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An interval fixed-mix stochastic programming method for greenhouse gas mitigation in energy systems under uncertainty

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ABSTRACT

In this study, an interval fixed-mix stochastic programming (IFSP) model is developed for greenhouse gas (GHG) emissions reduction management under uncertainties. In the IFSP model, methods of interval-parameter programming (IPP) and fixed-mix stochastic programming (FSP) are introduced into an integer programming framework, such that the developed model can tackle uncertainties described in terms of interval values and probability distributions over a multi-stage context. Moreover, it can reflect dynamic decisions for facility-capacity expansion during the planning horizon. The developed model is applied to a case of planning GHG-emission mitigation, demonstrating that IFSP is applicable to reflecting complexities of multi-uncertainty, dynamic and interactive energy management systems, and capable of addressing the problem of GHG-emission reduction. A number of scenarios corresponding to different GHG-emission mitigation levels are examined; the results suggest that reasonable solutions have been generated. They can be used for generating plans for energy resource/electricity allocation and capacity expansion and help decision makers identify desired GHG mitigation policies under various economic costs and environmental requirements.

1. Introduction

Currently, climate change is one of the hot topics in making energy and environmental policies, and it makes a global challenge with serious consequences for social and economic infrastructures as well as natural systems. A number of research works demonstrate that an increase in greenhouse gas (GHG) (e.g. carbon dioxide, methane, fluorine chlorination carbon, nitrous oxide, and ozone) concentrations in the terrestrial atmosphere that discharged by human activities induce global warming [1–4]. Most CO_2 emissions are emitted mainly from burning fossil fuels such as coal, oil and natural gas [5]. A number of impact factors, such as population growth, global economic development, rapid urbanization and industrialization, energy demand increase, lead to an increasing consumption of fossil fuels. This would inevitably result in conflicts among economic objective, energy demand/supply, and environmental requirement. Therefore, effective energy systems planning method with GHG-emission mitigation is desired.

Previously, many deterministic models for GHG management in planning energy systems were developed [6–11]. For example, Kwaczek et al. [12] presented an optimization model for understanding economic impacts of various emission-reduction strategies on energy activities in Saskatchewan, Canada. Sailor [13] conducted an integrated assessment of climate change impacts on renewable energy supply and demand technologies at many locations. Zhang et al. [14] scrutinized relationships between global warming and structural shift in the power-generation sector in south China. Unger and Ekvall [15] used MARKAL (MARK et Allocation Model) for exploring CO_2-abatement costs under bilateral trades of electricity, natural gas and emission-permits among Nordic countries. Chinese et al. [16] developed an optimization model to assess technical and economic feasibilities of renewable energy utilizations and thus to minimize GHG emissions in a region. Klaassen and Riahi [17] employed the long-term MESSAGE (Model for Energy Supply Strategy Alternatives and their General Environmental Impact) to analyze energy planning and climate change response. Chung et al. [18] used a hybrid E-IO (Energy top-down approach) table with higher classification sector resolution to determine the intensities of

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energy use and GHG emission in Korea. However, the above models could only reflect the relationships of various energy activities (e.g. demand and supply) and GHG emissions under deterministic conditions. In fact, energy system is complicated with various uncertain factors associated with economic and technique parameters as well as dynamics of facility expansion related to issues of timing, sizing and siting. Moreover, many processes are linked to energy system management, such as exploration/exploitation, conversion/processing, and supply/demand of energy resources. In addition, energy system planning is highly convoluted, involving a large number of social, economic, environmental, technical, and political factors, coupled with complex temporal and spatial variabilities and cascading effects. All of these processes and factors are associated with uncertainties and complexities, which are difficult to be handled by decision makers without considerable expertise [19]. Such uncertainties and complexities could not effectively be addressed in the previous deterministic models. Therefore, it is desired to develop more robust methods to deal with these uncertainties and complexities in energy systems.

As a result, many inexact optimization methods were developed for energy systems planning; their results could effectively provide desired decision alternatives under various uncertainties [20–26]. For instance, Loulou and Kanudia [27,28] analyzed marginal costs associated with GHG mitigation in provinces of Ontario, Quebec, and Alberta, Canada, which might lead to transfers from fossil fuels to renewable energy resources in these areas; they further used MARKAL to compare the key results of minimax regret and minimum expected value strategies for GHG abatement in the Province of Quebec. Kanudia and R. Loulou [29] developed a multi-stage stochastic programming strategy to create a flexible energy plan that took into consideration climate change and economic growth factors, which was a stochastic version of Extended MARKAL model, and used to study the greenhouse gas emission control in Quebec. Messner et al. [30] introduced a stochastic version of MESSAGE III and analyzed the structures of energy development strategies derived from the deterministic and stochastic versions, where the stochastic version deals with uncertainties concerning future investment costs by incorporating the expectation of incurring higher costs due to these uncertainties into the objective function. Spangardt et al. [31] proposed a stochastic programming model for power planning and GHG-emission reduction, where power demand was expressed as random variable. Li et al. [25] advanced an interval-parameter robust minimax-regret programming method for the planning of energy and environmental systems, where methods of robust programming, interval-parameter programming (IPP), and minimax regret analysis were incorporated within a general optimization framework to enhance the robustness of the optimization effort. Lin and Huang [32] developed an inexact-dynamic stochastic programming model to plan energy systems management and GHG-emission control in the municipality of Beijing, where techniques of mixed integer, IPP and two-stage stochastic programming (TSP) method were incorporated to deal with uncertainties in energy systems. Chen et al. [33] formulated a two-stage inexact-stochastic programming model for CO_2-emission trading planning in an integrated energy and environmental management system, where IPP and TSP were integrated into a general framework to deal with uncertainties existed as intervals and probabilities.

Among the above approaches, TSP is an effective method for problems where an analysis of policy scenarios is desired and the related data are mostly uncertain; however, it cannot adequately reflect the dynamic variations of system conditions, especially for sequential structure of large-scale problems [34]. To deal with such a dynamic feature, a number of multi-stage stochastic programming (MSP) methods were developed as extensions of dynamic stochastic optimization methods [34–36]. Fixed-mix stochastic programming (FSP) is a MSP method, which is based on the simple decision rule of constant rebalancing, can permit revised decisions in each time stage based on the uncertainty realized so far [28,37]. FSP is applicable to large-scale practical problems over a long-term planning context. However, few studies focused on FSP methods for GHG management.

The existing FSP methods are effective in handling probabilistic uncertainties in the model's right-hand sides which are often related to resources availability; however they have difficulties in dealing with independent uncertainties of the model's left-hand sides and cost coefficients. Interval-parameter programming (IPP) is an alternative for handling uncertainties in the model's left- and/or right-hand sides as well as those that cannot be quantified as membership or distribution functions, since interval numbers are acceptable as its uncertain inputs [38]. Previously, a number of inexact optimization methods based on the IPP approach were developed for dealing with uncertainties presented as intervals, fuzzy sets and/or random variables [21,34,39,40]. Nevertheless, no previous studies were focused on development of interval fixed-mix stochastic programming (IFSP) method through integrating IPP and FSP into a general framework for GHG-emission management in energy systems.

Therefore, the objective of this study is to develop an interval fixed-mix stochastic programming method (IFSP) for greenhouse gas (GHG) mitigation in energy systems under uncertainty. This is the first attempt that interval-parameter programming (IPP) and fixed-mix stochastic programming (FSP) methods are integrated into a general framework to manage GHG emissions under uncertainties presented as interval values and probabilities within a multi-stage context. A case study will then be provided for demonstrating how the IFSP method will support energy and environmental management systems planning under uncertainty. Furthermore, it will be shown how it can be used to mitigate GHG emissions in the energy systems, as well as determine which of these designs can most efficiently lead to the optimized system objectives.

2. Model development

A typical energy system often contains various components such as energy supply/demand, processing and transformation technologies, and electricity generation. These components are related to an array of economic activities and energy-consumption behaviors. Energy supply options are typically classified as fossil- or renewable resources. Each of the resources has its own subsectors representing the characteristics of its related technologies. Fossil resources include coal, crude oil and natural gas; renewable resources usually include biomass, hydro, solar, geothermal and wind energy. When the supply of mined resources and renewable resources cannot meet the end-user demand, import becomes necessary. When the productions are greater than domestic demands and exporting is profitable, export becomes possible [10,24].

In an energy system, technologies are utilized to deal with supply- and demand-side options. On the supply side, only a small group of energy resources can be used directly; a large number of energy resources needs to be converted or processed before it can be utilized by consumers or technologies. Processing technologies are used to transform energy resources into usable forms of energy carriers; for example, crude oil is converted into gasoline, diesel, alcohol, etc. With respect to demand-side technologies, all energy carriers including electricity can be used by end-users with various devices. Since different technologies have different characteristics regarding energy efficiency, GHG emission, capital investment and operation/maintenance cost, they compete against each other to provide a mixture of options to decision makers. Electricity is an important component in the energy system. It can be used not only to satisfy end-use demands but also to drive other technologies. A large amount of electricity is generated from fossil resources such as coal, and natural gas; nuclear power is a popular alternative to provide electricity with large-scale capacity in many energy systems; and electricity generations from renewable sources are encouraged because they are much more sustainable and cleaner in comparison with fossil resources. Among the options based on renewable resources, hydropower has been developed extensively in the past decades, and installations of wind, solar, and biomass power facilities are still at high costs. This leads to limited utilization of renewable resources other than hydro energy [19,32].

Consider an energy system wherein a manager is responsible for allocating energy flows to multiple users over a multi-period planning horizon. The decision maker can formulate the problem as minimizing the expected cost of various energy activities in the region over the planning horizon. Moreover, decision makers always seek to control the emissions of environmental pollutants (e.g., sulfur dioxide (SO_2), nitrogen oxides (NO_x), particulate matter (PM)) and greenhouse gas (GHG) in order to meet the regional environmental requirement. Given a quantity of electricity that is promised to users, if the quantity is delivered, it will bring about net benefit to the local economy; however, if the promised quantity is not delivered, it will result in penalty on the local economy. In general, the study system (as shown in Fig. 1) is related to a number of energy supply, conversion and demand activities and various cost-effective demand-side management programs (e.g., heating, mass transportation, heat and power co-generation, and renewable energy utilization). Furthermore, multiple factors and processes are involved in the system, such as economic costs, emissions of GHG and pollutants, and energy supply/demand. These processes and factors are generally complex and associated with a variety of uncertainties, which are further complicated by intensive competitions among various energy supply options, conversion/processing technologies and end-users.

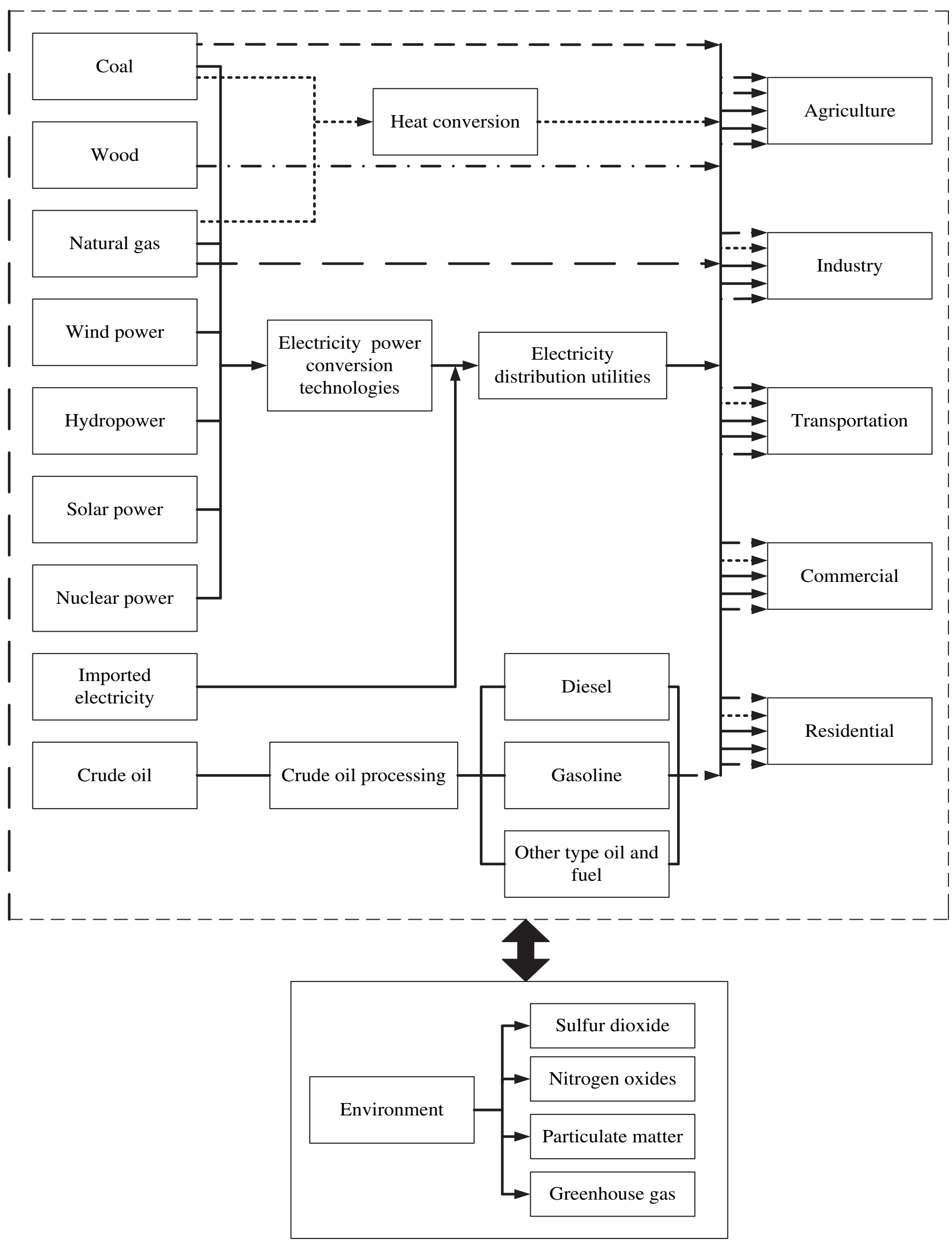

Fig. 1. Municipal energy system flowchart.

Fixed-mix stochastic programming (FSP) method is useful for dealing with the complexities and uncertainties. FSP is a static approach based on MSP technique, and determined by a matrix p_{th}, $t = 1,2,3, \ldots.T$; $h = 1,2,3,\ldots H$ ("t" denotes "period", and "h" denotes "scenario"), with $p_{th} > 0$ and $\sum_{h=1}^{H} p_{th} = 1$. FSP prescribes that each scenario in each time period would correspond to a fixed probability level p_{th}. The dynamics of the strategic decision are given by $p_{th} = p_{t-1,h}$ and $\lambda_t = \sum_{h=1}^{H} p_{th} \cdot \lambda_{th}$. A strategy λ is called a fixed-mix strategy associated with the matrix $p = p_{th}$ [37,41]. Fig. 2 shows the structure of FSP, where uncertainties are allowed to be described in terms of outcome streams or scenarios, the nodes represent decisions, while the arcs are for realizations of the uncertain variables. "L", "M" and "H" denote the scenarios with a fixed low, medium, and high probability levels, respectively. Each scenario would correspond to a fixed probability level p_{th} in each time period (e.g. L - L - L -… - L), and the sum of low, medium, and high probability in each time period is 1. Although FSP is incapable of exploiting the foresight as implied in the second stage and the later, this method has advantages in reflecting uncertainties for large-scale problems with a long planning period.

In addition, in real-world energy and environmental management problems, many uncertainties presented as different formats may exist. For example, it may often be difficult for a planner to promise a deterministic target to end-users when the available energy resources and/or demands are uncertain. The economic data (i.e. benefit and cost) conversion efficiency, and produce capacities may not be available as deterministic values. Based on the above considerations, interval-parameter programming (IPP) can be introduced into the FSP framework to reflect multiple uncertainties. IPP is useful for handling interval format uncertainties in both the left- and right-hand sides of the constraints as well as the coefficients in the objective function [39]. On the other hand, from a long-term planning point of view, energy demands from multiple end-users may keep increasing due to population increases and economic development. Moreover, the available capacities of energy-generation facilities may also vary among different time periods. This tendency could often result in insufficient capacities of energy-generation facilities to meet the overall demand. Consequently, capacity expansion for energy-generation facilities is a crucial issue in energy systems planning, where a related optimization analysis will typically require the use of integer variables to indicate whether a particular facility development or expansion option needs to be undertaken. 0–1 integer programming is used to tackle facility expansion issues. Therefore, through incorporating IPP and FSP techniques within an 0–1 integer programming framework, an interval fixed-mix stochastic programming (IFSP) model for planning energy systems with GHG-emission mitigation consideration can be formulated as follows (Model A): the objective function is to minimize the expected value of system cost, which includes (a) cost for purchasing coal, nature gas, crude oil, diesel and gasoline, (b) operation cost for coal-fired power, gas-fired power, hydropower, wind power, solar power, and nuclear power (c) capacity expansion cost, and (d) air pollutant mitigation cost. In the IFSP model, the decision variables can be classified into two types: continuous and 0–1 integer variables. The continuous variables represent energy resources allocation and technology utilization; the 0–1 integer variables stand for the expansion options of power conversion facilities, and each facility may have multiple options with different expansion scales.

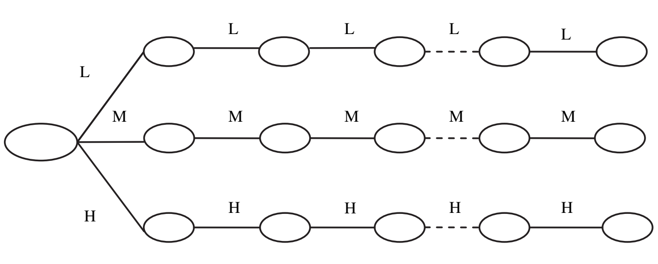

Fig. 2. T-stage fixed mix approach scenario tree.

$$\text{Minmize}\ f^{\pm} = (1) + (2) + (3) + (4) \tag{1}$$

$$(1) = \sum_{t=1}^{T} \sum_{i=1}^{I} Z_{it}^{\pm} \cdot PES_{it}^{\pm} \tag{2}$$

$$(2) = \sum_{t=1}^{T} \sum_{k=1}^{K} PV_{kt}^{\pm} \cdot W_{kt}^{\pm} + \sum_{t=1}^{T} \sum_{k=1}^{K} \sum_{h=1}^{H} p_h \cdot \left(PV_{kt}^{\pm} + PP_{kt}^{\pm}\right) \cdot Q_{kth}^{\pm} + \sum_{t=1}^{T} \sum_{k_r=1}^{K_r} PVR_{k_r t}^{\pm} \cdot RZ_{k_r t}^{\pm} \tag{3}$$

$$(3) = \sum_{t=1}^{T} \sum_{k=1}^{K} \sum_{m=1}^{M} \sum_{h=1}^{H} p_h \cdot Y_{ktmh}^{\pm} \cdot EC_{kmt} \cdot IC_{kmt} \tag{4}$$

$$(4) = \sum_{k=1}^{K} \sum_{t=1}^{T} \sum_{h=1}^{H} \sum_{r=1}^{R} \left(W_{kt}^{\pm} + p_h \cdot Q_{kth}^{\pm}\right) \cdot PT_{rkt}^{\pm} \cdot CT_{rkt}^{\pm} \tag{5}$$

where $f^{\pm}$ = the net expected system cost (million dollar); $Z_{it}^{\pm}$ = the supply of energy resource i in period t (PJ), where $i = 1$ for coal, $i = 2$ for natural gas, $i = 3$ for crude oil, $i = 4$ for gasoline, $i = 5$ for diesel, $i = 6$ for imported power; $PES_{it}^{\pm}$ = the supply cost of energy sources i in period t ($million/PJ); $PV_{kt}^{\pm}$ = the variable cost for electricity generated by technology k in period t ($million/GWh), where $k = 1$ for coal-fired power, $k = 2$ for natural gas-fired power, $k = 3$ for hydropower, $k = 4$ for wind power, $k = 5$ for solar power, $k = 6$ for nuclear power;- $PP_{kt}^{\pm}$ = penalty cost of excess electricity generated by technology k in period t ($million/GWh); $W_{kt}^{\pm}$ = allowable power generation by technology k during period t; $Q_{kth}^{\pm}$ = excess power generation by technology k in scenario h during period t; p_{th} = probability of occurrence for scenario h in period t; $PVR_{k_r t}^{\pm}$ = variable cost for heat supply technology k_r in period t ($million/GWh), where $k_r = 1$ for coal-fired boiler heat, $k_r = 2$ for gas-fired boiler heat; $RZ_{k_r t}^{\pm}$ = heat supply from technology k_r in period t (PJ); $Y_{ktmh}^{\pm}$ = binary variable for technology k with expansion option m in scenario h during period t; EC_{kmt} = capacity expansion size option m for power generation technology k in period t (GW); IC_{kmt} = capacity cost of capacity expansion size m for power generation technology k in period t ($Million/GW); $PT_{rkt}^{\pm}$ = the emission intensity of pollutant r from power generation technology k in period t (kiloton/GWh), where $r = 1$ for sulfur dioxide, $r = 2$ for nitrogen oxides, $r = 3$ for particulate matter; $CT_{rkt}^{\pm}$ = the removal cost of pollutant r from power generation technology k in period t (dollar/kiloton).

2.1. Mass balance constraints

The mass balance constraints describe the balance of energy flows in an energy system. They can be classified into three groups: (1) balance for energy resource (6), (2) balance for electricity generation (7), (8) and (9), and (3) balance for heat generation (10). These constraints are established to ensure that the input energy is greater than the output one.

$$FE_{kt}^{\pm} \cdot \left(W_{kt}^{\pm} + Q_{kth}^{\pm}\right) + \sum_{s=1}^{S} D_{ist}^{\pm} \le Z_{it}^{\pm}, \forall t, h, i \tag{6}$$

$$\sum_{k=1}^{K}\left(W_{kt}^{\pm}+Q_{kth}^{\pm}\right)+ZIE_{t}^{\pm}\geq DTE_{th}^{\pm},\forall t,h \tag{7}$$

$$W_{kt\max}^{\pm}\geq W_{kt}\geq Q_{kth}^{\pm}\geq 0,\forall k,t,h \tag{8}$$

$$W_{kt}^{\pm}+Q_{kth}^{\pm}\leq ST_{kt}^{\pm}\cdot\left[RC_{k}+\sum_{t=1}^{T}\sum_{m=1}^{M}Y_{ktmh}^{\pm}\cdot EC_{kmt}\right],\forall k,t,h \tag{9}$$

$$RZ_{k_rt}^{\pm}\cdot\eta_{k_rt}^{\pm}\geq DTR_{t}^{\pm}\cdot\beta_{k_rt},\forall t,k_r \tag{10}$$

2.2. Capacity constraints of technologies

For an individual technology, it is assumed that its output or production should be less than the amount that total installed capacity can provide. If this requirement is not satisfied, investments will be made for additional capacities.

$$Y_{ktmh}^{\pm}=\begin{cases}\leq 1\\ \geq 0 \quad \forall k,t,m,h\\ \text{integer}\end{cases} \tag{11}$$

$$\sum_{m=1}^{M}Y_{ktmh}^{\pm}\leq 1 \quad \forall k,t,h, \tag{12}$$

2.3. Environmental constraints

For an energy system planning, it is assumed that environmental requirement should be considered as an important constraint. Eq. (13) is the constraint of pollutants emission of power generation technologies; Eq. (14) is the constraint of GHG emission of the energy system.

$$\sum_{k=1}^{K}\left(W_{kt}^{\pm}+Q_{kth}^{\pm}\right)\cdot PT_{krt}^{\pm}\cdot\left(1-\eta_{krt}^{\pm}\right)\leq \mathrm{EP}_{rt}^{\pm},\forall t,h,r; \tag{13}$$

$$\sum_{s=1}^{S}\sum_{i=1}^{I}D_{ist}^{\pm}\cdot INT_{s}^{\pm}+\sum_{k=1}^{K}\left(W_{kt}^{\pm}+Q_{kth}^{\pm}\right)\cdot COT_{kt}^{\pm}\leq EC_{th}^{\pm},\forall t,h \tag{14}$$

where $FE_{kt}^{\pm}$ = the conversion efficiency of power generation technology k in period t (PJ/GW); $D_{ist}^{\pm}$ = the demand of energy resource i in sector s during period t; $ZIE_{t}^{\pm}$ = import electricity supply in period t (GWh); $DTE_{th}^{\pm}$ = electricity demand in scenario h during period t (GWh); $ST_{kt}^{\pm}$ = the working hours of power generation technology k in period t (hour); RC_k = residual capacity of power generation technology k (GW); $\eta_{k_rt}^{\pm}$ = the proportion of heat supply from technology k_r account for the total in period t; $DTR_{t}^{\pm}$ = heat demand during period t (PJ); β_{k_rt} = the efficiency of heat supply from technology k_r in period t; $\eta_{krt}^{\pm}$ = the removal efficiency of pollutant r from power generation technology k; $EP_{\mathrm{rt}}^{\pm}$ = the total allowable emissions of pollutant r in period t (kiloton); $INT_{s}^{\pm}$ = CO_2 emission intensity of sector s (kiloton/PJ); $COT_{kt}^{\pm}$ = CO_2 emission intensity of power generation technology k in period t (kiloton/GWh); $EC_{th}^{\pm}$ = the total allowable CO_2 emissions in scenario h during period t (kiloton).

In the IFSP model, when the allowable amount of power generation ($W_{kt}^{\pm}$) are known, model A can be transformed into two sets of deterministic submodels, which correspond to the upper and lower bounds of the desired objective-function value. This transformation process is based on an interactive algorithm, which is different from normal interval analysis and best/worst case analysis, and the existing methods for solving inexact linear programming problems cannot be used directly [17,21]. In this study, an optimized set of target values will be identified by having u_{kt} being decision variables; this optimized set will correspond to minimized system cost under the uncertain electricity demands and supplies. Accordingly, let $W_{kt}^{\pm}=W_{kt}^{-}+\Delta W_{kt}u_{kt}$, where $\Delta W_{kt}=W_{kt}^{+}-W_{kt}^{-}$ and $u_{kt}\in[0,1]$. u_{kt} are decision variables that are used for identifying an optimized set of target values ($W_{kt}^{\pm}$) in order to support the related policy analyses. For example, when $W_{kt}^{\pm}$ approach their upper bounds (i.e., when $u_{kt}=1$), a relatively low cost would be obtained if the electricity demands are satisfied; a low penalty may have to be paid when the promised electricity is delivered. Conversely, when $W_{kt}^{\pm}$ reach their lower bounds (i.e., when $u_{kt}=0$), we may have a high cost and a higher risk of violating the promised targets. Therefore, by introducing decision variables u_{kt}, and according to Huang and Loucks [42], the model can be transformed into two deterministic submodels based on an interactive algorithm. Since the objective is to minimize the net system cost, the submodel corresponding to lower-bound objective function value (f^{-}) is first desired, where the lower bounds of cost coefficients and energy demands will correspond to f^{-}. Thus, we have (Model B):

$$\text{minmize } f^{-}=(1)+(2)+(3)+(4) \tag{15}$$

$$(1)=\sum_{t=1}^{T}\sum_{i=1}^{I}Z_{it}^{-}\cdot PES_{it}^{-} \tag{16}$$

$$(2)=\sum_{t=1}^{T}\sum_{k=1}^{K}PV_{kt}^{-}\cdot W_{kt}+\sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{h=1}^{H}p_h\cdot\left(PV_{kt}^{-}+PP_{kt}^{-}\right)\cdot Q_{kth}^{-}+\sum_{t=1}^{T}\sum_{k_r=1}^{K_r}PVR_{k_rt}^{-}\cdot RZ_{k_rt}^{-} \tag{17}$$

$$(3)=\sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{h=1}^{H}p_h\cdot Y_{ktmh}^{-}\cdot EC_{kmt}\cdot IC_{kmt} \tag{18}$$

$$(4)=\sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{h=1}^{H}\sum_{r=1}^{R}\left(W_{kt}+p_h\cdot Q_{kth}^{-}\right)\cdot PT_{rkt}^{-}\cdot CT_{rkt}^{-} \tag{19}$$

subject to:

$$W_{kt}=W_{kt}^{-}+\left(W_{kt}^{+}-W_{kt}^{-}\right)\cdot u_{kt},\forall k,t \tag{20}$$

$$0\leq u_{kt}\leq 1,\forall k,t \tag{21}$$

$$FE_{kt}^{+}\cdot\left(W_{kt}+Q_{kth}^{-}\right)+\sum_{s=1}^{S}D_{ist}^{-}\leq Z_{it}^{-},\forall t,h,i \tag{22}$$

$$\sum_{k=1}^{K}\left(W_{kt}+Q_{kth}^{-}\right)+ZIE_{t}^{-}\geq DTE_{th}^{-},\forall t,h \tag{23}$$

$$W_{kt}\geq Q_{kth}^{-}\geq 0,\forall k,t,h \tag{24}$$

$$W_{kt}+Q_{kth}^{-}\leq ST_{kt}^{-}\cdot\left[RC_k+\sum_{t=1}^{T}\sum_{m=1}^{M}Y_{ktmh}^{-}\cdot EC_{kmt}\right],\forall k,t,h \tag{25}$$

$$RZ_{k_rt}^{-}\cdot\eta_{k_rt}^{+}\geq DTR_{t}^{-}\cdot\beta_{k_rt},\forall t,k_r \tag{26}$$

$$Y_{ktmh}^{-}=\begin{cases}\leq 1\\ \geq 0 \quad \forall k,t,m,h\\ \text{integer}\end{cases} \tag{27}$$

$$\sum_{m=1}^{M} Y_{ktmh}^{-} \leq 1 \quad \forall k, t, h, \tag{28}$$

$$\sum_{k=1}^{K} \left(W_{kt} + Q_{kth}^{-}\right) \cdot PT_{krt}^{-} \cdot \left(1 - \eta_{krt}^{-}\right) \leq EP_{rt}^{-}, \forall t, h, r; \tag{29}$$

$$\sum_{s=1}^{S} \sum_{i=1}^{I} D_{ist}^{-} \cdot INT_{s}^{+} + \sum_{k=1}^{K} \left(W_{kt} + Q_{kth}^{-}\right) \cdot COT_{kt}^{+} \leq EC_{th}^{-}, \forall t, h \tag{30}$$

where Q_{kth}^{-}, Z_{it}^{-}, u_{kt}, and $RZ_{k_rt}^{-}$ are continuous decision variables, and Y_{kthm}^{-} are binary ones. Solution for f^{-} provides the extreme lower bound of system cost under uncertain inputs. Then, the optimized electricity targets would be $W_{ktopt} = W_{kt}^{-} + \Delta W_{kt} u_{kt\,opt}$. Consequently, the submodel (Model C) corresponding to the upper bound of the objective function value (i.e.,f^{+}) is:

$$\text{minmize } f^{+} = (1) + (2) + (3) + (4) \tag{31}$$

$$(1) = \sum_{t=1}^{T} \sum_{i=1}^{I} Z_{it}^{+} \cdot PES_{it}^{+} \tag{32}$$

$$(2) = \sum_{t=1}^{T} \sum_{k=1}^{K} PV_{kt}^{+} \cdot W_{ktopt} + \sum_{t=1}^{T} \sum_{k=1}^{K} \sum_{h=1}^{H} p_h \cdot \left(PV_{kt}^{+} + PP_{kt}^{+}\right) \cdot Q_{kth}^{+} + \sum_{t=1}^{T} \sum_{k_r=1}^{K_r} PVR_{k_rt}^{+} \cdot RZ_{k_rt}^{+} \tag{33}$$

$$(3) = \sum_{t=1}^{T} \sum_{k=1}^{K} \sum_{m=1}^{M} \sum_{h=1}^{H} p_h \cdot Y_{ktmh}^{+} \cdot EC_{kmt} \cdot IC_{kmt} \tag{34}$$

$$(4) = \sum_{k=1}^{K} \sum_{t=1}^{T} \sum_{h=1}^{H} \sum_{r=1}^{R} \left(W_{kt\text{ opt}} + p_h \cdot Q_{kth}^{+}\right) \cdot PT_{rkt}^{+} \cdot CT_{rkt}^{+} \tag{35}$$

subject to:

$$FE_{kt}^{-} \cdot \left(W_{kt\text{ opt}} + Q_{kth}^{+}\right) + \sum_{s=1}^{S} D_{ist}^{+} \leq Z_{it}^{+}, \forall t, h, i \tag{36}$$

$$\sum_{k=1}^{K} \left(W_{kt\text{ opt}} + Q_{kth}^{+}\right) + ZIE_{t}^{+} \geq DTE_{th}^{+}, \forall t, h \tag{37}$$

$$W_{kt\text{ opt}} \geq Q_{kth}^{+} \geq 0, \forall k, t, h \tag{38}$$

$$W_{kt\text{opt}} + Q_{kth}^{+} \leq ST_{kt}^{+} \cdot \left[RC_k + \sum_{t=1}^{T} \sum_{m=1}^{M} Y_{ktmh}^{+} \cdot EC_{kmt}\right], \forall k, t, h \tag{39}$$

$$RZ_{k_rt}^{+} \cdot \eta_{k_rt}^{-} \geq DTR_{t}^{+} \cdot \beta_{k_rt}, \forall t, k_r \tag{40}$$

$$Y_{ktmh}^{+} = \begin{cases} \leq 1 \\ \geq 0 \\ \text{integer} \end{cases} \quad \forall k, t, m, h \tag{41}$$

$$\sum_{m=1}^{M} Y_{ktmh}^{+} \leq 1 \quad \forall k, t, h, \tag{42}$$

$$\sum_{k=1}^{K} \left(W_{kt\text{opt}} + Q_{kth}^{+}\right) \cdot PT_{krt}^{+} \cdot \left(1 - \eta_{krt}^{+}\right) \leq \text{EP}_{\text{rt}}^{+}, \forall t, h, r; \tag{43}$$

$$\sum_{s=1}^{S} \sum_{i=1}^{I} D_{ist}^{+} \cdot INT_{s}^{-} + \sum_{k=1}^{K} \left(W_{kt\text{opt}} + Q_{kth}^{+}\right) \cdot COT_{kt}^{-} \leq EC_{th}^{+}, \forall t, h \tag{44}$$

$$Z_{it}^{+} \geq Z_{it\text{ opt}}^{-}, \forall i, t \tag{45}$$

$$Q_{kth}^{+} \geq Q_{kth\text{ opt}}^{-}, \forall k, t, h \tag{46}$$

$$RZ_{k_rt}^{+} \geq RZ_{k_rt\text{ opt}}^{+}, \forall t, k_r \tag{47}$$

$$Y_{ktmh}^{+} \geq Y_{ktmh\text{ opt}}^{-}, \forall k, t, m, h \tag{48}$$

where Q_{kth}^{+}, Z_{it}^{+} and $RZ_{k_rt}^{+}$ are continuous variables, and Y_{kthm}^{+} are binary ones; $Z_{it\text{ opt}}^{-} Q_{kth\text{ opt}}^{-} RZ_{k_rt\text{ opt}}^{+}$, and $Y_{ktmh\text{ opt}}^{-}$ are solutions of the first submodels. Thus, the solutions for model under the optimized targets can obtain through incorporating the solutions of the two submodels."

3. Case study

The following GHG-emission management problem in energy systems is used to demonstrate the applicability of the developed IFSP model. In this study system, a decision maker is responsible for allocating energy resources/services from multiple facilities to multiple end-users through multiple technologies within a multi-period horizon based on different GHG-emission levels. Based on different GHG-emission mitigation levels (e.g., 0%, 20%, 40%, 60% and 80% of total GHG emissions), managers are considering expected energy and electricity demand to optimize fossil fuel production, manage power generation, and plan the facility expansion. Generally, increasing energy demand can be met through capacity expansion, fuel exploitation, and energy import. However, sustainable development cannot be achieved due to the ever-increasing economic and environmental costs as well as unlimited energy expansion and exploitation. Therefore, the problem under consideration is how to incorporate different GHG mitigation targets into energy system planning.

In the study system, nine planning periods are considered, with each one being five years. Multiple energy resources/technologies need to be allocated to multiple end users (agricultural, transportation, industrial, and municipal/commercial sectors). Conventional energy resources (e.g., coal, diesel, gasoline, crude oil, natural gas) with limited availabilities are employed for meeting the energy demands. In detail, coal is used for power generation, municipal and industrial heat production, agriculture/industry and commercial sectors. Diesel and gasoline are mainly used for transportation activities. Natural gas is used for power generation, municipal and industrial heat production. Renewable energy resources (e.g., solar, wind, nuclear power and hydropower) are mainly employed for power generation. The energy demands of the 5 end users are affected by many uncertainty factors (e.g., the growing population, energy-consumption rate, and related costs); all of those factors will lead to the uncertainties of the energy demands. Furthermore, these uncertainties are complicated by a variety of imprecise information such as socio-economic, environmental and geographic conditions, and energy carrier characteristics. They can hardly be available as deterministic data, which can be expressed as intervals or distribution information. Once these energy sources are determined, costs, efficiencies and capacities of corresponding technologies can be defined.

Under different GHG-mitigation levels, decision-makers are responsible for (i) assigning power load to six conversion technologies (including coal-fired power, gas-fired power, hydropower, wind power, solar power, and nuclear power), and heat load to two conversion technologies (including coal boiler heating technology and nature-gas boiler technology); (ii) planning the capacity expansion of electricity generation; (iii) managing the producing quantities of fossil fuels (including coal, nature gas, crude oil, diesel and gasoline). If energy supply cannot sufficiently meet end-user demands, decision-makers will face a dilemma of either investing more funds on capacity expansion of existing facilities or turning to other energy production options with higher costs.

In this study, GHG is considered as the typical gaseous emission generated from the power conversion, agricultural, transportation, industrial, and municipal/commercial sectors; based on the GHG emission intensity and specific demand by fuel of these sectors, the total amount of GHG emission is calculated. The fuel demand of the five sectors has been predicted in each period, whether or not consider GHG-emission reduction, the fuel supply of the end-use sectors would be determined to meet the fuel demand. Therefore, under the scenarios of GHG-emission reduction, six power generation processes are chosen to decarbonize in the energy system. Meanwhile, GHG emission intensity of these sectors are affected by many uncertain factors (e.g., GHG emission inventory, control measures, related costs), which can be expressed as intervals without distribution information. Availabilities of electricity demand are directly affected by natural fluctuations, which can be presented as probability distributions. Most of the other parameters (such as energy demand, technological efficiency and utilization factors) are expressed as intervals. Table 1 presents the available electricity demands under different probability distributions. The related economic data are shown in Table 2. Table 3 lists GHG emission intensity of the sectors. All of the three tables are shown in Appendix. Besides, coal-fired power has a residual capacity of 1.0 GW, natural gas-fired power has a residual capacity of 0.28 GW, hydropower has a residual capacity of 0.26 GW. The representative costs and technical data are investigated based on governmental reports and other related literature [21,24,43–52].

4. Results and discussion

The objective of the IFSP model is to minimize the expected value of the costs under different GHG mitigation levels over the planning horizon. Solutions provide an effective linkage between the predefined environmental policies and the associated economic implications (e.g., losses and penalties caused by improper policies). The solutions contain a combination of deterministic, interval and distributional information, and can thus facilitate the reflection for different forms of uncertainties [34]. The interval solutions can help managers obtain multiple decision alternatives, as well as provide bases for further analyses of tradeoffs between energy management cost and GHG-emission reduction; the binary-variable solutions represent the decisions of facility expansion, where several alternatives are generated; the continuous variable solutions are related to decisions of electricity generation and energy resources supply.

4.1. Solutions without considering GHG-emission reduction

This case is proposed as a reference one to show the pattern of resource production and system development without constraints on GHG emissions reduction (i.e. 0% GHG-emission reduction).

Fig. 3 shows the results of energy supply schemes under this case. Coal would be the largest energy source among all energy supplies during the planning periods. Because coal demands

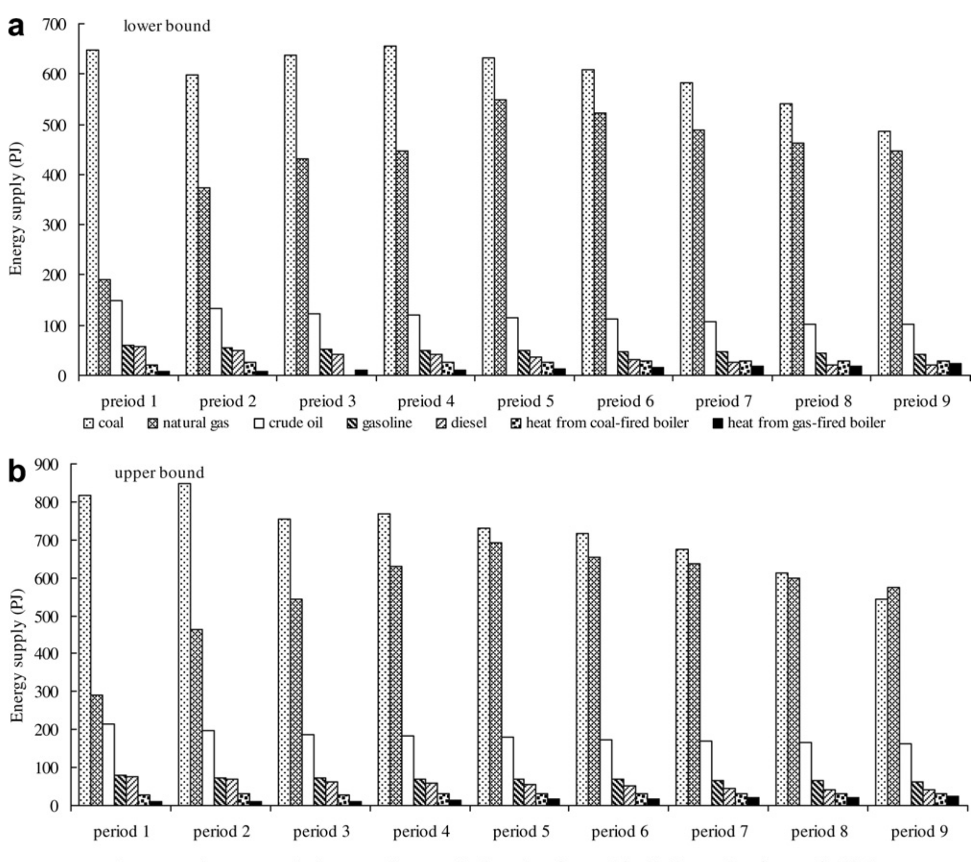

Fig. 3. Results of energy supply without GHG emissions.

fluctuate and coal-fired power generations change, coal supply would fluctuate over the planning horizon, for example, the upper bound would increase from 817.9 PJ in period 1 to 847.3 PJ in period 2, and then decrease from 754.9 PJ in period 3 to 541.9 PJ in period 9. Natural gas needs would increase from [191.7, 284.3] PJ in period 1 to [548.5, 693.1] PJ in period 5, and then decrease to [445.4, 573.6] PJ in period 9. A significant portion of coal and natural gas are directly used by commercial, industry and municipal sectors, which would be used for electricity generation. Diesel and gasoline would mainly be used for transportation. Along with clean fuels use increase in transportation, diesel and gasoline supplies show a downward trend. Diesel supply would decrease from [56.5, 76.5] PJ in period 1 to [20.2, 40.2] PJ in period 9, and gasoline demand would decrease from [61.2, 81.2] PJ in period 1 to [42.9, 62.9] PJ in period 9. Crude oil is refined into gasoline, diesel fuel, gasoline, liquid petroleum gas, propane, ethanol and many other products. Due to diesel and gasoline supplies with a downward trend, the amount of crude oil supply would be reduced from [148.6, 213.6] PJ in period 1 to [101.7, 163.6] PJ in period 9. The heat from coal and natural gas-fired facilities would vary in meeting the increasing residential and commercial heating demands. The coal-fired heat production would fluctuate during the planning horizon, and would always have an advantage over gas-fire one, increasing from [6.9, 8.8] PJ in period 1to [22.4, 24.6] PJ in period 9.

As a part of intermediate energy conversion, the electricity generation technologies include coal-fired power, natural gas-fired power, hydropower, wind power, solar power, and nuclear power. Fig. 4 shows that electricity production would increase steadily over the planning horizon, which would increase from [70.8, 80] $\times$ 10^3 GWh to [154, 165] $\times$ 10^3 GWh. The amount of power load is given in Table 1, which is same as the trend of power increase as shown in Fig. 3. The major power generation technologies include coal-fired power, gas-fired power, hydropower, and nuclear power. The pre-regulated electricity generated by coal-fired power, gas-fired power, and hydropower conversion technologies would increase, and

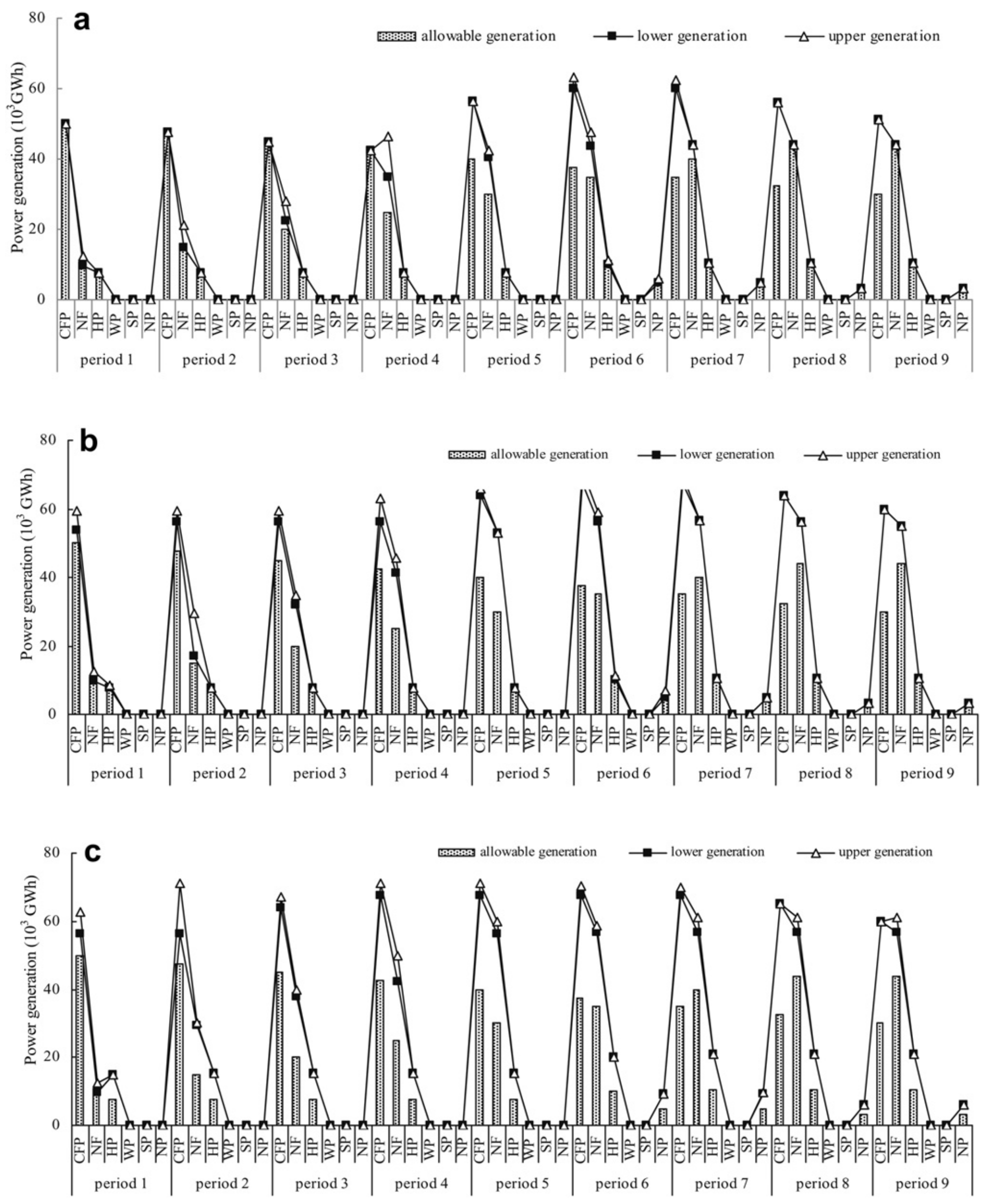

Fig. 4. Amount of power generation without GHG-emission reduction. [(a) low electricity demand, (b) medium electricity demand, (c) high electricity demand] ("CFP", "NFP","HP","WP","SP" and "NP" denote "coal-fired power", "gas-fired power", "hydropower, "wind power", "solar power" and "nuclear power", respectively.)

electricity would be generated primarily by coal-fired facilities. The pre-regulated coal-fired power generation would be decreased from 50.00×10^3 GWh in period 1 to 30.00×10^3 GWh in period 9. For the nature gas-fired power, its pre-regulated targets would be increased from 9.75×10^3 GWh in period 1 to 43.92×10^3 GWh in period 9. For the hydropower, its pre-regulated targets would be 7.50×10^3 GWh in period 1, 7.70×10^3 GWh in periods 2 to 6, 10.00×10^3 GWh in period 7, and 10.45×10^3 GWh in periods 8 and 9. The pre-regulated nuclear power targets would be increased from 0 in periods 1 to 5 to 3.10×10^3 GWh from period 9. The pre-regulated wind and solar power targets would both be zero over the planning horizon. If the electricity targets cannot meet the random demand, excess electricity have to be produced under different demand levels. The excess generation quantities of every power conversion technology would be different from those under the scenario of 0% GHG-emission reduction as shown in Fig. 4. 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. In addition, as the level of electricity demand growth, excess electricity generated by coal-fired power technologies would increase. For example, in period 1, the total electricity generated from coal-fired power facility would be 50.00×10^3 and $[56.25, 62.65] \times 10^3$ GWh under low and high power demand levels, respectively; excess electricity generated by coal-fired power technologies would be 0 GWh under low demand [Fig. 4(a)], and $[6.25, 12.65] \times 10^3$ GWh under high demand [Fig. 4(c)].

Fig. 5 displays the solutions of capacity expansion schemes of each conversion technology under the scenario of 0% GHG-emission reduction in the whole planning horizon. 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 the low demand level, coal-fired power conversion technology would be expanded with

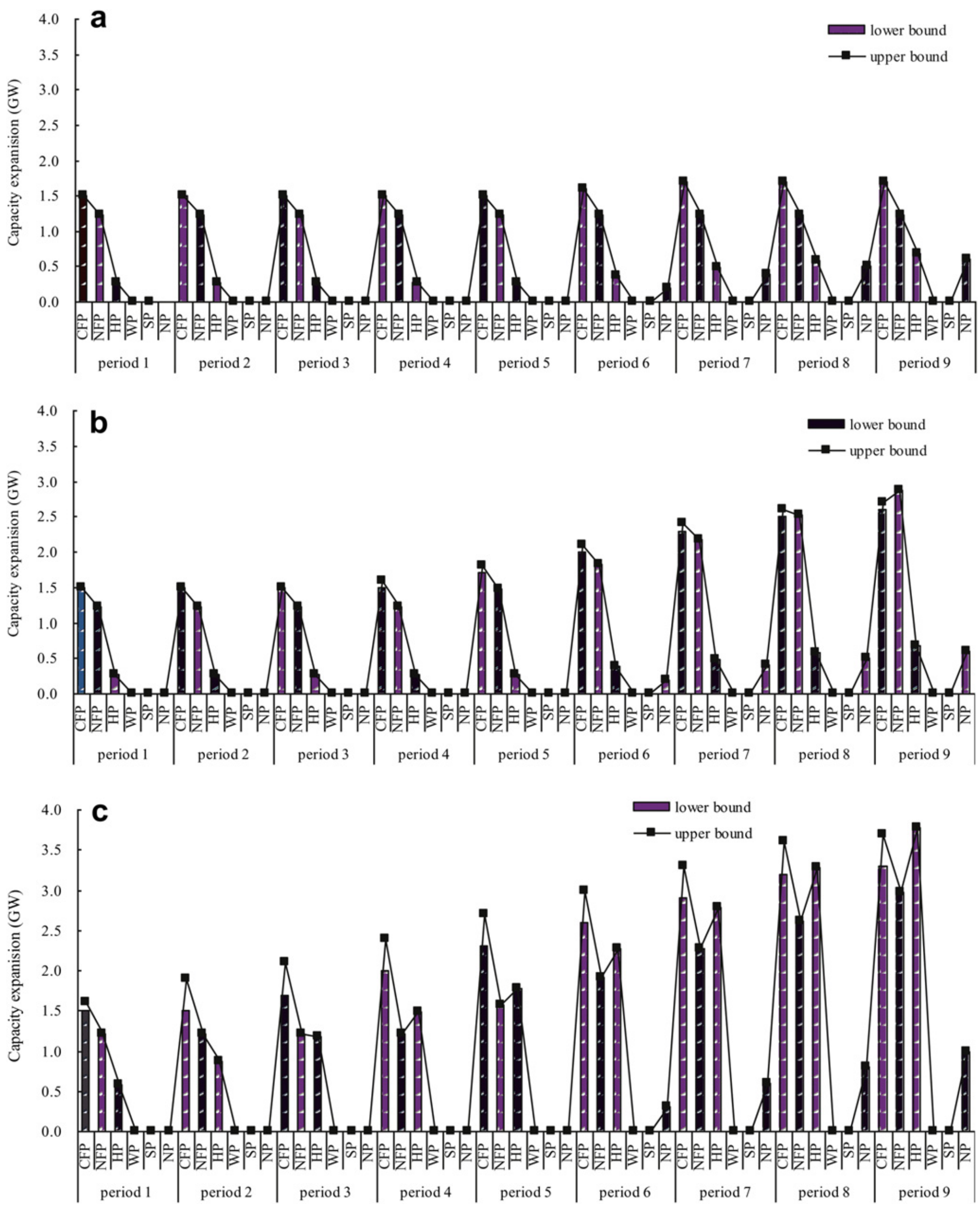

Fig. 5. Capacity of various power generation technologies without GHG emissions reduction. [(a) low electricity demand, (b) medium electricity demand, and (c) high electricity demand].

0.1 GW in periods 6 and 7; installed capacity of gas-fired power would be maintained at 1.22 GW over the planning horizon. Under the medium demand level, coal-fired power facilities would be expanded from [1.70, 1.80] GW in period 5 to [2.60, 2.70] GW in period 9; and the capacity of nature gas-fired power would be expanded from 1.47 GW in period 5 to 2.87 GW in period 9. Under the high demand level, more capacities for electricity generation would be required to meet the increased energy demand, especially for coal-fired power and hydropower generation technologies. For example, in period 9, the hydropower capacity would increase to 3.78 GW, while the capacities of coal-fired and gas-fired power would respectively reach to [3.30, 3.70] and 2.97 GW. It indicates that as the level of power demand growth, the capacity of coal-fired and gas-fired power generation technologies would be expanded more than other technologies, because of low operating and penalty costs, and low capital cost for capacity expansion.

GHG emissions associated with energy-related activities can be categorized into electricity generation, agriculture, residential, commercial, industrial, and transportation sectors. Fig. 6 presents the detailed solutions of GHG emissions by sectors and electricity generation technologies in a 45-year horizon. Different energy resources would be supplied to the five sectors to meet their demands; the amount of GHG emissions would be related to energy activities. Among all the five sectors (agriculture, residential, commercial, industrial, and transportation), the order of GHG emissions from highest to lowest is transportation, agriculture, industry, residential, and commercial. For example, in period 1, the amount of GHG-emission from transportation, agriculture, industry, residential, and commercial would be [2272.8, 3202.8], [1740.0, 2640], [1047.4, 1587.4], [909.4, 1169.4], and [277.8, 592.8] kilotons. The coal-fired power generation technologies would be the largest GHG emission source in the whole planning horizon, and GHG emissions of coal-fired power generation technologies are twice more than natural gas-fired power generation technologies. For example, the largest amount of GHG emissions generated by coal-fired power generation technologies would be [54000.0, 67545.0] kilotons in period 6; and [24018.5, 35292.0] kilotons generated by natural gas-fired power generation technologies in period 6. The total GHG emissions are shown in Fig. 7. It indicates that as the power demand growth during the whole planning horizon, the total amount of GHG emissions would increase from period 1 to 9. Energy system planning with GHG mitigation is based on the total amount of GHG emissions to calculate GHG-emission reduction.

4.2. Solutions under GHG-emission reduction

In this study, four scenarios of GHG-emission reduction are considered (i.e. 20%, 40%, 60%, and 80% of total GHG-emission reduction). The results indicate that increased substantive capacity expansion investment for clean energy (to reduce GHG emissions) could lead to an increased system cost. In this study, coal and natural gas would be supplied based on the results of the scenario of 0% GHG-emission reduction; this is to guarantee the security of energy supplies under uncertainty. Fig. 8 shows coal supply under the different GHG-emission reductions. Compared with the result without considering GHG-emission reduction, the amount of coal

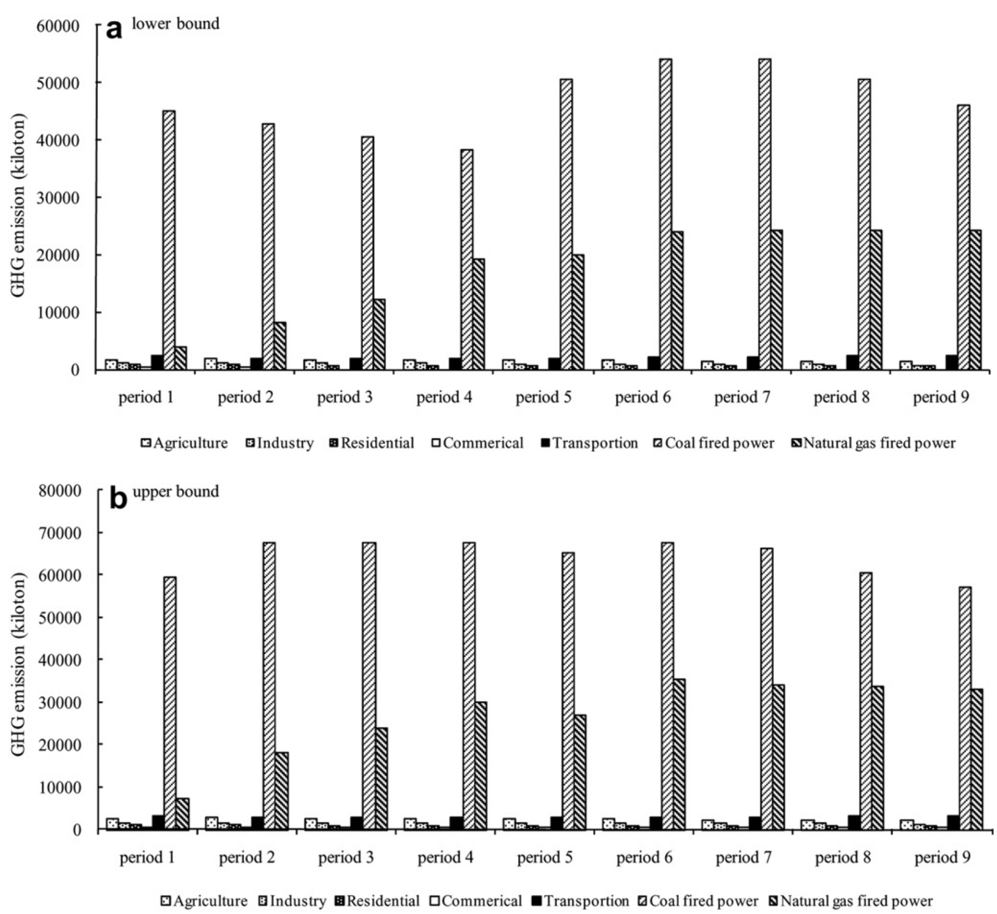

Fig. 6. Amount of GHG emissions in different sectors and electricity generation technologies.

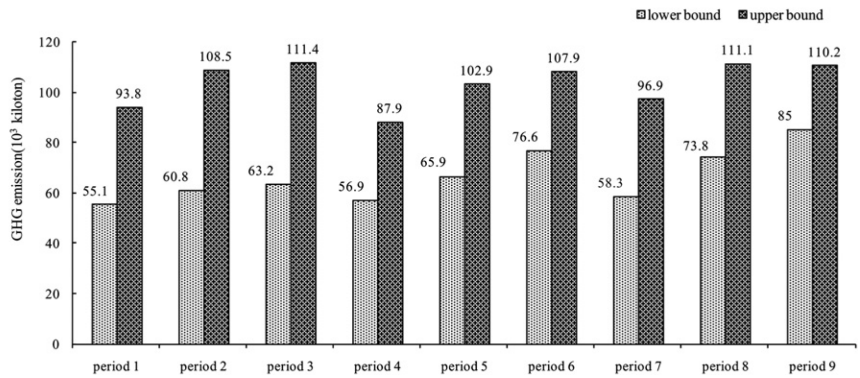

Fig. 7. Amount of GHG emission under different electricity generation technologies.

would be largely decreased, and there would be a significant variation of coal supply. For example, coal supplies would be [647.8, 817.9] PJ under 0% GHG-emission reduction and [12.2, 22.2] PJ under 80% GHG emissions reduction in period 1. This is because, with GHG-emission reduction increasing, strict environmental policies for GHG mitigation management would be adopted. Thus, electricity generated from coal-fired power conversion technologies would significantly decrease. Fig. 9 shows nature-gas supply under different scenarios of GHG-emission reduction. Natural gas supply under scenarios of 20% and 40% GHG-emission reduction would increase insignificantly, compared to that under 0% GHG-emission reduction condition. Conversely, under the scenarios of 60% and 80% GHG-emission reduction, the natural gas would decrease with GHG-emission reduction increasing. For example, in period 5, natural gas supply would be [548.5, 693.1] PJ under 0% GHG-emission reduction, [548.9, 693.1] PJ under 40% GHG-emission reduction, and [206.3, 329.6] PJ under 80% GHG-emission reduction. Compared the two energy resources' supplies under GHG mitigation condition in each period, natural gas supplies would be greater than coal supplies. Therefore, it recommends that natural gas is more popular than coal in considering the case of GHG-emission reduction. This is because the totaling amount of

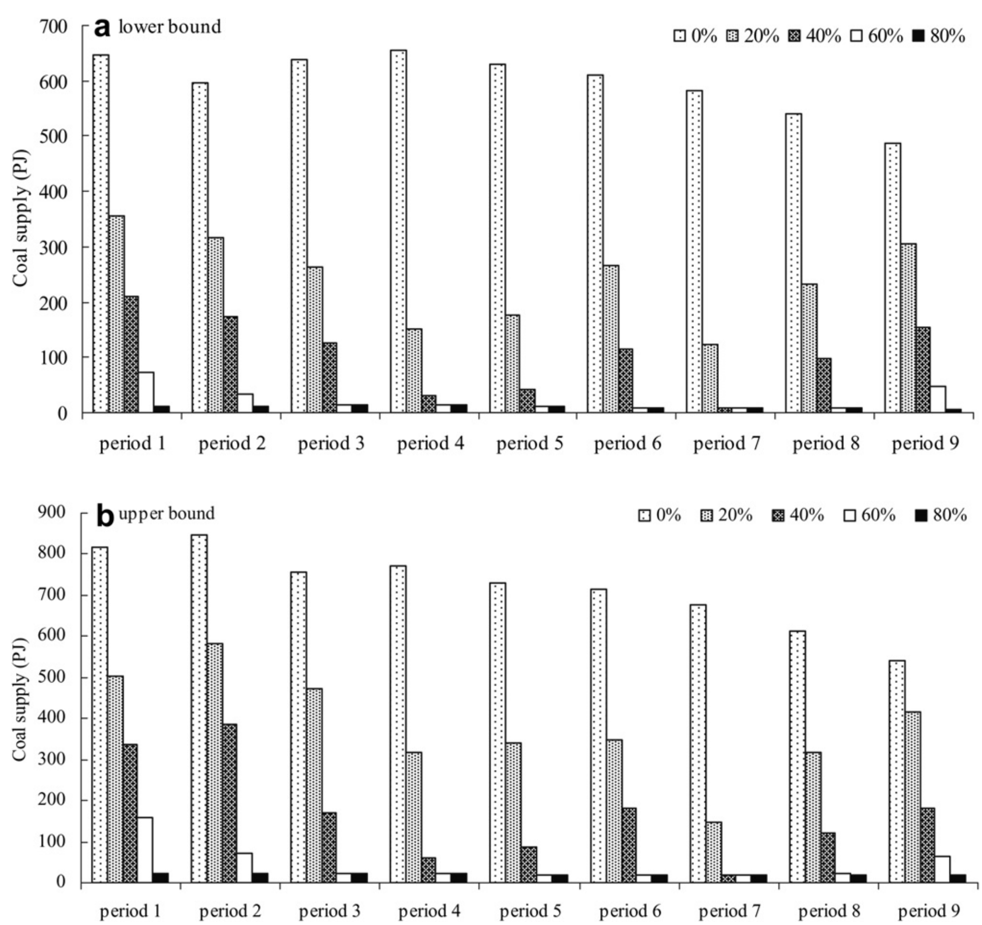

Fig. 8. Coal supply patterns under different GHG reduction scenarios. ("20%", "40%", "60%" and "80%" denote the "scenario under 20% GHG emissions reduction", "scenario under 40% GHG emissions reduction", "scenario under 60% GHG emissions reduction and "scenario under 80% GHG emissions reduction", respectively).

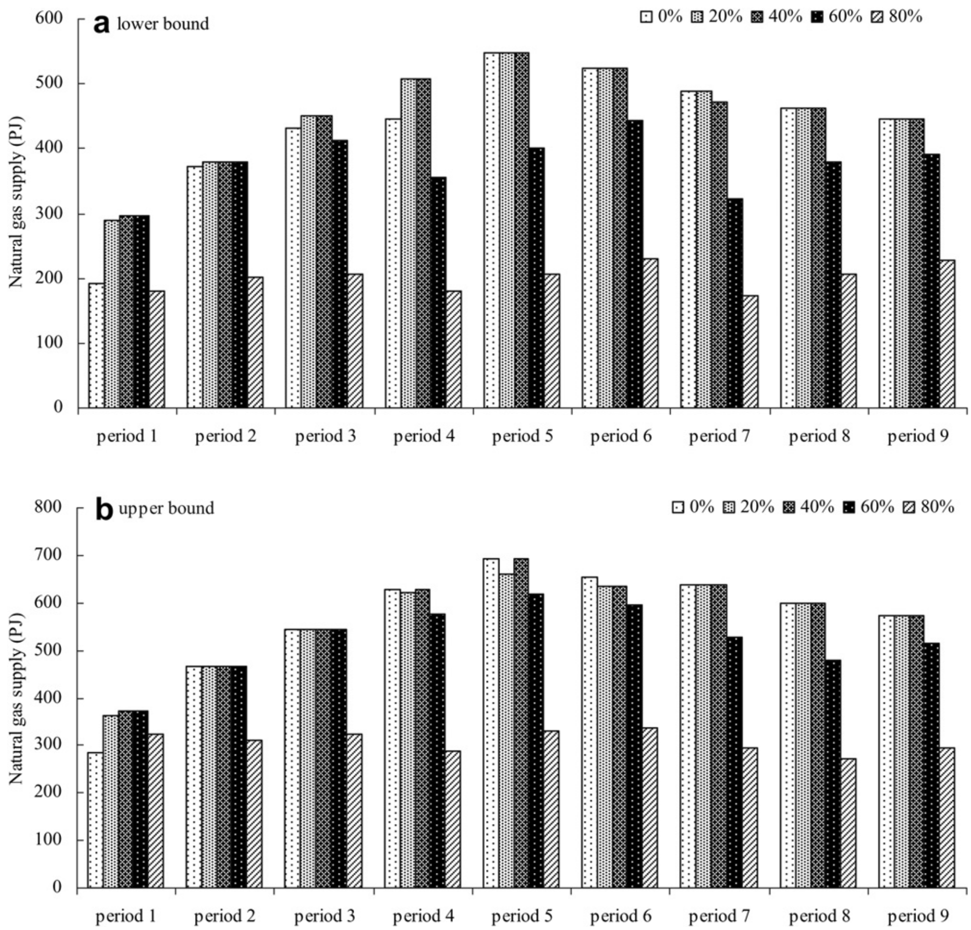

Fig. 9. Nature gas supply patterns under different GHG reduction scenarios.

GHG emissions would be confined with a certain level during the planning periods, while coal-fired power conversion technology corresponds to a higher GHG-emission rate, compared with natural gas-fired conversion technologies. Crude oil is refined into gasoline, diesel fuel, gasoline, liquid petroleum gas, propane, ethanol and many other products to meet the energy demand from agricultural, transportation, industrial, and municipal/commercial sectors. Under different GHG-emission reduction level, the energy demand of the five sectors is not changed in each period, and the objective of the model A is to minimize the system cost, therefore, whether or not consider the GHG-emission reduction, the amount of crude oil is only to meet the demand of the sectors, and not increase or decrease with GHG-emission reduction increasing in each period. Along with clean fuels use increase in transportation, diesel and gasoline supplies show a downward trend, the amount of crude oil supply would be reduced from [148.6, 213.6] PJ in period 1 to [101.7, 163.6] PJ in period 9 under different level of GHG-emission reduction.

Fig. 10 shows the results for power generation under 60% GHG-emission reduction. Coal-fired electricity would no longer be cost-effective option under this scenario. Natural gas-fired power, hydropower, and nuclear power technologies are the main way to generate power. Coal-fired power facilities would be only used in period 1, 2 and 9, solar power facilities would be operated in period 1to 5, and power generations of the two technologies are smaller than other power generation modes. Moreover, the pre-regulated targets for coal-fired power, wind power, and solar power would be different from those under 0% GHG-emission reduction condition. Under 60% GHG-emission reduction, the pre-regulated coal-fired power generation would decrease, being 5.34, 2.11, 0.07, and 2.53×10^3 GWh in periods 1, 2, 8, and 9, and 0 in the rest periods. Wind power technologies would be operated, being 1.60×10^3 GWh in period 1 and 0.80×10^3 GWh in periods 2 to 4; solar power would be adopted in periods 1 to 5, being 3.20×10^3 GWh in each period. The excess power generation would increase with demand level increasing. For example, under the low demand level, the pre-regulated power generation can meet the power demands [Fig. 10(a)]; under high demand level, the excess gas-fired power generation would increase from 10.00×10^3 GWh in period 1 to $[15.87, 20.00] \times 10^3$ GWh in period 3, then increase from $[6.42, 19.58] \times 10^3$ GWh in period 4 to $[10.96, 15.96] \times 10^3$ GWh in period 6, and decrease from $[0, 14.65] \times 10^3$ GWh in period 7 to $[21.19, 26.45] \times 10^3$ GWh in period 9; the excess hydropower and solar power generation would be the same as the pre-regulated power generation in each period [Fig. 10(c)].

Fig. 11 shows the facility expansion schemes under different power demand levels. Under GHG-emission mitigation conditions, the capacity of coal-fired power would be maintained at 1.5 GW without expansion in the low, medium and high power demand level. Through comparing Fig. 11(a), (b), (c), it is indicated that the expansion capacities for the traditional power conversion technologies (e.g., coal-fired power and gas-fired power) would be decreased. The nature gas-fired power technologies would not be expanded and maintained at 1.22 GW under the low level of power demand, and expanded in the condition of medium and high power demand levels. For example, in the scenario of 60% GHG-emission

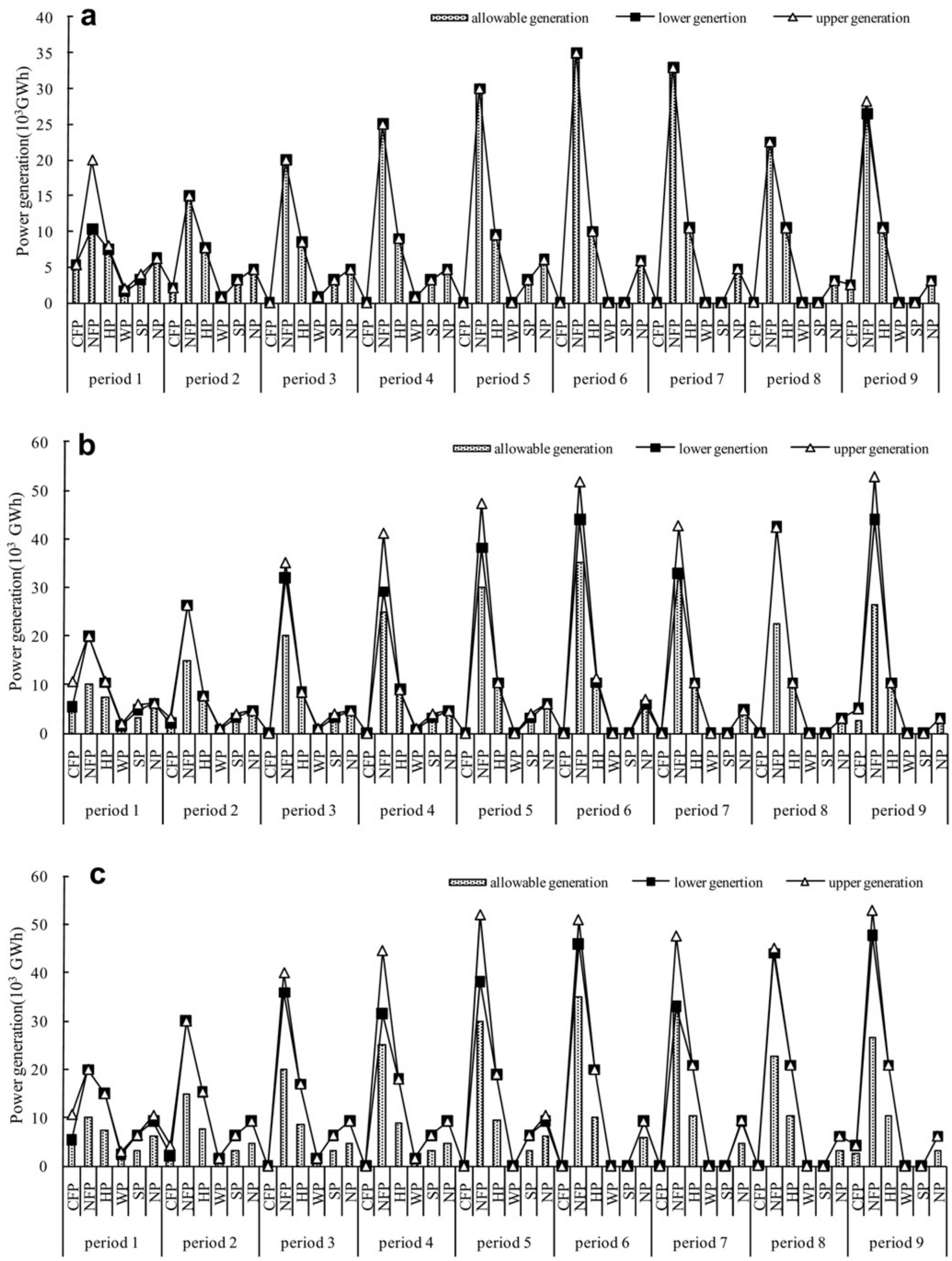

Fig. 10. Amount of power generation with 60% GHG reduction. [(a) low electricity demand, (b) medium electricity demand, and (c) high electricity demand].

reduction, the capacity of nature gas-fired power technologies would be expanded in periods 6 to 9 with medium power demand, being [1.22, 1.37] GW in each period, and enlarged from [1.22, 1.37] GW in period 5 to [1.52, 1.67] GW in period 9 with high power demand. Correspondingly, more renewable power conversion technologies (e.g., hydropower, wind power, solar power, and nuclear power) would be expanded over the planning horizon, especially when the demand levels and GHG-emission reduction requirement are both high. For example, under the condition of low power demand level and 20% GHG-emission reduction, hydropower would be expanded in each period, from 0.28 GW in period 1 to 0.98 GW in period 9 [Fig. 11(a)]; under the condition of high power demand level and 80% GHG-emission reduction, it would be from 0.55 GW in period 1 to 4.38 GW in period 9 [Fig. 11(c)].

4.3. Discussion

Compared the various power generation technologies' contribution to the medium electricity demand, it indicates that different power conversion technologies have varied generation quantities under changed GHG-emission reduction scenarios. As the previous section analysis, coal-fired power would be the most important electricity supply source under 0% GHG-emission reduction. Gas-fired power conversion technology would play the most important part in the electricity generation activities, coal-fired power would be the secondary important electricity supply source, while hydropower and nuclear power would be the supplement under 20% GHG-emission reduction. This is because coal-fired power conversion technology has relatively low

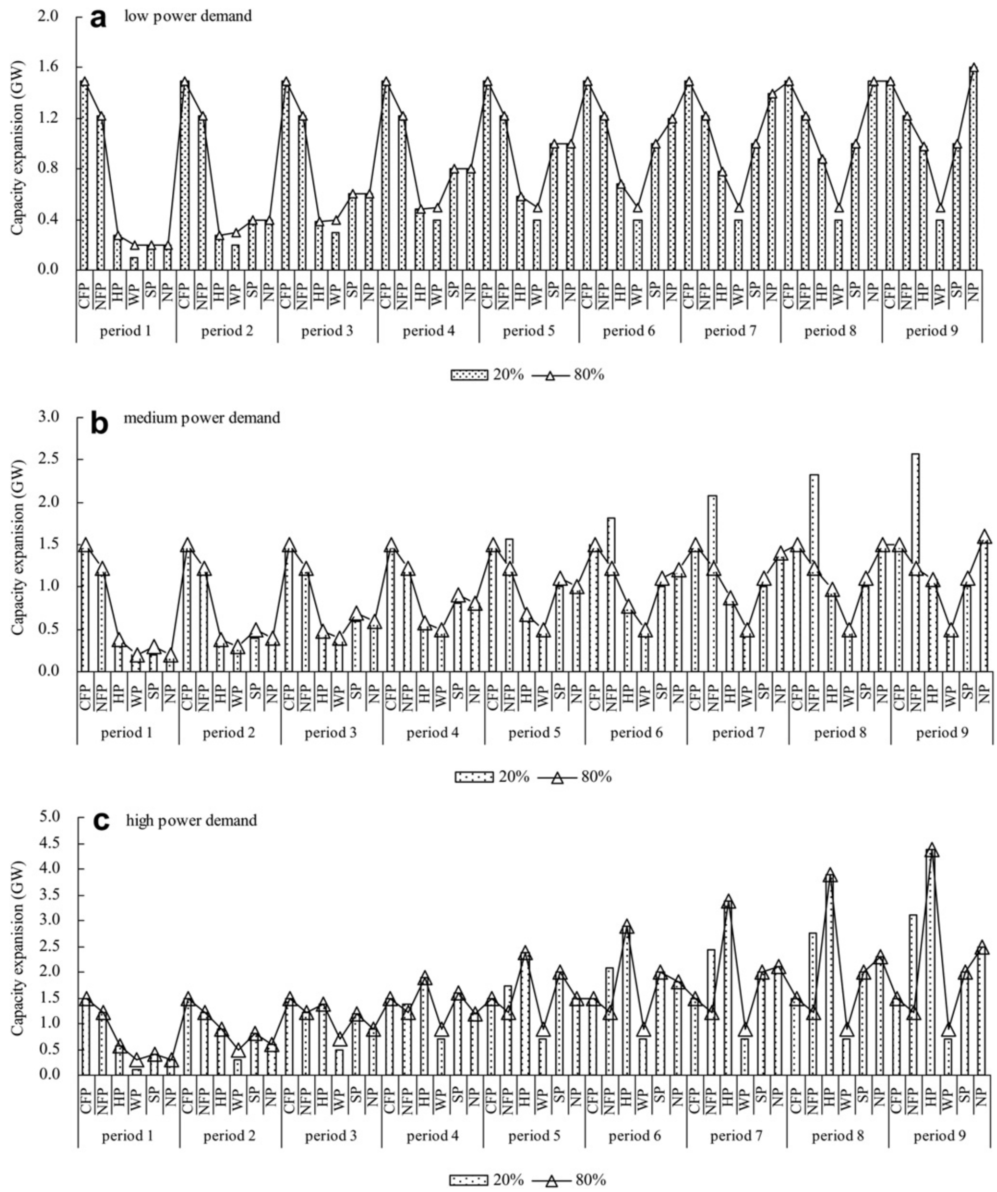

Fig. 11. Facility expansion schemes under different GHG reduction scenarios. [(a) low electricity demand, (b) medium electricity demand, and (c) high electricity demand].

operating and penalty costs and comparatively low capital cost for capacity expansion with higher GHG-emission, and the related cost of gas-fired power conversion technology is slightly higher than coal-fired power and the GHG-emission from gas-fired power generation process is smaller than coal-fired power. The maximum optimized hydropower generation would be 10.45×10^3 GWh in periods 7 to 9; this is due to the relatively high operating cost and 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 dominant role of coal-fired power would be replaced by the other conversion technologies with an increased requirement for GHG-emission reduction. For example, under 80% GHG-emission reduction, the optimized target of coal-fired power would decrease to zero in each period. Although gas-fired power would decrease, and the optimized targets of hydropower, wind power, nuclear power and solar power would have slight increase, gas-fired power and the hydropower would play an important role to meet the power demand. It is indicated that more and more environment-friendly power conversion technologies would be chosen for electricity generation to satisfy the ever-increasing electricity demands and enhancing GHG-emission reduction requirements.

Table 1 shows the imported electricity under different GHG-emission levels. As GHG-emission reduction increasing, coal-fired and gas-fired power would both decrease, and the optimized targets of hydropower, wind, nuclear and solar power would have slightly increase; this would inevitably result in increasing loss of power supply, and capacity expansion and imported power would be the choices to fill the power shortage in the energy system. The total external power would be $[50.9, 108.3] \times 10^3$, $[238.2, 307.6] \times 10^3$, $[425.2, 488.0] \times 10^3$, $[593.9, 652.6] \times 10^3$, and $[803.9, 891.2] \times 10^3$ GWh under the scenarios of 0%, 20%, 40%, 60% and 80% GHG-emission reduction, respectively. From that point, it indicates that as one of the recourse actions to be chosen, imported electricity would not be the first selection under the scenario of 0%

Table 1
Imported power under different scenarios.

Period	GHG-emission reduction level (10^3GWh)				
	0%	20%	40%	60%	80%
$t=1$	0	0	10.4	[22.6, 24.4]	39.3
$t=2$	[0, 3.5]	9.2	[22.7, 26.1]	[36.2, 53.1]	[56.9, 71.9]
$t=3$	[0, 14.5]	[17.1, 21.2]	[31.2, 49.4]	[46.8, 62.7]	[69.8, 84.6]
$t=4$	[0, 3.5]	26.1	[38.7, 50.0]	[58.3, 60.1]	[79.0, 89.4]
$t=5$	[0.6, 8.5]	30.7	[45.3, 52.2]	67.1	[91.1, 98.6]
$t=6$	1.7	41.6	58.6	79.7	[107.6, 109.4]
$t=7$	[5.8, 13.4]	[6.2, 68.7]	[75.7, 82.4]	[96.9, 97.0]	[118.1, 125.8]
$t=8$	[16.4, 26.7]	[56.1, 58.9]	[72.5, 80.7]	[93.8, 107.7]	[120.6, 135.6]
$t=9$	[26.4, 36.8]	51.2	[70.1, 78.3]	[92.5, 100.7]	[121.6, 136.6]

GHG-emission reduction. As GHG-emission reduction increasing, imported electricity would be one of the most important recourses, especially in the scenarios of 60% and 80% GHG-emission reduction. In addition, because of the power demand increasing in the nine periods, whether or not consider GHG mitigation; imported power would increase from period 1 to period 9. For example, under 80% GHG-emission reduction, the imported electricity would increase from 39.3 $\times 10^3$ GWh in period 1 to [121.6, 136.6] $\times 10^3$ GWh in period 9.

As shown in Fig. 12, the system cost would rise up along with increasing GHG-emission reduction. Without GHG emissions reduction, the system cost would be [50259.73, 83197.44] $\times 10^6$ dollar, while the system cost would be [62693.13, 95957.44] $\times 10^6$, [71018.65, 110392.9] $\times 10^6$, [80483.35, 122754.21] $\times 10^6$, [92833.15, 140124.20] $\times 10^6$ dollar under 20%, 40%, 60%, and 80% GHG-emission reduction, respectively. The main reason is that considering restrictions on GHG emission, the traditional power generation technologies (coal-fired power and gas-fired power) would gradually be replaced by hydropower, wind power, solar power, and nuclear power, more and more imported power would be purchased to fill the power shortage. Besides, the increasing electricity demand leads to various power generating facilities to be expanded, bringing about a high capital cost.

The cost of GHG mitigation (per kiloton) would increase, being \$[0.066, 0.107] $\times 10^6$, \$[0.056, 0.114] $\times 10^6$, \$[0.054, 0.116] $\times 10^6$, and \$[0.057, 0.119] $\times 10^6$ under 20%, 40%, 60%, and 80% GHG-emission reduction, respectively. The energy resource supply (including imported electricity) cost would be \$[36669.57, 65222.88] $\times 10^6$, \$[50663.04, 81307.01] $\times 10^6$, \$[52771.09, 96377.59] $\times 10^6$, \$[69158.11, 110652.29] $\times 10^6$, and \$[83752.66, 128644.36] $\times 10^6$ under 0%, 20%, 40%, 60%, and 80% GHG-emission reduction, respectively. This indicates that the strict environmental policies would lead to an increased energy resources supply cost.

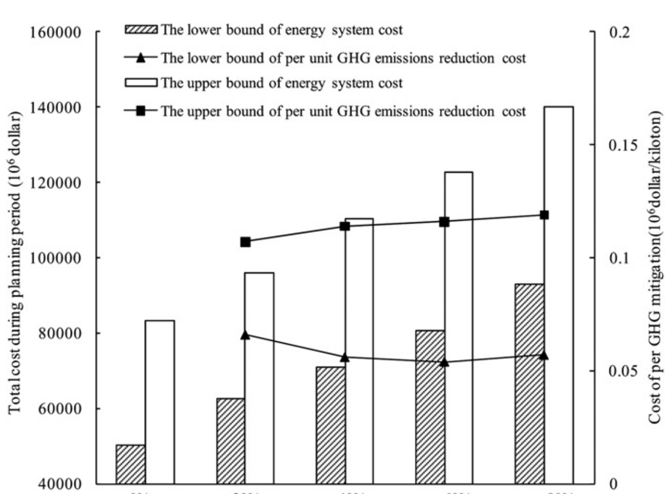

Fig. 12. Costs under different GHG reduction scenarios.

Table 2
Results of energy resources supply from model A without ILP under 0% GHG emissions.

Period	Energy resources (PJ)						
	Coal	Natural gas	Crude oil	Gasoline	Diesel	Coal-fired boiler heat	Gas boiler heat
$t=1$	732.9	241.1	181.1	71.2	66.5	24.9	7.9
$t=2$	722.4	419.3	165.7	64.2	60.2	28.0	8.8
$t=3$	696.3	488.2	154.5	61.4	51.7	27.3	11.1
$t=4$	712.3	537.6	152.2	60.3	50.5	29.0	12.0
$t=5$	680.8	620.8	146.9	59.2	46.2	28.5	14.8
$t=6$	662.4	589.2	143.1	58.1	42.0	30.0	15.8
$t=7$	629.5	562.9	137.7	56.4	36.4	29.4	18.9
$t=8$	576.0	529.9	133.7	55.3	31.7	30.7	19.8
$t=9$	514.4	509.5	132.7	52.9	30.2	29.6	23.5

Without ILP, the GHG-emission management and planning problem can also be solved through fixed-mix stochastic programming approach by replacing the interval parameters by their mid-point values. Although further sensitivity analysis could be undertaken, the model still cannot effectively reflect interactions among various uncertainties since each solution of the energy system can only provide a single response to variations of the uncertain inputs (as shown in Tables 2 and 3). Similarly, if best/worst case submodels are solved, only solutions under two extreme scenarios (i.e. best and worst conditions) are obtained. They are useful for judging the system's capability to realize the desired goal but will not necessarily construct a set of stable intervals for decision variables. Therefore, the best/worst case analysis is not directly useful for generating decision alternatives. It is, in fact, a special type of sensitivity analysis for extreme cases [40].

From the above analyses, it is indicated that the solutions obtained from the IFSP model are able to supporting decisions of energy resources allocation, capacity expansion of electricity generations, and GHG-emission management. The interval solutions are effective to generate decision alternatives which represent various options reflecting environmental-economic tradeoffs. Through planning GHG-emission management in energy systems, cost-effective options can be obtained based on a least-cost strategy. However, if GHG emissions reduction is considered, the pre-regulated targets of energy resources (e.g., coal, nature gas) supply and power generations from various technologies tend to be reallocated, the prearranged capacity-expansion options of electricity generation technologies could be reselected.

Table 3
Imported power under different scenarios from model A without ILP.

Period	GHG-emission reduction level (10^3GWh)				
	0%	20%	40%	60%	80%
$t=1$	0	0	10.4	23.5	39.3
$t=2$	1.8	9.2	22.4	44.7	64.4
$t=3$	7.3	19.2	40.3	54.8	77.2
$t=4$	1.8	26.1	44.4	59.2	84.2
$t=5$	4.6	30.7	48.8	67.1	94.9
$t=6$	1.7	41.6	58.6	79.7	108.5
$t=7$	9.6	37.5	79.1	97.0	122.0
$t=8$	21.6	57.5	76.6	100.8	128.1
$t=9$	31.6	51.2	74.2	96.6	129.1

5. Conclusions

An interval fixed-mix stochastic programming (IFSP) model has been developed for planning GHG-emission management and energy systems under uncertainty. This method is based on an integration of interval-parameter programming (IPP), fixed-mix stochastic programming (FSP), and 0–1 integer programming techniques. It allows uncertainties presented as both probability distributions and interval values to be incorporated within a general optimization framework. Moreover, IFSP can address dynamics of capacity expansion issues and emission-reduction scenarios associated with different levels of economic implications. Probabilistic distributions of electricity demand can be integrated into the optimization process under a series of fixed levels through the introduction of FSP, which has advantages in reflecting uncertainties for large-scale problems with a long planning period. Then, the developed method has been applied to a case of long-term GHG-emission management planning. The results of the case study suggest that the methodology is applicable to reflecting complexities of large-scale energy management systems, and addressing GHG emissions reduction issue with a long planning period.

The proposed method could help energy managers identify desired management policies under various environmental and economic considerations. However, there is still much space for improvement of the proposed model. Compared with other approaches, especially two-stage stochastic programming (TSP) methods, FSP can reflect the dynamic variations of system conditions, especially for sequential structure of large-scale problems, and simplify a large amount of the design scenarios that will normally lead to the problem of “dimension disaster”. This study is attempted to integrate FSP and IPP methods into a general framework, and apply the IFSP for GHG-emission management under uncertainty. The optimization algorithm is also applicable to many other environmental problems where complex uncertainties exist in a long planning period. It is also possible that other programming techniques (such as fuzzy programming and dynamic programming) be integrated with FSP for handling more complicated cases.

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Appendix

Table 1
Electricity targets for users.

Electricity demand (10^3 GWh)			
Level	Low	Medium	High
Probability	0.2	0.6	0.2
$t=1$	[60, 70]	[71, 80]	[81, 90]
$t=2$	[65, 80]	[81, 100]	[101, 120]
$t=3$	[75, 95]	[96, 116]	[117, 137]
$t=4$	[85, 100]	[105, 120]	[125, 140]
$t=5$	[105, 115]	[125, 135]	[140, 155]
$t=6$	[120, 130]	[140, 150]	[155, 160]
$t=7$	[125, 135]	[145, 155]	[160, 175]
$t=8$	[130, 140]	[150, 160]	[165, 180]
$t=9$	[135, 145]	[155, 165]	[170, 185]

Table 2
Economic date.

	$t=1$	$t=2$	$t=3$	$t=4$	$t=5$	$t=6$	$t=7$	$t=8$	$t=9$
Energy sources supply cost ($\$10^6$/PJ, besides the unit of PIE is $\$10^6$/GWh)									
Coal	[2.72,3.32]	[2.56,2.78]	[2.15, 2.25]	[1.90,2.00]	[1.65,1.75]	[1.40,1.50]	[1.15,1.25]	[1.00,1.15]	[0.75,1.00]
Oil	[9.95,11.65]	[8.75,10.55]	[8.25,10.15]	[7.85,9.95]	[7.25, 9.45]	[6.85,9.00]	[6.45,8.75]	[6.00, 8.25]	[5.50,7.75]
Diesel	[10.45,13.40]	[9.95,13.00]	[9.50,12.75]	[8.75,12.25]	[8.50,12.0]	[8.25,11.75]	[7.75,11.25]	[7.25,10.75]	[7.00,10.25]
Gasoline	[12.55,16.00]	[11.75,15.5]	[10.85,14.75]	[10.25,14.25]	[9.75,14.0]	[9.25,13.75]	[9.00,13.25]	[8.25,12.75]	[7.75,12.25]
Natural gas	[3.45, 4.17]	[3.03,3.72]	[2.75,3.30]	[2.69,3.00]	[2.50, 2.75]	[2.25,2.50]	[2.00,2.25]	[1.75,2.00]	[1.50,1.75]
Electricity	[0.145, 0.153]	[0.115,0.13]	[0.095,0.121]	[0.085,0.108]	[0.085,0.1]	[0.075,0.10]	[0.075,0.095]	[0.065,0.085]	[0.055,0.075]
Regular costs for power generation by each power conversion technology ($\$10^3$/GWh)									
Coal	[4.89, 5.78]	[4.27, 5.15]	[3.74,4.56]	[3.25, 4.15]	[2.95,3.95]	[2.75,3.45]	[2.25,3.15]	[2.00,2.95]	[1.85,2.75]
Natural gas	[5.55,6.95]	[4.98,6.37]	[4.36,5.75]	[4.12,5.25]	[3.95,4.85]	[3.70,4.55]	[3.25,4.15]	[3.00,3.85]	[2.75,3.55]
Hydropower	[8.85,10.21]	[7.95,9.33]	[7.55,8.39]	[7.00,7.76]	[6.75,7.15]	[6.25,6.75]	[5.75,6.15]	[5.25,5.85]	[5.00,5.25]
Wind power	[2.57,3.29]	[2.15,2.89]	[1.78,2.46]	[1.55,2.05]	[1.25,1.86]	[1.00,1.53]	[0.79,1.22]	[0.56,0.95]	[0.45,0.75]
Solar power	[2.21,2.97]	[1.96,2.64]	[1.57,2.10]	[1.25,1.85]	[1.00,1.68]	[0.91,1.24]	[0.75,1.00]	[0.55,0.91]	[0.45,0.85]
Nuclear power	[15.0,16.57]	[13.0,14.72]	[11.32,12.00]	[9.75,10.25]	[9.25,9.55]	[8.75,9.15]	[8.25,8.75]	[7.85,8.25]	[7.25,7.75]
Surplus costs for power generation by each power conversion technology ($\$10^3$/GWh)									
Coal	[1.98,2.75]	[1.57,2.29]	[1.18,1.89]	[1.21,1.42]	[0.98,1.13]	[0.65,0.98]	[0.55,0.78]	[0.45,0.75]	[0.35,0.68]
Natural gas	[2.65,3.43]	[2.07,2.88]	[1.66,2.37]	[1.32,2.01]	[1.08,1.86]	[0.94,1.75]	[0.85,1.55]	[0.75,1.20]	[0.65,0.95]
Hydropower	[3.77,4.68]	[3.12,3.99]	[2.76,3.40]	[2.25,3.25]	[2.15,3.05]	[2.00,2.85]	[1.75,2.55]	[1.55,2.25]	[1.25,2.15]
Wind power	[1.56,2.33]	[1.30,1.99]	[1.06,1.72]	[0.86,1.56]	[0.75,1.21]	[0.55,0.95]	[0.45,0.84]	[0.35,0.75]	[0.25,0.70]
Solar power	[0.97,1.25]	[0.78,1.03]	[0.65,0.85]	[0.55,0.80]	[0.45,0.75]	[0.35,0.70]	[0.25,0.65]	[0.15,0.60]	[0.10,0.50]
Nuclear power	[6.57,7.23]	[5.88,6.45]	[5.15,5.75]	[4.75,5.25]	[4.25,4.75]	[4.00,4.55]	[3.75,4.25]	[3.55,3.91]	[3.15,3.52]

Table 3
GHG emission intensity.

Period	GHG emission intensity (kilotonnes/GWh)			GHG emission intensity (kilotonnes/PJ)			
	Coal-fired power	Gas-fired power	Agricultural	Transportation	Industrial	Municipal	Commercial
$t=1$	[0.93,0.98]	[0.60,0.75]	[28.6, 31.5]	[25.3,29.6]	[18.9,23.2]	[17.4,21.9]	[15.4,17.6]
$t=2$	[0.92,0.97]	[0.59,0.74]	[28.4, 31.3]	[25.1,29.4]	[18.7,23.0]	[17.3,21.7]	[15.2,17.5]
$t=3$	[0.91,0.96]	[0.58,0.73]	[28.2,31.1]	[24.8,29.2]	[18.6,22.8]	[17.1,21.5]	[14.0,17.2]
$t=4$	[0.90,0.95]	[0.57,0.72]	[28.0,30.8]	[24.6,29.0]	[18.4,22.6]	[16.9,21.3]	[13.8,17.0]
$t=5$	[0.89,0.94]	[0.56,0.71]	[27.8,30.60]	[24.4,28.8]	[18.2,22.4]	[16.7,21.2]	[13.7,16.8]
$t=6$	[0.88,0.93]	[0.55,0.70]	[27.6,30.4]	[24.2,28.6]	[18.0,22.2]	[16.5,21.0]	[13.5,16.6]
$t=7$	[0.87,0.92]	[0.54,0.69]	[27.4,30.2]	[24.0,28.4]	[17.8,22.0]	[16.3,20.8]	[13.3,16.4]
$t=8$	[0.86,0.91]	[0.53,0.68]	[27.2,30.0]	[23.8,28.2]	[17.6,21.8]	[16.2,20.6]	[13.2,16.2]
$t=9$	[0.85,0.90]	[0.52,0.67	[27.0,29.8]	[23.6,28.0]	[17.4,21.6]	[16.0,20.4]	[13.0,16.0]

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