflected and addressed through the inexact fuzzy-stochastic programming approach, improving the robustness of the IDSS for real-world applications. Thus, it can be used as an efficient tool for analyzing and visualizing impacts of energy and environmental policies, regional sustainable development strategies, and emission reduction measures in an interactive, flexible and dynamic context [57].

The study problem can also be tackled through the multistage interval-stochastic integer linear programming (MISIP) approach by simply expressing uncertainties in the model's left- and right-hand side into interval values [39,58]. The expected system costs from MISIP are \$[26.32,44.58] $\times 10^9$ under case 1, \$[18.57,40.25] $\times 10^9$ under case 2 and \$[33.91,54.28] $\times 10^9$ under case 3; they have larger width for interval values than that of the IFS-EM. Compared with IFS-EM, the main limitation of the MISIP is its over-simplification of the fuzzy membership information into interval values. This leads to a lack of system satisfaction information as defined by $\lambda^{\pm}$ in the obtained solutions. Besides, the IFS-EM can directly incorporate uncertainties expressed as discrete intervals, fuzzy sets and random variables within its optimization framework, and thus has advantages over the IMSIP in reflecting the uncertainties and tackling the tradeoffs among system reliability and objective. Moreover, the IFS-EM improves upon the conventional two-stage stochastic programming method [20]. In IFS-EM, since uncertainties are tackled through a multilayer scenario tree, such dynamic and uncertain information can be incorporated within the modeling framework. The IFS-EM can thus permit revised decisions in each time stage based on the sequentially realized uncertain events. For the energy system planning problem, dynamics of electricity demand, deficit, and capacity expansion could be taken into account, such that recourse actions (i.e. economic penalties) that hedge against the multilayer scenario tree can be dynamically undertaken.

However, as far as the modeling approach is concerned, there is much space to investigate and improve it. Firstly, only one $\lambda^{\pm}$ is used for all constraints of the modeling formation, based on an assumption that the uncertain features of all constraints are dependent upon each other. Using one $\lambda^{\pm}$ may make some constraints not well satisfied while the others over-satisfied. Secondly, merely the randomness of electricity demand is reflected in the developed model. As a long-term optimization model for EES management, the randomness of other parameters, such as stochastic interest and inflation rates [59], should be considered in the modeling formulation and thus joint probabilistic programming approach could be adopted to solve this problem. Thirdly, the developed IFS-EM is just a single-objective model, where finite constraints (for resources, capacities, and policies) are considered in the modeling formulation. Although the resulting solutions can be interpreted to clarify the interactions among system components and the associated trade-offs, they have limitations in adequately reflecting the multiple and interactive characteristics of EES. In comparison, multiobjective programming method [60] is useful for multi-criterion decision analysis under multiple objectives subjected to a set of constraints. Therefore, development of multiobjective IFS-EM is desired for more robustly reflecting the complexities of EES planning problems.

5. Conclusions

An inexact fuzzy-stochastic energy model (IFS-EM) is developed for supporting effective regional-scale EES planning under uncertainty. The proposed IFS-EM can tackle uncertainties presented in terms of interval values, fuzzy sets and probability distributions within a multi-facility, multi-period, multi-demand-level, and multi-option context. It can be used for analyzing various policy scenarios associated with different levels of economic penalties when the promised policy targets are violated, through incorporating pre-regulated energy and environmental policies directly into its optimization process. Moreover, it can obtain optimal decisions of electricity-generation plans, air pollution mitigation schemes and capacity expansion projects within a multistage context. It can also help quantify the satisfaction degree of the system objective and constraints under uncertainty, as defined by $\lambda_{\text{opt}}^{\pm}$ in the obtained solutions.

The developed IFS-EM has been applied to a case of regional-scale energy and environmental system planning, where different cases are considered based on varied energy and environmental management policies. The solutions contain a combination of deterministic, interval and distributional information, and can thus facilitate the reflection for different forms of uncertainties. The binary-variable solutions represent the decisions of facility expansion, where several alternatives are generated; the continuous-variable solutions are related to decisions of energy supply schemes and pollution control plans. Besides, it can also promote in-depth analysis of tradeoffs between system cost and decision maker's satisfaction degree. The results also indicate that the study system would attain a relatively low cost if no environmental constraints are added over the whole planning horizon. However, a comparatively high system cost would be achieved if gross control of air-pollutants emissions is considered. In summary, the results obtained are valuable for supporting (a) adjustment or justification of allocation patterns of regional energy resources and services, (b) formulation of local policies regarding energy consumption, economic development and environmental protection, and (c) analysis of interactions among energy-supply security, economic cost and environmental requirement as well as tradeoffs between system cost and decision maker's satisfaction degree.

Since electricity is considered as the most important energy in our daily life, it is desired to tackle the EES management problem from a comprehensive view, including not only the electricity generation sector but also the non-electricity ones. Moreover, besides the advanced air pollution mitigation techniques to be adopted, emissions trading may also be an advisable alternative to control air-pollutant emissions. Emission trading (also known as cap and trade) is an administrative approach used to control pollution by providing economic incentives for achieving reductions in the emissions of pollutants (*source*: http://en.wikipedia.org/wiki/Emissions_trading). For example, for SO_2 emission trading, the most cost-effective way to use available resources to comply with the criterion of allowable levels of SO_2 emissions could be identified, through the market-based allowance trading system, utilities (i.e. power plants in EES) regulated under the program, rather than a governing agency, Utilities can reduce SO_2 emissions through various ways, including employing energy conservation measures, increasing reliance on renewable energy, reducing usage, employing SO_2 emissions control technologies, switching to lower sulfur fuel, or developing other alternate strategies. Utilities that reduce their emissions below the number of allowances that they hold may trade allowances with other utilities in their system, sell them to other utilities on the open market, or bank them to cover emissions in future years (*source*: http://www.epa.gov/airmarkets/trading/factsheet.html). Therefore, through trading scheme, each utility is no longer constrained by its own emission permit but theoretically by the aggregate number of SO_2 emission limit from their system, which can minimize the system cost at a certain level of SO_2 emission permit. Allowance trading provides incentives for energy conservation and technology innovation that can both lower the cost of compliance and yield pollution prevention benefits.

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Appendix A. Solution method

A two-step method is proposed for solving the IFMP model. The submodel for λ^{+} corresponding to f^{-} can be formulated in the first step when the system objective is to be minimized; the other submodel (corresponding to f^{+}) can then be formulated based on the solution of the first submodel. Thus, the first submodel is formulated (assume that $B^{\pm} > 0$ and $f^{\pm} > 0$) as follows [39]:

$$\text{Max} \quad \lambda^+ \tag{A.1a}$$

$$\text{s.t.} \quad \sum_{t=1}^{T}\left(\sum_{j=1}^{j_1} c_{jt}^- x_{jt}^- + \sum_{j=j_1+1}^{n_1} c_{jt}^- x_{jt}^+\right) + \sum_{t=1}^{T}\sum_{k=1}^{K_t} p_{tk}\left(\sum_{j=1}^{j_2} d_{jtk}^- y_{jtk}^- + \sum_{j=j_2+1}^{n_2} d_{jtk}^- y_{jtk}^+\right) \leqslant f^+ - \lambda^+(f^+ - f^-) \tag{A.1b}$$

$$\sum_{j=1}^{j_1} |a_{rjt}|^+ \text{Sign}\left(a_{rjt}^+\right) x_{jt}^- + \sum_{j=j_1+1}^{n_1} |a_{rjt}|^- \text{Sign}\left(a_{rjt}^-\right) x_{jt}^+ \leqslant b_{rt}^+ - \lambda^+(b_{rt}^+ - b_{rt}^-), \quad \forall r;\ t \tag{A.1c}$$

$$\sum_{j=1}^{j_1} |a_{rjt}|^+ \text{Sign}\left(a_{rjt}^+\right) x_{jt}^- + \sum_{j=j_1+1}^{n_1} |a_{rjt}|^- \text{Sign}\left(a_{rjt}^-\right) x_{jt}^+ + \sum_{j=1}^{j_2} \left|a'_{ijtk}\right|^+ \text{sign}\left(a'^+_{ijtk}\right) y_{jtk}^- + \sum_{j=j_2+1}^{n_2} \left|a'_{ijtk}\right|^- \text{sign}\left(a'^-_{ijtk}\right) y_{jtk}^+ \leqslant w_{itk}^+ - \lambda^+(w_{itk}^+ - w_{itk}^-), \quad \forall i;\ t;\ k = 1,2,\ldots,K_t \tag{A.1d}$$

$$x_{jt}^- \geqslant 0, \quad \forall t;\ j = 1,2,\ldots,\ j_1 \tag{A.1e}$$

$$x_{jt}^+ \geqslant 0, \quad \forall t;\ j = j_1+1, j_1+2,\ldots,n_1 \tag{A.1f}$$

$$y_{jtk}^- \geqslant 0, \quad \forall t;\ j = 1,2,\ldots,\ j_2;\ k = 1,2,\ \ldots,K_t \tag{A.1g}$$

$$y_{jtk}^+ \geqslant 0, \quad \forall t;\ j = j_2+1, j_2+2,\ldots,n_2;\ k = 1,2,\ldots,K_t \tag{A.1h}$$

$$0 \leqslant \lambda^+ \leqslant 1 \tag{A.1i}$$

where $x_{jt}^{\pm}$ $(j = 1,2,\ldots,j_1)$ are the first-stage decision variables with positive coefficients in the objective function, and $x_{jt}^{\pm}$ $(j = j_1+1,\ j_1+2,\ldots,n_1)$ with negative coefficients; $y_{jtk}^{\pm}$ $(j = 1,2,\ldots,j_2$ and $k = 1,2,\ldots,K_t)$ are the second-stage decision variables with positive coefficients in the objective function, and $y_{jtk}^{\pm}$ $(j = j_2+1,\ j_2+2,\ldots,n_2$ and $k = 1,2,\ldots,K_t)$ with negative coefficients. Solutions of x_{jtopt}^- $(j = 1,2,\ldots,j_1)$, x_{jtopt}^+ $(j = j_1+1, j_1+2,\ldots,n_1)$, y_{jtkopt}^- $(j = 1,\ 2,\ldots,j_2$ and $k = 1,2,\ldots,K_t)$, y_{jtkopt}^+ $(j = j_2+1, j_2+2,\ldots,n_2$ and $k = 1,2,\ldots,K_t)$ and λ_{opt}^+ can be obtained from submodel (9). Based on the above solutions, the second submodel for λ^- (corresponding to f^+) can be formulated as follows [35]:

$$\text{Max} \quad \lambda^- \tag{A.2a}$$

$$\text{s.t.} \quad \sum_{t=1}^{T}\left(\sum_{j=1}^{j_1} c_{jt}^+ x_{jt}^+ + \sum_{j=j_1+1}^{n_1} c_{jt}^+ x_{jt}^-\right) + \sum_{t=1}^{T}\sum_{k=1}^{K_t} p_{tk}\left(\sum_{j=1}^{j_2} d_{jtk}^+ y_{jtk}^+ + \sum_{j=j_2+1}^{n_2} d_{jtk}^+ y_{jtk}^-\right) \leqslant f^+ - \lambda^-(f^+ - f^-) \tag{A.2b}$$

$$\sum_{j=1}^{j_1} |a_{rjt}|^- \text{Sign}\left(a_{rjt}^-\right) x_{jt}^- + \sum_{j=j_1+1}^{n_1} |a_{rjt}|^+ \text{Sign}\left(a_{rjt}^+\right) x_{jt}^- \leqslant b_{rt}^+ - \lambda^-(b_{rt}^+ - b_{rt}^-), \quad \forall r;\ t \tag{A.2c}$$

$$\sum_{j=1}^{j_1} |a_{rjt}|^- \text{Sign}\left(a_{rjt}^-\right) x_{jt}^+ + \sum_{j=j_1+1}^{n_1} |a_{rjt}|^+ \text{Sign}\left(a_{rjt}^+\right) x_{jt}^- + \sum_{j=1}^{j_2} |a'_{ijtk}|^- \text{sign}\left(a'^-_{ijtk}\right) y_{jtk}^+ + \sum_{j=j_2+1}^{n_2} |a'_{ijtk}|^+ \text{sign}\left(a'^+_{ijtk}\right) y_{jtk}^- \leqslant w_{itk}^+ - \lambda^-(w_{itk}^+ - w_{itk}^-), \quad \forall i;\ t;\ k = 1,2,\ldots,K_t \tag{A.2d}$$

$$x_{jt}^+ \geqslant x_{jtopt}^-, \quad \forall t;\ j = 1,2,\ldots,j_1 \tag{A.2e}$$

$$0 \leqslant x_{jt}^- \leqslant x_{jtopt}^+, \quad \forall t;\ j = j_1+1, j_1+2,\ldots,n_1 \tag{A.2f}$$

$$y_{jtk}^+ \geqslant y_{jtkopt}^-, \quad \forall t;\ j = 1,2,\ldots,j_2;\ k = 1,2,\ldots,K_t \tag{A.2g}$$

$$0 \leqslant y_{jtk}^- \leqslant y_{jtkopt}^+, \quad \forall t;\ j = j_2+1, j_2+2,\ldots,n_2;\ k = 1,2,\ldots,K_t \tag{A.2h}$$

$$0 \leqslant \lambda^- \leqslant 1 \tag{A.2i}$$

Solutions of x_{jtopt}^+ $(j = 1,2,\ldots,j_1)$, x_{jtopt}^- $(j = j_1+1, j_1+2,\ldots,n_1)$, y_{jtkopt}^+ $(j = 1,2,\ldots,j_2$ and $k = 1,2,\ldots,K_t)$, y_{jtkopt}^- $(j = j_2+1, j_2+2,\ldots,n_2$ and $k = 1,2,\ldots,K_t)$ and λ_{opt}^- can be obtained through solving submodel (10). Therefore, combining solutions of submodels (9) and (10), solution for the IFMP model can be obtained as follows:

$$x_{jtopt}^{\pm} = \left[x_{jtopt}^-,\ x_{jtopt}^+\right], \quad \forall j;\ t$$

$$y_{jtkopt}^{\pm} = \left[y_{jtkopt}^-,\ y_{jtkopt}^+\right], \quad \forall j;\ t;\ k = 1,2,\ldots,K_t$$

$$\lambda_{opt}^{\pm} = \left[\lambda_{opt}^-,\ \lambda^+{}_{opt}\right]$$

$$f_{opt}^{\pm} = \left[f_{opt}^-,\ f_{opt}^+\right]$$

Appendix B. Nomenclatures for parameters and variables

$f^{\pm}$	expected system cost for EES management over the planning horizon ($\$10^9$)
i	type of power conversion technology, $i = 1,2,\ldots,I$; $i = 1$ for coal-fired power conversion technology, $i = 2$ for natural gas-fired power conversion technology, $i = 3$ for hydropower, $i = 4$ for wind power; $i = 5$ for solar power, $i = 6$ for nuclear power
j_s	type of SO_2 control measure, $j_s = 1,2,\ldots,n_s$; $j_s = 1$ for soda ash scrubber (SAS); $j_s = 2$ for wet limestone scrubber (WLS); $j_s = 3$ for lime spray dryer (LSD)
j_n	type of NO_x control measure, $j_n = 1,2,\ldots,n_n$; $j_n = 1$ for selective catalytic reduction (SCR); $j_n = 2$ for selective non-catalytic reduction (SNCR)
j_p	type of particulate matter (PM) control measure, $j_p = 1,2,\ldots,n_p$; $j_p = 1$ for fabric filiter/baghouse (BH); $j_p = 2$ for electrostatic precipitator (ESP); $j_p = 3$ for wet collector (WC)
t	time period, $t = 1,2,\ldots,T$
h	electricity demand-level, $h = 1,2,\ldots,H_t$

Parameters:

$PEC_t^{\pm}$	cost for coal supply in period t ($\$10^3$/TJ)
$PEN_t^{\pm}$	cost for natural gas supply in period t ($\$10^3$/TJ)
$PIE_t^{\pm}$	cost for imported electricity supply in period t ($\$10^3$/GW h)
$UPH_t^{\pm}$	upper bound of the availability of hydropower in period t (10^3 TJ)
$UPW_t^{\pm}$	upper bound of the availability of wind power in period t (10^3 TJ)
$UPS_t^{\pm}$	upper bound of the availability of solar power in period t (10^3 TJ)
$UPU_t^{\pm}$	upper bound of the availability of nuclear power in period t (10^3 TJ)
$PV_{it}^{\pm}$	operating cost of power conversion technology i for pre-regulated electricity generation in period t ($\$10^3$/GW h);
$PP_{it}^{\pm}$	penalty cost of power conversion technology i for excess electricity generation in period t ($\$10^3$/GW h);
$CS_{j_s t}^{\pm}$	operating cost of control measure j_s for pre-regulated SO_2 emissions during period t ($/tonne)
$CN_{j_n t}^{\pm}$	operating cost of control measure j_n for pre-regulated NO_x emissions during period t ($/tonne)
$CP_{j_p t}^{\pm}$	operating cost of control measure j_p for pre-regulated PM emissions during period t ($/tonne)
$DS_{j_s t}^{\pm}$	operating and penalty cost of control measure j_s for excess SO_2 emissions during period t ($/tonne)
$DN_{j_n t}^{\pm}$	operating and penalty cost of control measure j_n for excess NO_x emissions during period t ($/tonne)

$DP^{\pm}_{j_pt}$ operating and penalty cost of control measure j_p for excess PM emissions during period t ($/tonne)
ST_{it} average service time of power conversion technology i in period t (h)
V_t peak load demand in period t (GW)
p_{th} probability of demand-level h occurrence in period t (%)
$d^{\pm}_{th}$ random variable of total electricity demand during period t (GW h)
$A^{\pm}_{it}$ fixed-charge cost for capacity expansion of power conversion technology i in period t ($\$10^6$)
$B^{\pm}_{it}$ variable cost for capacity expansion of power conversion technology i in period t ($\$10^6$/GW)
RC_i residual capacity of conversion technology i (GW)
$FE^{\pm}_{it}$ units of energy carrier per units of electricity production for power conversion technology i in period t (TJ/GW h)
M_{it} variable upper bounds for capacity expansion of power conversion technology i in period t (GW)
N_{it} variable lower bounds for capacity expansion of power conversion technology i in period t, and $N_{it} \geqslant 0$ (GW)
$INS^{\pm}_{it}$ units of SO_2 emission per unit of electricity production for power conversion technology i in period t (tonne/GW h)
$INN^{\pm}_{it}$ units of NO_x emission per unit of electricity production for power conversion technology i in period t (tonne/GW h)
$INP^{\pm}_{it}$ units of PM emission per unit of electricity production for power conversion technology i in period t (tonne/GW h)
$\eta^{\pm}_{j_s}$ average efficiency of SO_2 control measure j_s (%)
$\eta^{\pm}_{j_n}$ average efficiency of NO_x control measure j_n (%)
$\eta^{\pm}_{j_p}$ average efficiency of PM control measure j_p (%)
$ES^{\pm}_t$ SO_2 emission allowance in period t (tonne)
$EN^{\pm}_t$ NO_x emission allowance in period t (tonne)
$EP^{\pm}_t$ PM emission allowance in period t (tonne)

Decision variables:

$Z1^{\pm}_t$ coal supply in period t (TJ)
$Z2^{\pm}_t$ natural gas supply in period t (TJ)
$Z3^{\pm}_{th}$ imported electricity supply when electricity demand-level is h in period t (10^3 GW h)
$W^{\pm}_{it}$ pre-regulated electricity generation target of power conversion technology i which is promised to end-users during period t (10^3 GW h)
$Q^{\pm}_{ith}$ excess electricity generation of power conversion technology i by which electricity generation target (W_{kt}) is exceeded when electricity demand-level is h in period t (10^3 GW h)
$X^{\pm}_{ith}$ continuous variables about the amount of capacity expansion of power conversion technology i when electricity demand-level is h in period t (GW)
$Y^{\pm}_{ith}$ binary variables for identifying whether or not a capacity expansion action of power conversion technology i needs to be undertaken when electricity demand-level is h in period t
$XS^{\pm}_{ij_st}$ pre-regulated amount of SO_2 generated from power conversion technology i to be mitigated by control measure j_s in period t (tonne)
$YS^{\pm}_{ij_sth}$ excess amount of SO_2 generated from power conversion technology i to be mitigated by control measure j_s when electricity demand-level is h in period t (tonne)
$XN^{\pm}_{ij_nt}$ pre-regulated amount of NO_x generated from power conversion technology i to be mitigated by control measure j_n in period t (tonne)
$YN^{\pm}_{ij_nth}$ excess amount of NO_x generated from power conversion technology i to be mitigated by control measure j_n when electricity demand-level is h in period t (tonne)
$XP^{\pm}_{ij_pt}$ pre-regulated amount of PM generated from power conversion technology i to be mitigated by control measure j_p in period t (tonne)
$YP^{\pm}_{ij_pth}$ excess amount of PM generated from power conversion technology i to be mitigated by control measure j_p when electricity demand-level is h in period t (tonne)

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