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Identification of optimal strategies for energy management systems planning under multiple uncertainties

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ABSTRACT

Management of energy resources is crucial for many regions throughout the world. Many economic, environmental and political factors are having significant effects on energy management practices, leading to a variety of uncertainties in relevant decision making. The objective of this research is to identify optimal strategies in the planning of energy management systems under multiple uncertainties through the development of a fuzzy-random interval programming (FRIP) model. The method is based on an integration of the existing interval linear programming (ILP), superiority–inferiority-based fuzzy-stochastic programming (SI-FSP) and mixed integer linear programming (MILP). Such a FRIP model allows multiple uncertainties presented as interval values, possibilistic and probabilistic distributions, as well as their combinations within a general optimization framework. It can also be used for facilitating capacity-expansion planning of energy-production facilities within a multi-period and multi-option context. Complexities in energy management systems can be systematically reflected, thus applicability of the modeling process can be highly enhanced. The developed method has then been applied to a case of long-term energy management planning for a region with three cities. Useful solutions for the planning of energy management systems were generated. Interval solutions associated with different risk levels of constraint violation were obtained. They could be used for generating decision alternatives and thus help decision makers identify desired policies under various economic and system-reliability constraints. The solutions can also provide desired energy resource/service allocation and capacity-expansion plans with a minimized system cost, a maximized system reliability and a maximized energy security. Tradeoffs between system costs and constraint-violation risks could be successfully tackled, i.e., higher costs will increase system stability, while a desire for lower system costs will run into a risk of potential instability of the management system. Moreover, multiple uncertainties existing in the planning of energy management systems can be effectively addressed, improving robustness of the existing optimization methods.
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1. Introduction

Energy planning is crucial for securing technically safe, economically efficient and environmentally friendly energy management systems (EMS) at multiple scales [1]. In the past decades, rising energy demand, increasing environmental- and health-impact concerns, as well as shrinking energy reserves have forced planners to contemplate and propose comprehensive and ambitious plans for EMS [2–6,69,76]. However, such planning efforts are complicated with a variety of processes that should be considered by decision makers, including energy production, import/export, storage, conversion, transmission and consumption. Moreover, these complexities might be multiplied by many uncertain parameters as well as their interactions. Mathematical programming is a conventional tool for EMS planning, mainly in cost minimization problems subject to a series of technological, political and demand-satisfactory constraints [7–15]. It is thus desired to develop effective optimization methods for supporting EMS planning under uncertainty.

Previously, there were many optimization methods for assisting in the formulation of energy management plans throughout the world, which were effective in providing optimal decision alternatives under varying system conditions [16–29]. For example, the Brookhaven Energy System Optimization Model (BESOM) was used to identify optimal mixing patterns of energy sources, technologies and investments within an energy management system under the minimized economic cost [21,30,31]. The Time-stepped Energy System Optimization Model (TESOM) was proposed as a consecutive BESOM-type optimization modeling system for supporting energy management [32]. The Market Allocation Model (MARKAL) was developed as a large-scale, technology-oriented energy-activity analysis modeling system. Based on MARKAL, sectors of energy

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production, conversion, processing, transmission and consumption can be incorporated within a general framework to help formulate cost-effective energy-related plans [23,24,27,33–35]. The Multiple Energy System of Australia (MENSA) was developed to identify optimal combinations of demand- and supply-side technologies under the objective of the least economic cost [36]. The Energy Flow Optimization Model (EFOM) was established as an engineering-oriented bottom-up model for national energy management systems planning and was widely used in many European countries [31,37–40]. There were also a number of software packages, such as the Long-range Energy Alternatives Planning System (LEAP), the New Earth 21 Model (NE21), the National Energy Modeling System (NEMS) and the Energy 2020, which were developed for evaluating environmental and economic effects of various energy activities [22,41–44]. Moreover, in order to deal with facility expansion issues within EMS planning problems, mixed integer linear programming (MILP) through the adoption of binary variables was frequently employed to help decide whether or not particular facility expansion options should be undertaken [61,72–75]. However, most of these studies can hardly reflect complex linkages that exist among different energy activities and their socio-economic and environmental implications in a multi-sector, multi-period, and multi-objective context. Also, they cannot effectively handle multiple forms of uncertainties associated with dynamics of system conditions (e.g., temporal and/or spatial variations of energy resources and their associated economic implications).

In comparison, interval linear programming (ILP) can deal with uncertainties in objective function and system constraints which can be expressed as interval without distribution information. In this method, interval numbers are acceptable as its uncertain inputs [45–54]. ILP can be transformed into two deterministic submodels, which correspond to the lower and upper bounds of the objective function value [45–48,55,56]. It improves upon the existing methods with the following natures: (i) it allows uncertainties to be directly communicated into the optimization process and resulting solutions and (ii) it does not lead to more complicated intermediate models, and thus has a relatively low computational requirement [48]. In the past decade, ILP was successfully applied to the management of municipal solid waste, water resources and air quality; however, few applications to energy systems planning were reported [46,56,59–71,76,77]. Moreover, ILP has the following shortcomings: (a) it may become infeasible when the right-hand sides are highly uncertain [49–52]; (b) it cannot tackle uncertainties expressed as possibilistic and/or probabilistic distributions, leading to the loss of valuable information in many real-world planning problems; and (c) it encounters difficulties when multiple uncertainties embedded within an individual parameter (e.g., when the lower and upper bounds of interval numbers are available as possibilistic and/or probabilistic distributions rather than deterministic values).

On the other hand, superiority–inferiority-based fuzzy-stochastic programming (SI-FSP) was developed for handling uncertainties expressed as possibilistic and/or probabilistic distributions in both objective function and system constraints [57–61]. Through this method, uncertainties expressed as fuzzy-random variables (FRV) can be effectively addressed; onerous computational efforts as required by conventional fuzzy mathematical programming and stochastic programming methods can also be greatly reduced. It can directly reflect relationships among fuzzy/fuzzy-random coefficients through varying superiority and inferiority degrees (instead of discrete intervals under varying α-cut levels). Then through quantification of penalties associated with potential constraint violations (due to possibilistic and/or probabilistic uncertainties), the original model can be transformed into a deterministic one. The primary advantage of SI-FSP lies in its efficiency in addressing uncertain parameters in both objective function and constraints without oversimplification of uncertainties which exist as possibilistic and/or probabilistic distributions as well as their combinations into intervals with deterministic boundaries. In the SI-FSP model, the uncertain information can be modeled as fuzzy sets, probability distributions and their combinations. Solution approach for SI-FSP is based on the computation of varied degrees of superiority and inferiority for the objective function and each constraint, which are substantially efficient compared with conventional fuzzy mathematical programming methods. Although SI-FSP has strength in computational efficiency, there are few researchers introduced it to engineering problems. Also, it can hardly handle multiple uncertainties which can be expressed as intervals, possibilistic and/or probabilistic distributions, as well as their combinations. One potential approach for better accounting for the uncertainties associated with energy management systems is to incorporate the ILP and SI-FSP methods within a general modeling framework. Moreover, since these two methods cannot deal with facility expansion issues which are frequently involved in EMS planning problems, MILP is introduced through adopting a number of binary variables which are used to indicate whether or not particular facility expansion options are to be undertaken. This leads to a fuzzy-random interval programming (FRIP) model for EMS planning under multiple uncertainties.

Therefore, the objective of this study is to identify optimal strategies for the planning of EMS under multiple uncertainties (i.e., intervals, possibilistic and probabilistic distributions, as well as their combinations) through the development of such a fuzzy-random interval programming (FRIP) model. It can not only deal with uncertainties expressed as fuzzy-random variables and discrete intervals in both objective function and constraints, but also reflect multiple formats of uncertainties within an individual parameter, improving upon capabilities of the existing methods in terms of uncertainty reflection. FRIP can also be used for facilitating the generation of a range of decision alternatives, which are helpful for decision makers to formulate desired plans under uncertainties. A case study will then be provided for demonstrating applicability of the developed method. The results can help decision makers not only discern optimal energy-allocation patterns, but also gain deep insights into the tradeoffs between energy-security and economic objectives. In detail, this study will: (a) tackle competitive and interactive relationships among various sectors and processes of EMS in a region, (b) search for optimal patterns of energy generation, conversion and consumption, as well as facility capacity-expansion schemes under the minimized economic costs, (c) generate a number of decision alternatives under various system conditions, allowing comprehensive analysis of tradeoffs between relevant objectives, (d) facilitate the reflection of multiple forms of uncertainties in EMS, and (e) apply the proposed FRIP to long-term EMS planning.

2. Uncertainties and complexities in energy management systems

Energy is critical in supporting our daily life and continued human development [4]. Although great successes have been achieved, more than two billion people are still lacking of sufficient energy supply across the world [2,4–6,62]. On the other hand, large-scale energy activities without science-based planning have been of increasing concerns, causing great impacts on environment, ecosystem and human health. Also, economic costs and environmental objection to exploitation and consumption of conventional energy resources are enormous, posing as the major challenge for decision makers. Since economic and environmental performances of transferring different energy resources from the supply side to the demand ones are varied; identification of desired energy-flow patterns under the minimized economic cost is thus an important aspect of EMS planning. Nonetheless, two levels of complexities exist within the energy management systems.

Firstly, management of energy sources has complex interactions with many components of a region, such as environment, ecosystem and socio-economy. Generally, energy activities/services are responsible for relevant infrastructural investments and pollutant/GHG emissions, and conversely have impacts on local environment and ecosystems. Likewise, institutional measures and socio-economic activities have effects on energy management through various policies, actions and strategies, which would then have direct/indirect impacts on the components of the region. On the other hand, there are limited energy resources (particularly for locally available renewable energy resources) and economic investments, which implies necessity for efficient utilization of them. EMS planning is thus imperative for designing a variety of system activities under these limited "allowances" for energy allocation and resource consumption, as well as realizing desired socio-economic and environmental objectives (Fig. 1).

Secondly, relationships among different energy sectors (energy production, processing, transmission and consumption) and the related activities/services are complex in EMS. It is indicated that most of the sectors are interrelated to each other. Any changes in one sector would lead to a series of consequences to and responses from the others, resulting in variations in system costs. In planning such systems, independent consideration of one or several sectors would be unable to completely reflect the overall system characteristics. This means that a satisfactory plan for one or several sectors may not be unacceptable for the entire system if some significant factors/components are neglected. Therefore, employment of optimization methods for EMS planning would be essential for facilitating the reflection of such complexities. At the same time, interactive relationships exist among various energy-related activities and services, with varying economic and security implications (Fig. 2). If there are any changes in an activity, a series of consequences to the other activities and the associated economic costs and energy-supply security would be followed. For example, if local availabilities of renewable energy resources are insufficient to meet end-user energy demand, a certain degree of energy-supply risk may exist. This would result in shifts of the existing technologies/resources over a long term and induce additional economic cost. However, among the activities and the costs, as well as the incurred risks, there may exist potential compromises which can lead to optimal allocation of energy activities/services with satisfactory energy-supply security and minimized system cost. Consequently, in planning energy management systems, systematic analysis of the related resources, environmental and socio-economic objectives under various system conditions should be undertaken.

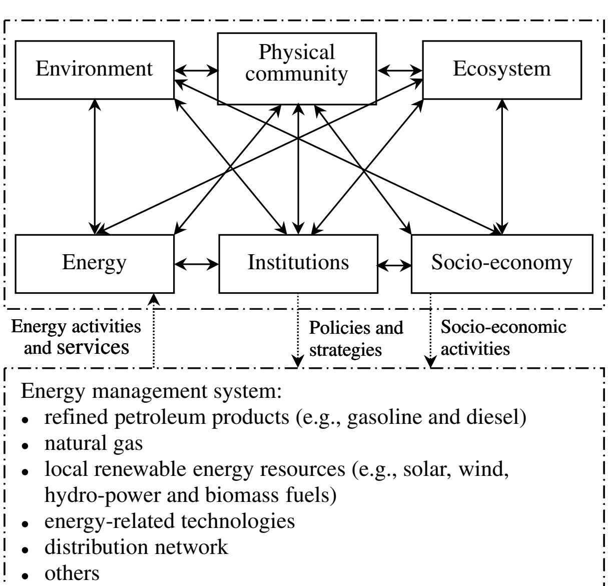


Fig. 1. Interactive relationships among different components in a region.

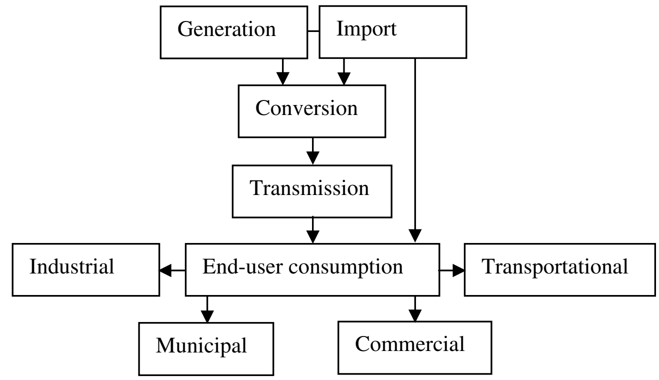


Fig. 2. Interactive relationships within an energy management system.

Moreover, there are a variety of uncertainties existing not only in energy production, supply, conversion, transmission and consumption, but also in many factors of these processes. Accordingly, effectively dealing with these uncertainties is of great significance to decision makers. Basically, these uncertainties can be classified into the following categories:

(a) Intervals, which can be expressed as $a^{\pm}$(or $[a^-, a^+]$, representing a number have a maximum value of a^+ and a minimum value of a^- without distribution information of a). Such an interval can be defined as: $a^{\pm} = [a^-, a^+] = [x \in \ a | a^- \leq x \leq a^+]$ where a^- and a^+ are the lower and upper bounds of $a^{\pm}$, respectively. When $a^- = a^+$, $a^{\pm}$ becomes a deterministic number, i.e., $a^{\pm} = a^- = a^+$. The interval numbers can be used for describing uncertain information of planning issues which fluctuates within a range without distribution information. In fact, many parameters in EMS can hardly be acquired as deterministic values. One of the easiest but might not the best ways for defining these parameters is to express them as such intervals with unknown distributions. For example, estimation of energy reserves in a region is highly uncertain due to economic and technological issues. In order to determine parameters related to energy reserves, decision makers might be unable to express a deterministic value, instead he might be able to say "the estimated natural gas reserve in this region would be [110.0, 230.0] PJ". This represents that the minimum and maximum reserves of natural gas would be 110.0 and 230.0 PJ in the study region, respectively.

(b) Fuzzy sets, which can be expressed as $\tilde{x}$ with a membership function $\mu(x)$, representing an interval with possibilistic distributions. Such fuzzy sets can be used for reflecting uncertain information which can be expressed as intervals subject to known possibilistic distributions. For uncertain parameters in EMS planning problems, intervals without possibilistic distributions may lead to a certain degree of oversimplification, resulting in the loss of valuable information. In contrast, fuzzy sets can remedy this shortage and improve uncertainty reflection of pure intervals. For example, as for the natural gas reserves, decision makers may still insist on "the estimated natural gas reserve in this region would be [110.0, 230.0] PJ" with additional information as "the most possible amount is 170.0 PJ and there is no possibility that the reserve of natural gas is lower than 110.0 PJ or more than 230.0 PJ", such that a triangle fuzzy number is assigned.

(c) Probability distributions, which can be expressed as $x(t)_\omega$ with a known distribution function $f(x)$. In fact, many parameters can be expressed as probability distributions during the process of EMS planning. Particularly, based on historical records and literature review, energy prices over a specific period can be expressed as certain types of probability distributions. These distributions can be described by either continuous functions or discrete values. For instance, in real-world cases, probability levels of low (8.0 $ per unit), low to medium ($9.0 per unit), medium ($10.0 per unit), medium to high ($11.0 per unit), and high energy prices ($12.0 per unit) could be 0.1, 0.2, 0.4, 0.2, and 0.1, respectively.

(d) Multiple uncertainties, which are combinations of the dual and/or more uncertainties (interval, possibilistic and probabilistic distributions). For example, when the boundaries of an interval number can merely be expressed as fuzzy sets, this leads to dual uncertainties, i.e., fuzzy boundary intervals. Meanwhile, when estimating lower and upper bounds of an interval parameter, different decision makers may have different subjective judgments; this leads to a variety of fuzzy sets subject to a certain type of probability distribution, representing multiple uncertainties. Such uncertainties can be described through fuzzy-random variables (FRV). Considering energy prices over a specific period, we can assume that the probability levels associated with low, low to medium, medium, medium to high, and high energy prices could be 0.1, 0.2, 0.4, 0.2, and 0.1, respectively. Under each individual probability level, a triangle fuzzy number can be assigned as: (i) low (the most possible price is $10.0 per unit, and there is no possibility for the price to be lower than $9.0 per unit or higher than $11.0 per unit), (ii) low to medium (the most possible price is $11.0 per unit, and there is no possibility for the price to be lower than $10.0 per unit or higher than $12.0 per unit), (iii) medium (the most possible price is $12.0 per unit, and there is no possibility for the price to be lower than $11.0 per unit or higher than $13.0 per unit), (iv) medium to high (the most possible price is $13.0 per unit, and there is no possibility for the price to be lower than $12.0 per unit or higher than $14.0 per unit), and (v) high (the most possible price is $14.0 per unit, and there is no possibility that the price is lower than $13.0 per unit or higher than $15.0 per unit). Such imprecise information can then lead to a fuzzy-random variable which is composed of five fuzzy sets under corresponding probabilities, reflecting multiple uncertainties associated with energy prices over a specific period.

Thus, there are multiple uncertainties in the planning of EMS, which can be expressed as intervals, fuzzy sets, probability distributions as well as their combinations. Such uncertainties further complicate the planning problems. Obviously, simple decision process based on direct analysis or expert consultation would not be satisfactory enough for effectively addressing system complexities and uncertainties. Therefore, development of suitable systems analysis approaches to integrate a variety of components (objectives, constraints and activities) into a general modeling framework is desired. The systems analysis methods should also be able to reflect interactive, complex, dynamic and uncertain features of EMS. Moreover, outputs from such methods can then be interpreted for generating desired planning alternatives, as well as formulating policies and strategies.

3. Methodology

3.1. Interval linear programming

ILP is an effective method for dealing with uncertainties existing as interval values without distribution information [49]. An interval number ($a^\pm$) can be expressed as $[a^-, a^+]$, representing an interval which can have a maximum value of a^+ and a minimum one of a^-. A set of basic definitions for interval numbers was described in [45]. And then, an interactive solution process was proposed to solve the ILP model [47,48]. According to Huang et al., an ILP model can be written as follows [45]:

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

$$\text{subject to:} \quad A^\pm X^\pm \leq B^\pm \tag{1b}$$

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

where $A^\pm \in \{R^\pm\}^{m\times n}$, $B^\pm \in \{R^\pm\}^{m\times 1}$, $C^\pm \in \{R^\pm\}^{1\times n}$, $X^\pm \in \{R^\pm\}^{n\times 1}$, and $R^\pm$ denotes a set of interval numbers.

An interactive solution algorithm was developed to solve the above problem through analyzing the detailed interrelationships between parameters and decision variables and between the objective function and constraints. The solution for model (1) can be obtained through a two-step method, where a submodel corresponding to f^- (when the objective function is to be minimized) is first formulated and solved, and then the relevant submodel corresponding to f^+ can be formulated based on the solutions of the first submodel. In detail, the first submodel can be formulated as follows (assume that $b_i^\pm > 0$, and $f^\pm > 0$) [45,47,48]:

$$\text{Min} \quad f^- = \sum_{j=1}^{k_1} c_j^- x_j^- + \sum_{j=k_1+1}^{n} c_j^- x_j^+ \tag{2a}$$

$$\text{subject to:} \quad \sum_{j=1}^{k_1} |a_{ij}|^+ Sign\left(a_{ij}^+\right) x_j^- + \sum_{j=k_1+1}^{n} |a_{ij}|^- Sign\left(a_{ij}^-\right) x_j^+ \leq b_i^+ \quad \forall i \tag{2b}$$

$$x_j^\pm \geq 0 \quad \forall j \tag{2c}$$

where $x_j^\pm$, $j = 1, 2, \ldots, k_1$, are interval variables with positive coefficients in the objective function, and $x_j^\pm$, $j = k_1 + 1, k_1 + 2, \ldots, n$, are interval variables with negative coefficients in the objective function. Thus, solutions of $x_{j\,\text{opt}}^-$ ($j = 1, 2, \ldots, k_1$) and $x_{j\,\text{opt}}^+$ ($j = k_1 + 1, k_1 + 2, \ldots, n$) can be obtained through solving submodel (2). Then the submodel corresponding to f^+ can be formulated as follows (assume that $b_i^\pm > 0$, and $f^\pm > 0$):

$$\text{Min} \quad f^+ = \sum_{j=1}^{k_1} c_j^+ x_j^+ + \sum_{j=k_1+1}^{n} c_j^+ x_j^- \tag{3a}$$

$$\text{subject to:} \quad \sum_{j=1}^{k_1} |a_{ij}|^- Sign\left(a_{ij}^-\right) x_j^+ + \sum_{j=k_1+1}^{n} |a_{ij}|^+ Sign\left(a_{ij}^+\right) x_j^- \leq b_i^- \quad \forall i \tag{3b}$$

$$x_j^\pm \geq 0 \quad \forall j \tag{3c}$$

$$x_j^+ \geq x_{j\,\text{opt}}^-, \quad j = 1, 2, \ldots, k_1 \tag{3d}$$

$$x_j^- \leq x_{j\,\text{opt}}^+, \quad j = k_1 + 1, k_2 + 2, \ldots, n \tag{3e}$$

Hence, solutions of $x_{j\,\text{opt}}^+$ ($j = 1, 2, \ldots, k_1$) and $x_{j\,\text{opt}}^-$ ($j = k_1 + 1, k_1 + 2, \ldots, n$) can be obtained through solving submodel (3). Thus, we can have the final solution of $f^\pm_{\text{opt}} = [f^-_{\text{opt}}, f^+_{\text{opt}}]$ and $x_{j\,\text{opt}}^\pm = \left[x_{j\,\text{opt}}^-, x_{j\,\text{opt}}^+\right]$.

3.2. Superiority–inferiority-based fuzzy-stochastic programming

According to Zimmerman and Van Hop [57,63], let $\widetilde{T}$ be a family of triangular fuzzy numbers which can be defined as follows:

$$\widetilde{T} = \{\tilde{\delta} = (\delta, a, b), a, b \geq 0\} \quad \text{and}$$

$$\mu_{\tilde{\delta}}(x) = \begin{cases} \max\left(0, 1 - \frac{\delta - x}{a}\right) & \text{if } x \leq \delta, \quad a > 0 \\ 1 & \text{if } a = 0 \quad \text{and/or} \quad b = 0 \\ \max\left(0, 1 - \frac{x - \delta}{b}\right) & \text{if } x > \delta, \quad b > 0 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

where scalars a and b ($a, b \geq 0$; $a,b \in R$) are named the left and right spreads, respectively. A crisp (i.e., deterministic) number ($\delta \in R$) can be illustrated as a triangular fuzzy set $\tilde{\delta} = (\delta, 0, 0)$.

Based on the above definitions, a method for comparing fuzzy sets can be proposed through measuring superiority and inferiority degrees. Beginning with the α-cut levels of two fuzzy sets ($\widetilde{P}$ and $\widetilde{Q}$) as shown in Fig. 3, we have [57]

$$\widetilde{P}_\alpha = \mu_{\widetilde{P}}(x) \geq \alpha \tag{5a}$$

$$\widetilde{Q}_\alpha = \mu_{\widetilde{Q}}(x) \geq \alpha \tag{5b}$$

If $\widetilde{P}_\alpha \leq \widetilde{Q}_\alpha$, then $\sup\{s : \mu_{\widetilde{Q}}(s) \geq \alpha\} - \sup\{t : \mu_{\widetilde{P}}(t) \geq \alpha\} \geq 0$.

Therefore, the total superiority of $\widetilde{Q}$ over $\widetilde{P}$ is defined as the area of $\widetilde{Q}$ larger than $\widetilde{P}$. Mathematically, this area can be presented as follows [57]:

$$S = \begin{cases} \int_0^1 \{\sup\{s : \mu_{\widetilde{Q}}(s) \geq \alpha\} - \sup\{t : \mu_{\widetilde{P}}(t) \geq \alpha\}\} d\alpha \geq 0 & \text{if } \widetilde{Q} \geq \widetilde{P} \\ 0 & \text{otherwise} \end{cases} \tag{6a}$$

Similar result can also be obtained for the inferior degree of $\widetilde{P}$ to $\widetilde{Q}$:

$$I = \begin{cases} \int_0^1 \{\inf\{s : \mu_{\widetilde{Q}}(s) \geq \alpha\} - \inf\{t : \mu_{\widetilde{P}}(t) \geq \alpha\}\} d\alpha \geq 0 & \text{if } \widetilde{Q} \geq \widetilde{P} \\ 0 & \text{otherwise} \end{cases} \tag{6b}$$

Thus, the superiority of $\widetilde{Q}$ over $\widetilde{P}$ can be defined as

$$S(\widetilde{Q}, \widetilde{P}) = \int_0^1 \max\{0, \sup\{s : \mu_{\widetilde{Q}}(s) \geq \alpha\} - \sup\{t : \mu_{\widetilde{P}}(t) \geq \alpha\}\} d\alpha \tag{7a}$$

Analogously, the inferiority of $\widetilde{Q}$ to $\widetilde{P}$ is

$$I(\widetilde{Q}, \widetilde{P}) = \int_0^1 \max\{0, \inf\{s : \mu_{\widetilde{Q}}(s) \geq \alpha\} - \inf\{t : \mu_{\widetilde{P}}(t) \geq \alpha\}\} d\alpha \tag{7b}$$

Consider two triangular fuzzy sets $\widetilde{P} = (u, a, b)$ and $\widetilde{Q} = (v, c, d) \in \widetilde{T}$, where $\widetilde{P} \leq \widetilde{Q}$ (Fig. 3). According to Van Hop, the superiority of $\widetilde{Q}$ over $\widetilde{P}$ can be quantified as [57]

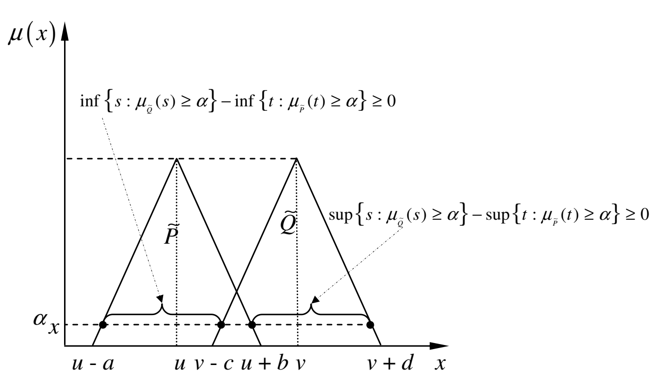


Fig. 3. Superiority and inferiority between $\widetilde{P}$ and $\widetilde{Q}$ at α-cut level.

$$S(\widetilde{Q}, \widetilde{P}) = v - u + \frac{d - b}{2} \tag{8a}$$

and the inferiority of $\widetilde{P}$ to $\widetilde{Q}$ can be presented as

$$I(\widetilde{P}, \widetilde{Q}) = v - u - \frac{c - a}{2} \tag{8b}$$

Based on Eqs. (8a) and (8b), the following can be obtained:

$$S(\tilde{f}_j(a_i), \tilde{f}_j(a_k)) \neq I(\tilde{f}_j(a_k), \tilde{f}_j(a_i)) \tag{9}$$

This method can also be extended to measure the superiority and inferiority between two fuzzy-random variables. Consider probabilistic space $(\Omega, \mathfrak{I}, P)$, a fuzzy-random variable on this space is a fuzzy set-valued mapping as follows:

$$\widetilde{\widetilde{X}} : \Omega \rightarrow F_0(R) \tag{10a}$$

$$\omega \rightarrow \widetilde{\widetilde{X}}_w \tag{10b}$$

For any Borel set (B) under a α-cut level (between 0 and 1) [68], we have

$$\widetilde{\widetilde{X}}_\alpha^{-1}(B) = \left\{\omega \in \Omega \middle| \widetilde{X}_\omega^\alpha \subset B\right\} \in \mathfrak{I} \tag{11}$$

where $F_0(R)$ and $\widetilde{X}_\omega^\alpha$ stand for the set of fuzzy numbers with compact supports and the α-cut level of fuzzy set $\widetilde{X}_\omega$, respectively; $\widetilde{\widetilde{X}}$ is a fuzzy-random variable if and only if $\omega \in \Omega$; $\widetilde{X}_\omega^\alpha$ is a random interval with $\alpha \in (0, 1]$ [57,64].

According to Van Hop [57], for two triangular fuzzy-random variables ($\widetilde{\widetilde{P}} \leq \widetilde{\widetilde{Q}}$), the superiority of fuzzy-random variable $\widetilde{\widetilde{Q}}$ over $\widetilde{\widetilde{P}}$ is

$$S\left(\widetilde{\widetilde{Q}}, \widetilde{\widetilde{P}}\right) = v(\omega) - u(\omega) + \frac{d(\omega) - b(\omega)}{2} \tag{12a}$$

Likewise, the inferiority of fuzzy-random variables $\widetilde{\widetilde{P}}$ to $\widetilde{\widetilde{Q}}$ is

$$I\left(\widetilde{\widetilde{P}}, \widetilde{\widetilde{Q}}\right) = v(\omega) - u(\omega) + \frac{c(\omega) - a(\omega)}{2} \tag{12b}$$

The above method for measuring superiority and inferiority can be utilized to solve fuzzy linear programming (FLP) or fuzzy-stochastic linear programming (FSLP) problems where fuzzy or fuzzy-stochastic coefficients exist in constraints and objective functions. Firstly, consider a FLP problem as follows:

$$\text{Max} \quad \sum_{j=1}^{n} \tilde{c}_j x_j \tag{13a}$$

$$\text{subject to:} \quad \sum_{j=1}^{n} (\tilde{a}_{ij}) x_j \leq \tilde{b}_i \quad i = 1, 2, \ldots, m \tag{13b}$$

$$x_j \geq 0, \quad j = 1, 2, \ldots, n \tag{13c}$$

An equivalent form of model (13) is

$$\text{Max} \quad \theta \tag{14a}$$

$$\text{subject to:} \quad \sum_{j=1}^{n} \tilde{c}_j x_j \geq \theta \tag{14b}$$

$$\sum_{j=1}^{n} (\tilde{a}_{ij}) x_j \leq \tilde{b}_i, \quad i = 1, 2, \ldots, m \tag{14c}$$

$$x_j \geq 0, \quad j = 1, 2, \ldots, n \tag{14d}$$

where θ is a crisp variable which can be fuzzified as $(\theta, 0, 0)$.

This problem requires a maximized objective function value subject to a superiority of the right-hand sides (RHS) over the left-hand sides (LHS) and an inferiority of LHS to RHS. This requirement corresponds to a maximized objective function value subject to a penalty for any violation of superiority of RHS over LHS or inferiority of LHS to RHS. Thus, problem (14) can be reformulated into [57]

$$\text{Max} \quad \theta - p_0\lambda_0^S - q_0\lambda_0^I - \sum_{i=1}^{m} p_i\lambda_i^S - \sum_{i}^{m} q_i\lambda_i^I \tag{15a}$$

$$\text{subject to}: \quad S\left(\theta, \sum_{j=1}^{n} \tilde{c}_j x_j\right) = \lambda_0^S \tag{15b}$$

$$I\left(\sum_{j=1}^{n} \tilde{c}_j x_j, \theta\right) = \lambda_0^I \tag{15c}$$

$$S\left(\sum_{j=1}^{n} (\tilde{a}_{ij}) x_j, \tilde{b}_i\right) = \lambda_i^S, \quad i = 1, 2, \ldots, m \tag{15d}$$

$$I\left(\tilde{b}_i, \sum_{j=1}^{n} (\tilde{a}_{ij}) x_j\right) = \lambda_i^I, \quad i = 1, 2, \ldots, m \tag{15e}$$

$$x_j \geq 0, \quad j = 1, 2, \ldots, n \tag{15f}$$

where $p_0 > 0$, $q_0 > 0$, $p_i > 0$s and $q_i > 0$ are penalty coefficients. The penalty costs (p_i and q_i) are determined by decision makers. Higher penalty costs would correspond to stricter policies in terms of constraint violations. Therefore, decision makers can identify suitable penalty levels based on projected applicable conditions. For example, in an optimistic case, decision makers can have p_i and q_i be minimum values, and vice versa. The above considerations can also be extended to the following fuzzy-stochastic linear program:

$$\text{Max} \quad \sum_{j=1}^{n} (\tilde{c}_j)_\omega x_j \tag{16a}$$

$$\text{subject to}: \quad \sum_{j=1}^{n} (\tilde{a}_{ij})_\omega x \leq (\tilde{b}_i)_\omega, \quad i = 1, 2, \ldots, m \tag{16b}$$

$$x_j \geq 0 \tag{16c}$$

$$\omega \in \Omega \tag{16d}$$

where C, A and B are $1 \times n$, $m \times n$ and $m \times 1$ matrices of fuzzy-random coefficients defined within probability space (Ω, F, P). Based on the concepts of superiority and inferiority degrees, problem (16) can be reformulated by applying penalty costs to the violated constraints as caused by variations in fuzziness and randomness. The corresponding deterministic program for problem (16) is

$$\text{Max} \quad \theta - p_0 E\left[\lambda_0^S(\omega)\right] - q_0 E\left[(\lambda_0^I(\omega)\right] - \sum_{i=1}^{m} p_i E\left[\lambda_i^s(\omega)\right] - \sum_{i=1}^{m} q_i E\left[\lambda_i^I(\omega)\right] \tag{17a}$$

$$\text{subject to}: \quad S_0\left(\theta, \sum_{j=1}^{n} (\tilde{c}_j)_w\right) = \lambda_0^S(\omega) \tag{17b}$$

$$I_0\left(\sum_{j=1}^{n} (\tilde{c}_j)_w, \theta\right) = \lambda_0^I(\omega) \tag{17c}$$

$$S_i\left(\sum_{j=1}^{n} (\tilde{a}_{ij})_w x_j, (\tilde{b}_i)_w\right) = \lambda_i^S(\omega), \quad i = 1, 2, \ldots, m \tag{17d}$$

$$I_i\left((\tilde{b}_i)_w, \sum_{j=1}^{n} (\tilde{a}_{ij})_w x_j\right) = \lambda_i^I(\omega), \quad i = 1, 2, \ldots, m \tag{17e}$$

$$x_j \geq 0 \tag{17f}$$

$$\omega \in \Omega \tag{17g}$$

where E denotes the expected value. The method uses the superiority and inferiority degrees rather than discrete intervals at α-cut levels of fuzzy numbers to defuzzify the problem. The number of constraints in the obtained deterministic model can thus be reduced drastically. Also, comparisons among fuzzy (random) coefficients through analyzing their interrelationships would help relax the constraints. The larger spreads of fuzzy numbers, the higher level of relaxation [57]. Then, solutions of the superiority–inferiority-based fuzzy-stochastic programming (SI-FSP) model can be successfully obtained.

3.3. Development of fuzzy-random interval programming

In order to handle multiple uncertainties which are combinations of interval, possibilistic and probabilistic distributions (Fig. 4) [56,59,64–67], the fuzzy-random interval programming model (FRIP) can be formulated through the integration of ILP and SI-FSP methods, which can be presented as follows:

$$\text{Min} \quad f^\pm = \tilde{\tilde{C}}_\omega^\pm X^\pm \tag{18a}$$

$$\text{subject to}: \quad \tilde{\tilde{A}}_\omega^\pm X^\pm \leq \tilde{\tilde{B}}_\omega^\pm \tag{18b}$$

$$X^\pm \geq 0 \tag{18c}$$

where $\tilde{\tilde{A}}_\omega^\pm \in \left\{\tilde{\tilde{R}}^\pm\right\}^{m\times n}$, $\tilde{\tilde{B}}_\omega^\pm \in \left\{\tilde{\tilde{R}}^\pm\right\}^{m\times 1}$, $\tilde{\tilde{C}}_\omega^\pm \in \left\{\tilde{\tilde{R}}^\pm\right\}^{1\times n}$, $X^\pm \in \{R^\pm\}$, $\tilde{\tilde{R}}^\pm$ denotes a set of interval numbers with fuzzy-random boundaries, $R^\pm$ denotes a set of interval numbers.

Then, solutions of FRIP can thus be obtained through a two-step method, where a sub-model corresponding to f^- (when the objective function is to be minimized) is firstly formulated, and then another sub-model corresponding to f^+ can be obtained based on the solution of the first sub-model (please see Huang et al. [46] for details). Consequently, submodel (1) corresponding to f^- can be firstly formulated as follows:

$$\text{Min} \quad f^- = \sum_{j=1}^{k_1} \tilde{\tilde{c}}^-_{j(\omega_{p_i})} x_j^- + \sum_{j=k_1+1}^{n} \tilde{\tilde{c}}^-_{j(\omega_{p_i})} x_j^+ \tag{19a}$$

$$\text{subject to}: \quad \sum_{j=1}^{k_1} \left|\tilde{\tilde{a}}_{ij(\omega_{p_i})}\right|^+ Sign(\tilde{\tilde{a}}^+_{ij(\omega_{p_i})}) x_j^- + \sum_{j=k_1+1}^{n} \left|\tilde{\tilde{a}}_{ij(\omega_{p_i})}\right|^- Sign(\tilde{\tilde{a}}^-_{ij(\omega_{p_i})}) x_j^+ \leq \tilde{\tilde{b}}^+_{i(\omega_{p_i})} \quad \forall I \tag{19b}$$

$$x_j^\pm \geq 0 \quad \forall j \tag{19c}$$

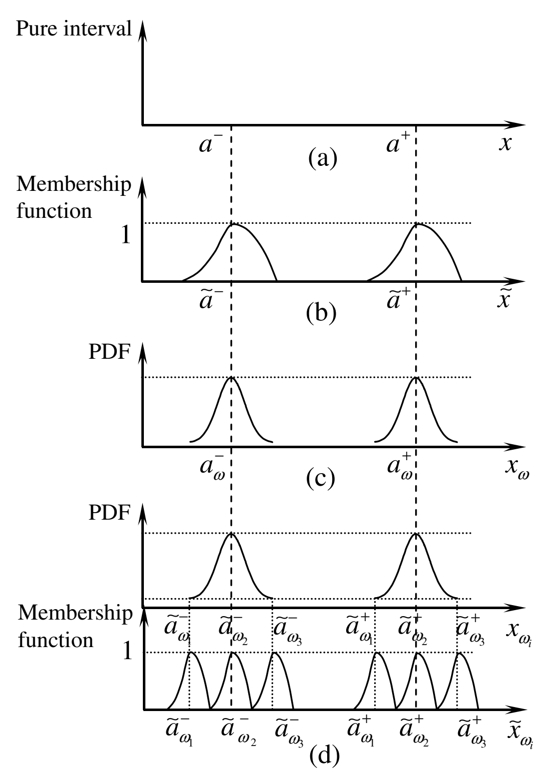


Fig. 4. Parameters expressed as: (a) pure interval, (b) interval with fuzzy lower and upper boundaries, (c) interval with random lower and upper boundaries, and (d) interval with fuzzy-random lower and upper boundaries.

where $x_j^{\pm}$, $j = 1, 2, \ldots, k_1$, are interval variables with positive coefficients in the objective function, and $x_j^{\pm}$, $j = k_1 + 1, k_1 + 2, \ldots, n$, are interval variables with negative coefficients in the objective function, p_i is the probability level for the related parameter. Then based on the method proposed by Van Hop [57], this submodel can be transformed into

$$\text{Min} \quad \theta^- \tag{20a}$$

$$\text{subject to:} \quad \sum_{j=1}^{k_1} \tilde{\tilde{c}}^-_{j(\omega_{p_i})} x_j^- + \sum_{j=k_1+1}^{n} \tilde{\tilde{c}}^-_{j(\omega_{p_i})} x_j^+ \le \theta^- \tag{20b}$$

$$\sum_{j=1}^{k_1} |\tilde{\tilde{a}}_{ij(\omega_{p_i})}|^+ Sign(\tilde{\tilde{a}}^+_{ij(\omega_{p_i})}) x_j^- + \sum_{j=k_1+1}^{n} |\tilde{\tilde{a}}_{ij(\omega_{p_i})}|^- Sign(\tilde{\tilde{a}}^-_{ij(\omega_{p_i})}) x_j^+ \le \tilde{\tilde{b}}^+_{i(\omega_{p_i})} \tag{20c}$$

$$x_j^{\pm} \ge 0 \quad \forall j \tag{20d}$$

The above model can then be transformed into

$$\text{Min} \quad \theta^- + p_0 E[\lambda_0^S(\omega_{p_i})] + q_0 E[(\lambda_0^I(\omega_{p_i})] + \sum_{i=1}^{m} p_i E[\lambda_i^s(\omega_{p_i})] + \sum_{i=1}^{m} q_i E[\lambda_i^I(\omega_{p_i})] \tag{21a}$$

$$\text{subject to:} \quad S_0\left(\left(\sum_{j=1}^{k_1} \tilde{\tilde{c}}^-_{j(\omega_{p_i})} x_j^- + \sum_{j=k_1+1}^{n} \tilde{\tilde{c}}^-_{j(\omega_{p_i})} x_j^+\right), \theta^-\right) = \lambda_0^S(w) \tag{21b}$$

$$I_0\left(\theta, \left(\sum_{j=1}^{k_1} \tilde{\tilde{c}}^-_{j(\omega_{p_i})} x_j^- + \sum_{j=k_1+1}^{n} \tilde{\tilde{c}}^-_{j(\omega_{p_i})} x_j^+\right)\right) = \lambda_0^I(w) \tag{21c}$$

$$S_i\left(\left(\sum_{j=1}^{k_1} |\tilde{\tilde{a}}_{ij(\omega_{p_i})}|^+ Sign(\tilde{\tilde{a}}^+_{ij(\omega_{p_i})}) x_j^-, + \sum_{j=k_1+1}^{n} |\tilde{\tilde{a}}_{ij(\omega_{p_i})}|^- Sign(\tilde{\tilde{a}}^-_{ij(\omega_{p_i})}) x_j^+\right) \tilde{\tilde{b}}^+_{i(\omega_{p_i})}\right) = \lambda_i^S(\omega), \quad i = 1, 2, \ldots, m \tag{21d}$$

$$I_i\left(\tilde{\tilde{b}}^+_{i(\omega_{p_i})}, \left(\sum_{j=1}^{k_1} |\tilde{\tilde{a}}_{ij(\omega_{p_i})}|^+ Sign(\tilde{\tilde{a}}^+_{ij(\omega_{p_i})}) x_j^+ \sum_{j=k_1+1}^{n} |\tilde{\tilde{a}}_{ij(\omega_{p_i})}|^- Sign(\tilde{\tilde{a}}^-_{ij(\omega_{p_i})}) x_j^+\right)\right) = \lambda_i^I(\omega), \quad i = 1, 2, \ldots, m \tag{21e}$$

$$x_j^{\pm} \ge 0 \quad \forall j \tag{21f}$$

Solutions of $x^-_{j\ \text{opt}}\ (j = 1, 2, \ldots, k_1)$ and $x^+_{j\ \text{opt}}\ (j = k_1 + 1, k_1 + 2, \ldots, n)$ can be obtained through solving submodel (21). Then the submodel corresponding to f^+ can be formulated as follows (assume that $\tilde{\tilde{b}}^+_{i(\omega_{p_i})} > 0$, and $f^{\pm} > 0$):

$$\text{Min} \quad f^+ = \sum_{j=1}^{k_1} \tilde{\tilde{c}}^+_{j(\omega_{p_i})} x_j^+ + \sum_{j=k_1+1}^{n} \tilde{\tilde{c}}^+_{j(\omega_{p_i})} x_j^- \tag{22a}$$

$$\text{subject to:} \quad \sum_{j=1}^{k_1} |\tilde{\tilde{a}}_{ij(\omega_{p_i})}|^- Sign(\tilde{\tilde{a}}^-_{ij(\omega_{p_i})}) x_j^+ + \sum_{j=k_1+1}^{n} |\tilde{\tilde{a}}_{ij(\omega_{p_i})}|^+ Sign(\tilde{\tilde{a}}^+_{ij(\omega_{p_i})}) x_j^- \le \tilde{\tilde{b}}^-_{i(\omega_{p_i})} \quad \forall I \tag{22b}$$

$$x_j^{\pm} \ge 0 \quad \forall j \tag{22c}$$

$$x_j^+ \ge x^-_{j\ \text{opt}}, \quad j = 1, 2, \ldots, k_1 \tag{22d}$$

$$x_j^- \le x^+_{j\ \text{opt}}, \quad j = k_1 + 1, k_2 + 2, \ldots, n \tag{22e}$$

Thus, the above model can be then transformed into

$$\text{Min} \quad \theta^+ + p_1 E[\lambda_0^S(\omega_{p_i})] + q_1 E[(\lambda_0^I(\omega_{p_i})] + \sum_{i=1}^{m} p_i E[\lambda_i^s(\omega_{p_i})] + \sum_{i=1}^{m} q_i E[\lambda_i^I(\omega_{p_i})] \tag{23a}$$

$$S_0\left(\left(\sum_{j=1}^{k_1} \tilde{\tilde{c}}^+_{j(\omega_{p_i})} x_j^+ + \sum_{j=k_1+1}^{n} \tilde{\tilde{c}}^+_{j(\omega_{p_i})} x_j^-\right), \theta\right) = \lambda_0^S(w) \tag{23b}$$

$$I_0\left(\theta, \left(\sum_{j=1}^{k_1} \tilde{\tilde{c}}^+_{j(\omega_{p_i})} x_j^+ + \sum_{j=k_1+1}^{n} \tilde{\tilde{c}}^+_{j(\omega_{p_i})} x_j^-\right)\right) = \lambda_0^I(w) \tag{23c}$$

$$S_i\left(\left(\sum_{j=1}^{k_1} |\tilde{\tilde{a}}_{ij(\omega_{p_i})}|^- Sign(\tilde{\tilde{a}}^-_{ij(\omega_{p_i})}) x_j^+ + \sum_{j=k_1+1}^{n} |\tilde{\tilde{a}}_{ij(\omega_{p_i})}|^+ Sign(\tilde{\tilde{a}}^+_{ij(\omega_{p_i})}) x_j^-\right), \tilde{\tilde{b}}^-_{i(\omega_{p_i})}\right) = \lambda_i^S(\omega), \quad i = 1, 2, \ldots, m \tag{23d}$$

$$I_i\left(\tilde{\tilde{b}}^-_{i(\omega_{p_i})}, \left(\sum_{j=1}^{k_1} |\tilde{\tilde{a}}_{ij(\omega_{p_i})}|^- Sign(\tilde{\tilde{a}}^-_{ij(\omega_{p_i})}) x_j^+ + \sum_{j=k_1+1}^{n} |\tilde{\tilde{a}}_{ij(\omega_{p_i})}|^+ Sign(\tilde{\tilde{a}}^+_{ij(\omega_{p_i})}) x_j^-\right)\right) = \lambda_i^I(\omega), \quad i = 1, 2, \ldots, m \tag{23e}$$

$$x_j^{\pm} \ge 0 \quad \forall j \tag{23f}$$

$$x_j^+ \ge x^-_{j\ \text{opt}}, \quad j = 1, 2, \ldots, k_1 \tag{23g}$$

$$x_j^- \le x^+_{j\ \text{opt}}, \quad j = k_1 + 1, k_2 + 2, \ldots, n \tag{23h}$$

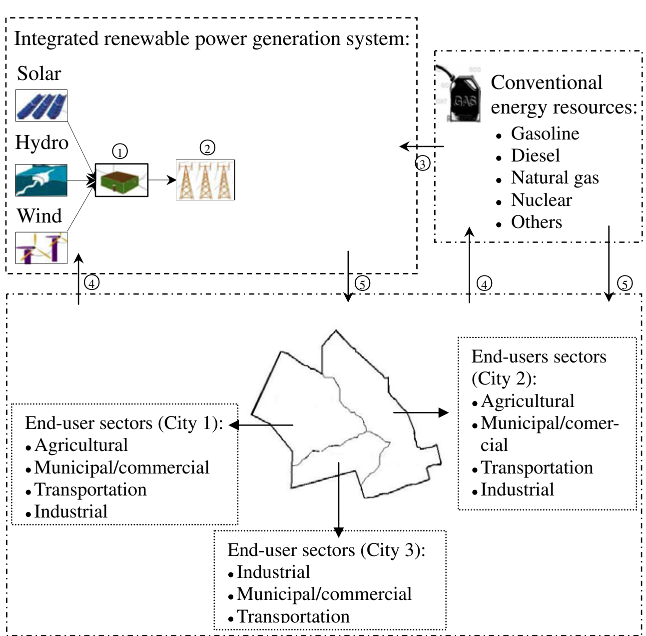
Hence, solutions of $x^+_{j\ \text{opt}}\ (j = 1, 2, \ldots, k_1)$ and $x^-_{j\ \text{opt}}\ (j = k_1 + 1, k_1 + 2, \ldots, n)$ can be obtained from submodel (23). Final solution for model (18): $f^{\pm}_{\text{opt}} = [f^-_{\text{opt}}, f^+_{\text{opt}}]$ and $x^{\pm}_{j\ \text{opt}} = [x^-_{j\ \text{opt}}, x^+_{j\ \text{opt}}]$ can then be obtained. These solutions are presented as intervals, and can be further interpreted for generating multiple decision alternatives.

Apparently, the FRIP model improves upon the existing methods in uncertainty reflection and dynamic analysis. In this model, two optimization techniques, namely ILP and SI-FSP are successfully incorporated into a general modeling framework. Each technique has a unique contribution to enhancing the model's capability in dealing with uncertainties embedded within EMS. Particularly, dual uncertainties which are combinations of possibilistic and probabilistic distributions can be handled through SI-FSP; uncertainties presented as discrete intervals can be reflected through ILP. Such multiple uncertainties can be directly communicated into the optimization process and resulting solution. However, these two methods cannot deal with facility capacity issues which are frequently involved in EMS planning. MILP is then introduced into the FRIP model. Thus, FRIP does not simply reduce the complexity of the programming problems; instead it allows decision makers to have a complete view of the effects of uncertainties as well as the relationships between uncertain inputs and the related solutions. Consequently, the programming robustness can be enhanced, subjective and uncertain inputs from decision makers can also be reflected through integration of possibilistic information into probability distributions to enlarge decision dimensions within the uncertain domain.

4. Application to energy management systems planning

4.1. Statement of problems

The following problem is used to demonstrate applicability of the developed FRIP model. In the study system, multiple energy resources need to be allocated to multiple end-users (municipal/commercial, industrial, transportational, and agricultural sectors) through multiple facilities in a region. Conventional and renewable energy resources (e.g., coal, refinery petroleum products, natural gas, solar, wind, hydropower and nuclear) with limited availabilities are employed for meeting local demands. In detail, coal and renewable energy resources are mainly employed for power generation. Natural gas is mostly used for heat generation. Refinery petroleum products (RPP) include diesel and gasoline in this research, which are primarily used for transportation and partially utilized for providing heat. Conversion and processing technologies include those for large-scale electricity generation, as well as those for small-scale renewable resources utilization. Normally, small-scale technologies are based on local renewable energy resources except hydropower. At the same time, large-scale technologies are mostly used for generating electricity from conventional energy resources such as coal and natural gas. In the region, if energy supply cannot sufficiently meet the end-user demands, decision makers will face a dilemma of either investing more funds in capacity expansions of the existing facilities or turning to other energy production options or putting extra funds into energy imports at raised prices. Moreover, the facilities considered in the study have overall-cumulative limits while regional energy demands are flexible. If the energy demands do not exceed capacity limits of corresponding facilities, it will result in a regular cost. Otherwise, capacity expansions would be considered, resulting in extra costs to the system. Thus, decision makers need to identify desired energy-flow allocation and facility-expansion schemes with a minimized system cost and a maximize system reliability. This leads to the application of the FRIP model to regional EMS planning, which is based on the integration of MILP, ILP and SI-FSP. The objective is to minimize net system cost, which is related to various energy flows. The decision variables represent key discrete points in the system, such as capacities of facilities, volumes of crude oil production, and gasoline consumed by vehicles. Furthermore, in the study system, parameters (such as energy demand, technological efficiency and utilization factors) are expressed as intervals with fuzzy-random boundaries. Such intervals can effectively reflect multiple uncertainties in relevant parameters without oversimplifying their associated distributions. For example, energy import costs are highly dependent on average resources prices in the energy market, which mostly fluctuate around a specific price and can be expressed as an interval. Also, lower and upper bounds of such an interval can be further expressed as fuzzy-random variables. In detail, the import price might be linguistically specified as "low", "medium" and "high" under probability levels of 0.15, 0.7 and 0.15, respectively, i.e., (a) low, "the coal import price is $\$[11.0, 15.0] \times 10^6$/PJ, and the most possible one is $\$13.0 \times 10^6$/PJ", (b) medium, "the coal import price is $\$[13.0, 17.0] \times 10^6$/PJ, and the most possible one is $\$15.0 \times 10^6$/PJ", and (c) high, "the coal import price is $\$[17.0, 21.0] \times 10^6$/PJ, and the most possible one is $\$19.0 \times 10^6$/PJ". Similarly, all of the related parameters can be expressed as a series of fuzzy-random variables under discrete probability levels.



Note:
① Power conditioner and controller
② Local power distribution system
③ Conventional electricity-generating facilities
④ Policies, strategies and regulations
⑤ Energy supply

Fig. 5. The study system.

4.2. Overview of the study system

The study system is assumed to include three cities, as shown in Fig. 5. Three time periods are considered, with each having a time interval of five years. Over the 15-year planning horizon, a number of facilities are available. Conventional and renewable energy resources, relevant technologies and multiple end-use sectors are included. Many parameters which are expressed as fuzzy-random variables are presented in Tables 1–5 (including end-user demands for coal, natural gas, diesel, gasoline and electricity from industrial, municipal/commercial and transportation sectors). Also, availabilities of many renewable energy resources (hydropower, nuclear power, and solar and wind energies) are provided in Table 6. Facil-

Table 1
End-user demands for coal (PJ)

End-user sector	Probability level	Period	Coal demand (lower bound)	Coal demand (upper bound)
Industrial	Low ($p = 0.15$)	1	(20.09, 5, 5)	(29.36, 5, 5)
	Medium ($p = 0.7$)	1	(30.13, 5, 5)	(38.81, 5, 5)
	High ($p = 0.15$)	1	(39.16, 5, 5)	(50.15, 5, 5)
	Low ($p = 0.15$)	2	(23.88, 5, 5)	(30.66, 5, 5)
	Medium ($p = 0.7$)	2	(31.50, 5, 5)	(40.88, 5, 5)
	High ($p = 0.15$)	2	(40.25, 5, 5)	(53.15, 5, 5)
	Low ($p = 0.15$)	3	(24.75, 5, 5)	(31.08, 5, 5)
	Medium ($p = 0.7$)	3	(32.99, 5, 5)	(42.11, 5, 5)
	High ($p = 0.15$)	3	(42.49, 5, 5)	(55.34, 5, 5)
Municipal/commercial	Low ($p = 0.15$)	1	(21.19, 5, 5)	(27.60, 5, 5)
	Medium ($p = 0.7$)	1	(28.26, 5, 5)	(36.80, 5, 5)
	High ($p = 0.15$)	1	(37.13, 5, 5)	(47.64, 5, 5)
	Low ($p = 0.15$)	2	(22.37, 5, 5)	(28.14, 5, 5)
	Medium ($p = 0.7$)	2	(29.84, 5, 5)	(37.85, 5, 5)
	High ($p = 0.15$)	2	(39.19, 5, 5)	(49.31, 5, 5)
	Low ($p = 0.15$)	3	(23.31, 5, 5)	(29.63, 5, 5)
	Medium ($p = 0.7$)	3	(30.41, 5, 5)	(42.18, 5, 5)
	High ($p = 0.15$)	3	(41.53, 5, 5)	(51.63, 5, 5)
Agricultural	Low ($p = 0.15$)	1	(3.33, 1, 1)	(4.19, 1, 1)
	Medium ($p = 0.7$)	1	(4.44, 1, 1)	(5.92, 1, 1)
	High ($p = 0.15$)	1	(5.97, 1, 1)	(7.20, 1, 1)
	Low ($p = 0.15$)	2	(3.51, 1, 1)	(4.42, 1, 1)
	Medium ($p = 0.7$)	2	(4.68, 1, 1)	(6.23, 1, 1)
	High ($p = 0.15$)	2	(6.28, 1, 1)	(7.60, 1, 1)
	Low ($p = 0.15$)	3	(3.80, 1, 1)	(4.79, 1, 1)
	Medium ($p = 0.7$)	3	(5.06, 1, 1)	(6.73, 1, 1)
	High ($p = 0.15$)	3	(6.78, 1, 1)	(8.24, 1, 1)
Transportational	Low ($p = 0.15$)	1	N/A	N/A
	Medium ($p = 0.7$)	1	N/A	N/A
	High ($p = 0.15$)	1	N/A	N/A
	Low ($p = 0.15$)	2	N/A	N/A
	Medium ($p = 0.7$)	2	N/A	N/A
	High ($p = 0.15$)	2	N/A	N/A
	Low ($p = 0.15$)	3	N/A	N/A
	Medium ($p = 0.7$)	3	N/A	N/A
	High ($p = 0.15$)	3	N/A	N/A

Table 2
End-user demands for natural gas (NGA) (PJ)

End-user sector	Probability level	Period	NGA demand (lower bound)	NGA demand (upper bound)
Industrial	Low ($p = 0.15$)	1	(19.21, 5, 5)	(25.75, 5, 5)
	Medium ($p = 0.7$)	1	(26.28, 5, 5)	(39.66, 5, 5)
	High ($p = 0.15$)	1	(34.96, 5, 5)	(44.96, 5, 5)
	Low ($p = 0.15$)	2	(20.76, 5, 5)	(26.75, 5, 5)
	Medium ($p = 0.7$)	2	(27.35, 5, 5)	(35.33, 5, 5)
	High ($p = 0.15$)	2	(35.65, 5, 5)	(46.43, 5, 5)
	Low ($p = 0.15$)	3	(21.39, 5, 5)	(27.85, 5, 5)
	Medium ($p = 0.7$)	3	(28.52, 5, 5)	(37.14, 5, 5)
	High ($p = 0.15$)	3	(37.47, 5, 5)	(48.08, 5, 5)
Municipal/commercial	Low ($p = 0.15$)	1	(18.69, 5, 5)	(24.48, 5, 5)
	Medium ($p = 0.7$)	1	(24.92, 5, 5)	(32.31, 5, 5)
	High ($p = 0.15$)	1	(32,59, 5, 5)	(41.30, 5, 5)
	Low ($p = 0.15$)	2	(19.72, 5, 5)	(24.82, 5, 5)
	Medium ($p = 0.7$)	2	(25.30, 5, 5)	(33.09, 5, 5)
	High ($p = 0.15$)	2	(33.38, 5, 5)	(42.61, 5, 5)
	Low ($p = 0.15$)	3	(20.40, 5, 5)	(25.99, 5, 5)
	Medium ($p = 0.7$)	3	(26.53, 5, 5)	(34.98, 5, 5)
	High ($p = 0.15$)	3	(34.61, 5, 5)	(44.37, 5, 5)
Agricultural	Low ($p = 0.15$)	1	(2.50, 1, 1)	(3.13, 1, 1)
	Medium ($p = 0.7$)	1	(3.34, 1, 1)	(4.50, 1, 1)
	High ($p = 0.15$)	1	(5.54, 1, 1)	(6.34, 1, 1)
	Low ($p = 0.15$)	2	(2.66, 1, 1)	(3.32, 1, 1)
	Medium ($p = 0.7$)	2	(3.54, 1, 1)	(4.76, 1, 1)
	High ($p = 0.15$)	2	(4.81, 1, 1)	(6.69, 1, 1)
	Low ($p = 0.15$)	3	(2.91, 1, 1)	(3.65, 1, 1)
	Medium ($p = 0.7$)	3	(3.88, 1, 1)	(5.20, 1, 1)
	High ($p = 0.15$)	3	(4.24, 1, 1)	(7.26, 1, 1)
Transportational	Low ($p = 0.15$)	1	N/A	N/A
	Medium ($p = 0.7$)	1	N/A	N/A
	High ($p = 0.15$)	1	N/A	N/A
	Low ($p = 0.15$)	2	N/A	N/A
	Medium ($p = 0.7$)	2	N/A	N/A
	High ($p = 0.15$)	2	N/A	N/A
	Low ($p = 0.15$)	3	N/A	N/A
	Medium ($p = 0.7$)	3	N/A	N/A
	High ($p = 0.15$)	3	N/A	N/A

Table 3
End-user demands for diesel (PJ)

End-user sector	Probability level	Period	Diesel demand (lower bound)	Diesel demand (upper bound)
Industrial	Low ($p = 0.15$)	1	(13.72, 5, 5)	(17.87, 5, 5)
	Medium ($p = 0.7$)	1	(18.96, 5, 5)	(23.83, 5, 5)
	High ($p = 0.15$)	1	(24.04, 5, 5)	(31.17, 5, 5)
	Low ($p = 0.15$)	2	(15.00, 5, 5)	(19.82, 5, 5)
	Medium ($p = 0.7$)	2	(20.00, 5, 5)	(25.76, 5, 5)
	High ($p = 0.15$)	2	(26.00, 5, 5)	(34.28, 5, 5)
	Low ($p = 0.15$)	3	(16.42, 5, 5)	(20.95, 5, 5)
	Medium ($p = 0.7$)	3	(22.22, 5, 5)	(27.94, 5, 5)
	High ($p = 0.15$)	3	(28.19, 5, 5)	(36.72, 5, 5)
Municipal/commercial	Low ($p = 0.15$)	1	(1.46, 0.5, 0.5)	(1.69, 0.5, 0.5)
	Medium ($p = 0.7$)	1	(1.59, 0.5, 0.5)	(2.25, 0.5, 0.5)
	High ($p = 0.15$)	1	(2.27, 0.5, 0.5)	(2.53, 0.5, 0.5)
	Low ($p = 0.15$)	2	(1.67, 0.5, 0.5)	(1.75, 0.5, 0.5)
	Medium ($p = 0.7$)	2	(1.76, 0.5, 0.5)	(2.30, 0.5, 0.5)
	High ($p = 0.15$)	2	(2.62, 0.5, 0.5)	(2.98, 0.5, 0.5)
	Low ($p = 0.15$)	3	(1.88, 0.5, 0.5)	(2.33, 0.5, 0.5)
	Medium ($p = 0.7$)	3	(1.94, 0.5, 0.5)	(2.47, 0.5, 0.5)
	High ($p = 0.15$)	3	(1.99, 0.5, 0.5)	(3.46, 0.5, 0.5)
Agricultural	Low ($p = 0.15$)	1	(3.16, 2, 2)	(3.97, 2, 2)
	Medium ($p = 0.7$)	1	(4.21, 2, 2)	(5.63, 2, 2)
	High ($p = 0.15$)	1	(5.68, 2, 2)	(6.82, 2, 2)
	Low ($p = 0.15$)	2	(3.67, 2, 2)	(4.63, 2, 2)
	Medium ($p = 0.7$)	2	(4.89, 2, 2)	(6.50, 2, 2)
	High ($p = 0.15$)	2	(6.55, 2, 2)	(7.95, 2, 2)
	Low ($p = 0.15$)	3	(3.70, 2, 2)	(4.62, 2, 2)
	Medium ($p = 0.7$)	3	(4.80, 2, 2)	(6.73, 2, 2)
	High ($p = 0.15$)	3	(6.49, 2, 2)	(8.16, 2, 2)
Transportational	Low ($p = 0.15$)	1	(10.80, 5, 5)	(13.29, 5, 5)
	Medium ($p = 0.7$)	1	(13.69, 5, 5)	(17.71, 5, 5)
	High ($p = 0.15$)	1	(17.79, 5, 5)	(23.03, 5, 5)
	Low ($p = 0.15$)	2	(11.11, 5, 5)	(14.38, 5, 5)
	Medium ($p = 0.7$)	2	(14.81, 5, 5)	(19.17, 5, 5)
	High ($p = 0.15$)	2	(19.26, 5, 5)	(24.92, 5, 5)
	Low ($p = 0.15$)	3	(12.02, 5, 5)	(15.00, 5, 5)
	Medium ($p = 0.7$)	3	(16.00, 5, 5)	(20.00, 5, 5)
	High ($p = 0.15$)	3	(21.00, 5, 5)	(27.00, 5, 5)

ities based on coal, hydropower, solar and wind energies, as well as nuclear are considered for electricity supply in this research. It is assumed that residual capacities are available for most of the facilities at the beginning of the 15-year planning horizon.

4.3. The FRIP model for regional energy systems planning

In the study region, the system for energy generation and allocation consists of multiple energy sources (domestic production and external importation), multiple technologies (those for energy transmission, storage and conversion) and multiple facilities, which form a complex network in the regional context. Increasingly, with consideration of energy security and market risks associated with energy imports, an integrated energy management system is adopted as a means for effectively managing various energy resources and technologies. This requires that a diversity of energy resources and technologies should be employed. Thus, a variety of system components and their interactions should be considered in a general modeling framework; it will also help facilitate a systematic analysis of the proposed problem as well as a comprehensive evaluation of the related activities and policy responses. The developed FRIP model is then applied to the planning of regional energy systems, which entails: (a) identification of desired capacity-expansion schemes for electricity-generating facilities, (b) allocation of various energy flows to each end-user sector, and (c) analysis of the tradeoff between the cost of energy management and the risk of system reliability. In detail, the model can be presented as follows:

$$\text{Min} \quad f^{\pm} = \sum_{i=1}^{I}\sum_{t=1}^{T} \widetilde{\overline{PRC}}^{\pm}_{i,t,\omega_{pi}} Z^{\pm}_{i,t} + \sum_{t=1}^{T}\sum_{j=1}^{J} \widetilde{\overline{PVRC}}^{\pm}_{j,t,\omega_{pi}} X^{\pm}_{j,t} + \sum_{t=1}^{T}\sum_{m=1}^{M}\sum_{j=1}^{J} INV_{j,m,t} \widetilde{\overline{ECE}}^{\pm}_{j,m,t,\omega_{pi}} Y^{\pm}_{j,m,t} \tag{24a}$$

$$\text{subject to}: \quad \sum_{l=1}^{3} \widetilde{\overline{DMD\_C}}^{\pm}_{l,t,\omega_{pi}} + \widetilde{\overline{RCON}}^{\pm}_{1,t,\omega_{pi}} X^{\pm}_{1,t} \le \sum_{i=1}^{2} Z^{\pm}_{i,t} \quad \forall t \tag{24b}$$

(Balance of coal)

$$\sum_{l=1}^{3} \widetilde{\overline{DMD\_N}}^{\pm}_{l,t,\omega_{pi}} + \widetilde{\overline{RCON}}^{\pm}_{2,t,\omega_{pi}} X^{\pm}_{2,t} \le \sum_{i=3}^{4} Z^{\pm}_{i,t} \quad \forall t \tag{24c}$$

(Balance of natural gas)

$$\sum_{l=1}^{L} \widetilde{\overline{DMD\_D}}^{\pm}_{l,t,\omega_{pi}} \le \sum_{i=5}^{6} Z^{\pm}_{i,t} \quad \forall t \tag{24d}$$

(Balance of diesel)

$$\sum_{l=1}^{L} \widetilde{\overline{DMD\_G}}^{\pm}_{l,t,\omega_{pi}} \le \sum_{i=7}^{8} Z^{\pm}_{i,t} \quad \forall t \tag{24e}$$

(Balance of gasoline)

$$\sum_{t=1}^{T} \left(\widetilde{\overline{RCON}}^{\pm}_{j,t,\omega_{pi}} X^{\pm}_{j,t} \right) \le \widetilde{\overline{AVI\_UP}}^{\pm}_{j,\omega_{pi}} \quad \forall j \ (j = 3, 4, 5 \text{ and } 6) \tag{24f}$$

Table 4
End-user demands for gasoline (PJ)

End-user sector	Probability level	Period	Gasoline demand (lower bound)	Gasoline demand (upper bound)
Industrial	Low ($p = 0.15$)	1	(32.86, 5, 5)	(42.52, 5, 5)
	Medium ($p = 0.7$)	1	(43.81, 5, 5)	(56.70, 5, 5)
	High ($p = 0.15$)	1	(56.96, 5, 5)	(73.71, 5, 5)
	Low ($p = 0.15$)	2	(34.43, 5, 5)	(44.56, 5, 5)
	Medium ($p = 0.7$)	2	(45.91, 5, 5)	(59.41, 5, 5)
	High ($p = 0.15$)	2	(59.68, 5, 5)	(77.23, 5, 5)
	Low ($p = 0.15$)	3	(35.57, 5, 5)	(46.03, 5, 5)
	Medium ($p = 0.7$)	3	(47.42, 5, 5)	(61.37, 5, 5)
	High ($p = 0.15$)	3	(61.65, 5, 5)	(79.78, 5, 5)
Municipal/ commercial	Low ($p = 0.15$)	1	(2.92, 0.5, 0.5)	(3.78, 0.5, 0.5)
	Medium ($p = 0.7$)	1	(3.89, 0.5, 0.5)	(5.04, 0.5, 0.5)
	High ($p = 0.15$)	1	(5.06, 0.5, 0.5)	(6.55, 0.5, 0.5)
	Low ($p = 0.15$)	2	(3.06, 0.5, 0.5)	(3.96, 0.5, 0.5)
	Medium ($p = 0.7$)	2	(4.08, 0.5, 0.5)	(5.28, 0.5, 0.5)
	High ($p = 0.15$)	2	(5.30, 0.5, 0.5)	(6.87, 0.5, 0.5)
	Low ($p = 0.15$)	3	(3.16, 0.5, 0.5)	(4.09, 0.5, 0.5)
	Medium ($p = 0.7$)	3	(4.22, 0.5, 0.5)	(5.46, 0.5, 0.5)
	High ($p = 0.15$)	3	(5.48, 0.5, 0.5)	(7.09, 0.5, 0.5)
Agricultural	Low ($p = 0.15$)	1	(7.30, 2, 2)	(9.45, 2, 2)
	Medium ($p = 0.7$)	1	(9.74, 2, 2)	(12.60, 2, 2)
	High ($p = 0.15$)	1	(12.66, 2, 2)	(16.38, 2, 2)
	Low ($p = 0.15$)	2	(7.65, 2, 2)	(9.90, 2, 2)
	Medium ($p = 0.7$)	2	(10.20, 2, 2)	(13.20, 2, 2)
	High ($p = 0.15$)	2	(13.26, 2, 2)	(17.16, 2, 2)
	Low ($p = 0.15$)	3	(7.90, 2, 2)	(10.23, 2, 2)
	Medium ($p = 0.7$)	3	(10.54, 2, 2)	(13.64, 2, 2)
	High ($p = 0.15$)	3	(13.70, 2, 2)	(17.73, 2, 2)
Transportational	Low($p = 0.15$)	1	(36.51, 5, 5)	(47.25, 5,5)
	Medium ($p = 0.7$)	1	(48.68, 5, 5)	(63.00, 5, 5)
	High ($p = 0.15$)	1	(63.28, 5, 5)	(81.90, 5, 5)
	Low ($p = 0.15$)	2	(38.26, 5, 5)	(49.51, 5, 5)
	Medium ($p = 0.7$)	2	(51.01, 5, 5)	(66.01, 5, 5)
	High ($p = 0.15$)	2	(66.31, 5, 5)	(85.81, 5, 5)
	Low ($p = 0.15$)	3	(39.52, 5, 5)	(51.14, 5, 5)
	Medium ($p = 0.7$)	3	(52.69, 5, 5)	(68.19, 5, 5)
	High ($p = 0.15$)	3	(68.50, 5, 5)	(88.65, 5, 5)

Table 5
End-user demands for electricity (PJ)

End-user sector	Probability level	Period	Electricity demand (lower bound)	Electricity demand (upper bound)
Industrial	Low ($p = 0.15$)	1	(11.60, 3, 3)	(15.02, 3, 3)
	Medium ($p = 0.7$)	1	(15.47, 3, 3)	(20.02, 3, 3)
	High ($p = 0.15$)	1	(20.11, 3, 3)	(26.03, 3, 3)
	Low ($p = 0.15$)	2	(14.98, 3, 3)	(19.39, 3, 3)
	Medium ($p = 0.7$)	2	(19.98, 3, 3)	(25.85, 3, 3)
	High ($p = 0.15$)	2	(25.97, 3, 3)	(33.61, 3, 3)
	Low ($p = 0.15$)	3	(18.36, 3, 3)	(23.76, 3, 3)
	Medium ($p = 0.7$)	3	(24.48, 3, 3)	(31.68, 3, 3)
	High ($p = 0.15$)	3	(31.82, 3, 3)	(41.18, 3, 3)
Municipal/ commercial	Low ($p = 0.15$)	1	(18.05, 1, 1)	(20.41, 1, 1)
	Medium ($p = 0.7$)	1	(20.73, 1, 1)	(23.89, 1, 1)
	High ($p = 0.15$)	1	(23.95, 1, 1)	(28.05, 1, 1)
	Low ($p = 0.15$)	2	(19.42, 1, 1)	(22.19, 1, 1)
	Medium ($p = 0.7$)	2	(22.56, 1, 1)	(26.26, 1, 1)
	High ($p = 0.15$)	2	(26.33, 1, 1)	(31.14, 1, 1)
	Low ($p = 0.15$)	3	(20.73, 1, 1)	(23.88, 1, 1)
	Medium ($p = 0.7$)	3	(24.31, 1, 1)	(28.51, 1, 1)
	High ($p = 0.15$)	3	(28.60, 1, 1)	(34.07, 1, 1)
Agricultural	Low ($p = 0.15$)	1	(16.96, 1, 1)	(19.01, 1, 1)
	Medium ($p = 0.7$)	1	(19.28, 1, 1)	(22.01, 1, 1)
	High ($p = 0.15$)	1	(22.07, 1, 1)	(25.62, 1, 1)
	Low ($p = 0.15$)	2	(18.99, 1, 1)	(21.63, 1, 1)
	Medium ($p = 0.7$)	2	(21.99, 1, 1)	(25.51, 1, 1)
	High ($p = 0.15$)	2	(25.58, 1, 1)	(30.16, 1, 1)
	Low ($p = 0.15$)	3	(21.02, 1, 1)	(24.26, 1, 1)
	Medium ($p = 0.7$)	3	(24.69, 1, 1)	(29.01, 1, 1)
	High ($p = 0.15$)	3	(29.09, 1, 1)	(34.71, 1, 1)
Transportational	Low ($p = 0.15$)	1	(10.58, 0.1, 0.1)	(10.75, 0.1, 0.1)
	Medium ($p = 0.7$)	1	(10.77, 0.1, 0.1)	(11.00, 0.1, 0.1)
	High ($p = 0.15$)	1	(11.01, 0.1, 0.1)	(11.30, 0.1, 0.1)
	Low ($p = 0.15$)	2	(10.75, 0.1, 0.1)	(10.97, 0.1, 0.1)
	Medium ($p = 0.7$)	2	(11.00, 0.1, 0.1)	(11.29, 0.1, 0.1)
	High ($p = 0.15$)	2	(11.30, 0.1, 0.1)	(11.68, 0.1, 0.1)
	Low ($p = 0.15$)	3	(10.92, 0.1, 0.1)	(11.19, 0.1, 0.1)
	Medium ($p = 0.7$)	3	(11.22, 0.1, 0.1)	(11.58, 0.1, 0.1)
	High ($p = 0.15$)	3	(11.59, 0.1, 0.1)	(12.06, 0.1, 0.1)

(Availabilities of energy resources for power generation)

$$Z_{9t}^{\pm} + \sum_{j=1}^{J} X_{j,t}^{\pm} \geq \sum_{l=1}^{L} \overline{\widetilde{DMD\_E}}_{l,t,\omega_{pi}}^{\pm} \quad \forall t \tag{24g}$$

(Electricity demand)

$$\sum_{m=1}^{M} \left[\overline{\widetilde{RCAP}}_{j,\omega_{pi}}^{\pm} + \sum_{p=1}^{t} \left(\overline{\widetilde{ECE}}_{j,m,p,\omega_{pi}}^{\pm} Y_{j,m,p}^{\pm} \right) \right] * Ucap \geq X_{j,t}^{\pm} \quad \forall j, t \tag{24h}$$

(Capacity constraint for electricity-generating facilities)

$$\sum_{t=1}^{T} Z_{i,t}^{\pm} \leq \widetilde{ENE\_UP}_{i,\omega_{pi}}^{\pm} \quad \forall i \tag{24i}$$

(Bound constraints for energy resources)

$$\sum_{j=1}^{J} X_{j,t}^{\pm} \leq \overline{\widetilde{ELE\_UP}}_{t,\omega_{pi}}^{\pm} \quad \forall t \tag{24j}$$

(Bound constraints for power generation)

$$Z_{i,t}^{\pm} \geq 0 \quad \forall i, t \tag{24k}$$

$$X_{j,t}^{\pm} \geq 0 \quad \forall j, t \tag{24l}$$

(Technical constraints)

$$Y_{j,m,t}^{\pm} = 0, 1 \quad \forall j, m, t \tag{24m}$$

(Binary constraints)

$$\sum_{t=1}^{T} \sum_{m=1}^{M} Y_{j,m,t}^{\pm} \leq 1 \quad \forall j \tag{24n}$$

(Constraints of capacity expansion once for each facility over the planning horizon)

where i = index for energy resources ($i = 1, 2 \ldots, 9$ for domestic and imported coal, imported natural gas, domestic and imported diesel, domestic and imported gasoline, as well as imported electricity, respectively); j is the index for electricity-generating facilities ($j = 1, 2 \ldots, 6$ for facilities based on coal, natural gas, hydropower, solar and wind energies, as well as nuclear, respectively); t is the index for periods, $t = 1, 2, 3$; m is the index for capacity expansion options of electricity-generating facilities, $m = 1, 2, 3$; l is the index for end-users ($l = 1, 2, 3$ and 4 for industrial, municipal/commercial, agricultural and transportational sectors); $Z_{i,t}^{\pm}$ is the primary energy resources i in period t (PJ); $X_{j,t}^{\pm}$ is the electricity generated from energy resources j in period t (PJ); $Y_{jmt}^{\pm}$ is the binary decision variables

Table 6
Availabilities of renewable energy resources (PJ)

Renewable energy sources	Probability level	Lower bound	Upper bound
Hydropower	Low ($p = 0.15$)	(12.50, 5, 5)	(15.00, 5, 5)
	Medium ($p = 0.7$)	(17.50, 5, 5)	(20.00, 5, 5)
	High ($p = 0.15$)	(22.50, 5, 5)	(25.00, 5, 5)
Solar energy	Low ($p = 0.15$)	(2.00, 1, 1)	(12.00, 1, 1)
	Medium ($p = 0.7$)	(3.00, 1, 1)	(13.00, 1, 1)
	High ($p = 0.15$)	(4.00, 1, 1)	(14.00, 1, 1)
Wind energy	Low ($p = 0.15$)	(0.13 0.1, 0.1)	(1.15, 0.1, 0.1)
	Medium ($p = 0.7$)	(0.18, 0.1, 0.1)	(1.20, 0.1, 0.1)
	High ($p = 0.15$)	(0.23, 0.1, 0.1)	(1.25, 0.1, 0.1)
Nuclear power	Low ($p = 0.15$)	(2.50, 1, 1)	(13.00, 1, 1)
	Medium ($p = 0.7$)	(3.50, 1, 1)	(14.00, 1, 1)
	High ($p = 0.15$)	(4.50, 1, 1)	(15.00, 1, 1)

for electricity-generating facilities j with option m at the start of period t; $PRC^{\pm}_{i,t,\omega_{pi}}$ is the average production/importation cost of energy resources i in period t under probability levels p_i (million \$/PJ); $PVRC^{\pm}_{i,t,\omega_{pi}}$ is the average production cost of electricity generated from energy resources i in period t under probability levels p_i (million \$/PJ); $INV_{j,m,t}$ is the capital cost for capacity expansion of power plant j under expansion option m at the beginning of period t (million \$/PJ); $ECE^{\pm}_{j,m,t,\omega_{pi}}$ is the capacity expansion for power generation facility j with option m under probability p_i at the beginning of period t (PJ); $DMD\_C^{\pm}_{l,t}$ is the allocated amount of coal to the sector l in period t (PJ); $DMD\_N^{\pm}_{l,t}$ is the allocated amount of natural gas to the sector l in period t (PJ); $DMD_D^{\pm}_{l,t}$is the allocated amount of diesel to the sector l in period t (PJ); $DMD\_G^{\pm}_{l,t}$ is the allocated amount of diesel to the sector l in period t (PJ); $DMD_E^{\pm}_{l,t}$is the allocated amount of electricity to the sector l in period t (PJ); $RCON^{\pm}_{l,t}$is the average conversion ratio from energy carrier l to electricity in period t; $RCAP^{\pm}_{j}$is the residual capacity for power facility j (PJ); $AVI_{j,t}$is the estimated availability of energy carrier j in period t (PJ); ENE_UP_j and ELE_UP_j is the bounds for the production and importation of the primary energy resources and electricity; $Ucap$ is the conversion coefficient from electricity-generating capacity to energy in a year (GW to PJ).

Obviously, the objective of model (24) is to minimize the sum of relevant costs associated with energy generation, import, conversion, transmission and consumption, which covers (a) expenses of energy supply and import in the region, (b) expenses of converting various primary energy resources to electricity, and (c) expenses of handling facility expansions. The system constraints define the interrelationships among the decision variables and the energy production/import, conversion, allocation and management conditions. In detail, constraints (24b)–(24e) denote that the total energy resources to direct utilization and electricity generation must not exceed the corresponding ones from domestic production and import; constraint (24f) means that the actual used renewable resources (hydropower, solar and wind energies) and nuclear must not exceed their availabilities/reserves in the region; constraint (24g) denotes that the total generated electricity must be more than the total electricity demand; constraint (24h) means that electricity generation must not exceed the allowable capacity limits within each period; constraints (24i) and (24j) denote that the generation/importation of energy and electricity can not exceed their individual upper bounds within the entire planning horizon; constraint (24m) defines the binary variables related to capacity-expansion decision variables; constraint (24n) denotes that the electricity-generating facilities can be expanded once in each period.

In the study system, multiple options of energy supply and multiple electricity-generating facilities would be employed to serve the energy needs. As discussed, the system cost equal to the total expenses for exploration, generation, importation, transmission, storage, conversion and consumption of energy resources and their corresponding products, as well as the expansions of electricity-generating facilities. Moreover, in model (24), decision variables involve two categories: continuous and binary ones. The continuous variables ($X^{\pm}_{j,t}$ and $Z^{\pm}_{i,t}$) include those of energy supply, electricity generation, and the binary ones ($Y^{\pm}_{j,m,t}$) are for capacity-expansion schemes of the electricity-generating facilities. Model (24) can effectively deal with complexities that exist not only within an individual sector/process but also between each other in an energy management system. It can also handle expansion schemes for electricity-generating facilities. Thus, competitions among energy resources, electricity-generating technologies and resource availabilities can be comprehensively reflected. Capacity expansion issues can also be successfully addressed. The above model can be solved through an interactive algorithm with two submodels. Since the objective function is to minimize the total economic cost associated with energy management systems, submodel corresponds to the lower bound of the objective function value should be solved firstly. The submodel can be formulated as follows:

Submodel (1):

$$\text{Min} \quad f^- = \sum_{i=1}^{I}\sum_{t=1}^{T}\widetilde{\overline{PRC}}^-_{i,t,\omega_{pi}}Z^-_{i,t} + \sum_{j=1}^{J}\sum_{t=1}^{T}\widetilde{\overline{PVRC}}^-_{j,t,\omega_{pi}}X^-_{j,t} + \sum_{j=1}^{J}\sum_{t=1}^{T}\sum_{m=1}^{M}INV_{j,t}\widetilde{\overline{ECE}}^-_{j,t,m,\omega_{pi}}Y^-_{j,t,m} \tag{25a}$$

$$\text{subject to:} \quad \sum_{l=1}^{3}\widetilde{\overline{DMD\_C}}^-_{l,t,\omega_{pi}} + \widetilde{\overline{RCON}}^+_{1,t,\omega_{pi}}X^-_{1,t} \le \sum_{i=1}^{2}Z^-_{i,t} \quad \forall t \tag{25b}$$

$$\sum_{l=1}^{3}\widetilde{\overline{DMD\_N}}^-_{l,t,\omega_{pi}} + \widetilde{\overline{RCON}}^+_{2,t,\omega_{pi}}X^-_{2,t} \le \sum_{i=3}^{4}Z^-_{i,t} \quad \forall t \tag{25c}$$

$$\sum_{l=1}^{L}\widetilde{\overline{DMD\_D}}^-_{l,t,\omega_{pi}} \le \sum_{i=5}^{6}Z^-_{i,t} \quad \forall t \tag{25d}$$

$$\sum_{l=1}^{L}\widetilde{\overline{DMD\_G}}^-_{l,t,\omega_{pi}} \le \sum_{i=7}^{8}Z^-_{i,t} \quad \forall t \tag{25e}$$

$$\widetilde{\overline{RCON}}^+_{j,t,\omega_{pi}}X^-_{j,t} \le \widetilde{\overline{AVI}}^+_{j,t,\omega_{pi}} \quad \forall j\ (j = 3, 4, 5 \text{ and } 6), t \tag{25f}$$

$$Z^-_{9t} + \sum_{j=1}^{J}X^-_{j,t} \ge \sum_{l=1}^{L}\widetilde{\overline{DMD\_E}}^-_{l,t,\omega_{pi}} \quad \forall t \tag{25g}$$

$$\sum_{m=1}^{M}\left[\widetilde{\overline{RCAP}}^+_{j,\omega_{pi}} + \sum_{p=1}^{t}\left(\widetilde{\overline{ECE}}^+_{j,m,p,\omega_{pi}}Y^-_{j,m,p}\right)\right] * Ucap \ge X^-_{j,t} \quad \forall j, t \tag{25h}$$

$$\sum_{t=1}^{T}Z^-_{i,t} \le \widetilde{\overline{UP}}^+_{i,\omega_{pi}} \quad \forall i \tag{25i}$$

$$\sum_{j=1}^{J}X^-_{j,t} \le \widetilde{\overline{UP}}^+_{t,\omega_{pi}} \quad \forall t \tag{25j}$$

$$Z^-_{i,t} \ge 0 \quad \forall i, t \tag{25k}$$

$$X^-_{j,t} \ge 0 \quad \forall j, t \tag{25l}$$

$$Y^{\pm}_{j,m,t} = 0, 1 \quad \forall j, m, t \tag{25m}$$

$$\sum_{t=1}^{T}\sum_{m=1}^{M}Y^-_{j,m,t} \le 1 \quad \forall j \tag{25n}$$

Then, the objective of this model can be transformed into

$$\text{Min} \quad \theta^- \tag{26a}$$

$$\text{subject to:} \quad \sum_{i=1}^{I}\sum_{t=1}^{T}\widetilde{\overline{PRC}}^-_{i,t,\omega_{pi}}Z^-_{i,t} + \sum_{t=1}^{T}\sum_{j=1}^{J}\widetilde{\overline{PVRC}}^-_{j,t,\omega_{pi}}X^-_{j,t} + \sum_{t=1}^{T}\sum_{m=1}^{M}\sum_{j=1}^{J}INV_{j,t}\widetilde{\overline{ECE}}^-_{j,m,t,\omega_{pi}}Y^-_{j,m,t} \le \theta^- \tag{26b}$$

Other constraints are the same with the model (25), i.e., (25b)–(25n)). Then, the original model (25) can be transformed into the following one:

$$\text{Min} = \theta^- + p_0E[\lambda^S_0(\omega_{p_i})^-] + q_0E[(\lambda^I_0(\omega_{p_i})^-] + \sum_{n=1}^{N}p_nE[\lambda^s_n(\omega_{p_i})^-] + \sum_{n=1}^{N}q_nE[\lambda^I_n(\omega_{p_i})^-] \tag{27a}$$

$$\text{subject to:} \quad S_0(f^-, \theta^-) = \lambda^S_0(\omega_{pi})^- \quad \forall p_i \tag{27b}$$

$$I_0(\theta^-, f^-) = \lambda^I_0(\omega_{pi})^- \quad \forall p_i \tag{27c}$$

$$S_n(A^+X^-, b^+) = \lambda^S_n(\omega_{pi})^- \quad \forall n = 1, 2, \ldots, N, p_i \tag{27d}$$

$$I_n(b^+, A^+X^-) = \lambda^I_n(\omega_{pi})^- \quad \forall n = 1, 2, \ldots, N, p_i \tag{27e}$$

$$Z^-_{i,t} \ge 0 \quad \forall i, t \tag{27f}$$

$$X^-_{j,t} \ge 0 \quad \forall j, t \tag{27g}$$

$$Y^{\pm}_{j,m,t} = 0, 1 \quad \forall j, m, t \tag{27h}$$

$$\sum_{t=1}^{T}\sum_{m=1}^{M}Y^-_{j,m,t} \le 1 \quad \forall j \tag{27i}$$

where $n = 1,2,3,\ldots,N$, indicating the number of the constraints (all of the constraints are reformulated into standardized formats as $A^{+}X^{-} \le b^{+}$) in the model. Through the model, solutions of $X^{-}_{j,t,\text{opt}}$, $Y^{-}_{j,m,t,\text{opt}}$, $Z^{-}_{i,t,\text{opt}}$ and f^{-}_{opt} can be successfully obtained. Then, the corresponding submodel to f^{+} can be formulated as follows:

Submodel (2):

$$\text{Min}\quad f^{+} = \sum_{i=1}^{I}\sum_{t=1}^{T}\overline{\widetilde{PRC}}^{+}_{i,t,\omega_{pi}}Z^{+}_{i,t} + \sum_{t=1}^{T}\sum_{j=1}^{J}\overline{\widetilde{PVRC}}^{+}_{j,t,\omega_{pi}}X^{+}_{j,t} + \sum_{t=1}^{T}\sum_{m=1}^{M}\sum_{j=1}^{J} INV_{j,t}\overline{\widetilde{ECE}}^{+}_{j,m,t,\omega_{pi}}Y^{+}_{j,m,t} \tag{28a}$$

subject to:

$$\sum_{l=1}^{3}\overline{\widetilde{DMD\_C}}^{+}_{l,t,\omega_{pi}} + \overline{\widetilde{RCON}}^{-}_{1,t,\omega_{pi}}X^{+}_{1,t} \le \sum_{i=1}^{2}Z^{+}_{i,t} \quad \forall t \tag{28b}$$

$$\sum_{l=1}^{3}\overline{\widetilde{DMD\_N}}^{+}_{l,t,\omega_{pi}} + \overline{\widetilde{RCON}}^{-}_{2,t,\omega_{pi}}X^{+}_{2,t} \le \sum_{i=3}^{4}Z^{+}_{i,t} \quad \forall t \tag{28c}$$

$$\sum_{l=1}^{L}\overline{\widetilde{DMD\_D}}^{+}_{l,t,\omega_{pi}} \le \sum_{i=5}^{6}Z^{+}_{i,t} \quad \forall t \tag{28d}$$

$$\sum_{l=1}^{L}\overline{\widetilde{DMD\_G}}^{+}_{l,t,\omega_{pi}} \le \sum_{i=7}^{8}Z^{+}_{i,t} \quad \forall t \tag{28e}$$

$$\overline{\widetilde{RCON}}^{-}_{j,t,\omega_{pi}}X^{+}_{j,t} \le \overline{\widetilde{AVI}}^{-}_{j,t,\omega_{pi}} \quad \forall j\ (j = 3,4,5,\ \text{and}\ 6), t \tag{28f}$$

$$Z^{+}_{9t} + \sum_{j=1}^{J}X^{+}_{j,t} \ge \sum_{l=1}^{L}\overline{\widetilde{DMD\_E}}^{+}_{l,t,\omega_{pi}} \quad \forall t \tag{28g}$$

$$\sum_{m=1}^{M}\left[\overline{\widetilde{RCAP}}^{-}_{j,\omega_{pi}} + \sum_{p=1}^{t}\left(\overline{\widetilde{ECE}}^{-}_{j,m,p,\omega_{pi}}Y^{+}_{j,m,p}\right)\right] * Ucap \ge X^{+}_{j,t} \quad \forall j,t \tag{28h}$$

$$\sum_{t=1}^{T}Z^{+}_{i,t} \le \widetilde{\overline{UP}}^{-}_{i,\omega_{pi}} \quad \forall i \tag{28i}$$

$$\sum_{j=1}^{J}X^{+}_{j,t} \le \widetilde{\overline{UP}}^{-}_{t,\omega_{pi}} \quad \forall t \tag{28j}$$

$$Z^{+}_{i,t} \ge \quad \forall i,t \tag{28k}$$

$$X^{+}_{j,t} \ge 0 \quad \forall j,t \tag{28l}$$

$$Y^{\pm}_{j,m,t} = 0,1 \quad \forall j,m,t \tag{28m}$$

$$\sum_{t=1}^{T}\sum_{m=1}^{M}Y^{+}_{j,m,t} \le 1 \quad \forall j \tag{28n}$$

$$Z^{+}_{i,t} \ge Z^{-}_{i,t,opt} \quad \forall i,t \tag{28o}$$

$$X^{+}_{j,t} \ge X^{-}_{j,t,opt} \quad \forall j,t \tag{28p}$$

$$Y^{+}_{j,t} \ge Y^{-}_{j,t,opt} \quad \forall j,t \tag{28q}$$

$$f^{+} \ge f^{-}_{\text{opt}} \tag{28r}$$

$$Y^{+}_{jmt} = 0,1 \quad \forall j,m,t \tag{28s}$$

Similarly, the above model can be transformed into

$$\text{Min} = \theta^{+} + p_0E\left[\lambda^{S}_{0}(\omega_{p_i})^{+}\right] + q_0E\left[(\lambda^{I}_{0}(\omega_{p_i})^{+}\right] + \sum_{n=1}^{N}p_nE\left[\lambda^{s}_{n}(\omega_{p_i})^{+}\right] + \sum_{n=1}^{N}q_nE\left[\lambda^{I}_{n}(\omega_{p_i})^{+}\right] \tag{29a}$$

$$S_0(f^{+},\theta^{+}) = \lambda^{S}_{0}(\omega_{pi})^{+} \quad \forall p_i \tag{29b}$$

$$I_0(\theta^{+},f^{+}) = \lambda^{I}_{0}(\omega_{pi})^{+} \quad \forall p_i \tag{29c}$$

$$S_n(A^{-}X^{+},b^{-}) = \lambda^{S}_{n}(\omega_{pi})^{+} \quad \forall n = 1,2,\ldots,N,p_i \tag{29d}$$

$$I_n(b^{-},A^{-}X^{+},) = \lambda^{I}_{n}(\omega_{pi})^{+} \quad \forall n = 1,2,\ldots,N,p_i \tag{29e}$$

$$Z^{+}_{i,t} \ge 0 \quad \forall i,t \tag{29f}$$

$$X^{+}_{j,t} \ge 0 \quad \forall j,t \tag{29g}$$

$$Y^{+}_{j,m,t} = 0,1 \quad \forall j,m,t \tag{29h}$$

$$\sum_{t=1}^{T}\sum_{m=1}^{M}Y^{+}_{j,m,t} \le 1 \quad \forall j \tag{29i}$$

$$Z^{+}_{i,t} \ge Z^{-}_{i,t,\text{opt}} \quad \forall i,t \tag{29j}$$

$$X^{+}_{j,t} \ge X^{-}_{j,t,\text{opt}} \quad \forall j,t \tag{29k}$$

$$Y^{+}_{j,t} \ge Y^{-}_{j,t,\text{opt}} \quad \forall j,t \tag{29l}$$

$$f^{+} \ge f^{-}_{\text{opt}} \tag{29m}$$

$$Y^{+}_{j,m,t} = 0,1 \quad \forall j,m,t \tag{29n}$$

Hence, solutions of f^{+}_{opt}, $X^{+}_{j,t,\text{opt}}$, $Y^{+}_{j,m,t,\text{opt}}$, and $Z^{+}_{i,t,\text{opt}}$ can be obtained through solving submodel (29). Thus, the final solutions of $f^{\pm}_{\text{opt}} = [f^{-}_{\text{opt}}, f^{+}_{\text{opt}}]$, and $\left(X^{\pm}_{i,t}\right)_{\text{opt}} = \left[X^{-}_{j,t,\text{opt}}, X^{+}_{j,t,\text{opt}}\right]$, $\left(Y^{\pm}_{j,m,t}\right)_{\text{opt}} = \left[Y^{-}_{j,m,t,\text{opt}}, Y^{+}_{j,m,t,\text{opt}}\right]$, and $(Z^{\pm}_{it})_{\text{opt}} = \left[Z^{-}_{i,t,\text{opt}}, Z^{+}_{i,t,\text{opt}}\right]$ can be successfully obtained.

4.4. Result analysis

Solutions of the developed model are displayed in Tables 7–9. The results indicated that most of the solutions can be expressed as intervals, reflecting that the majority of the decision alternatives would fluctuate within the obtained intervals in response to variations in end-user demands. Also, the results reflect that the patterns of energy supply and demand in the study region would be relatively stable over the planning horizon. Most of the resulting energy allotment values are expressed as intervals, implying that the related decision would be sensitive to the uncertain modeling inputs. Deficits of domestic energy production would occur if the available energy resources in local region can not sufficiently meet end-user demands over the planning horizon. In case of insufficient domestic energy supply, energy would be imported at a raised price from outside of the region. Since environmental performances are not considered in this study, economic cost is the pri-

Table 7
Solutions of the primary energy resources (PJ)

Variable	Energy resources	Period	Lower bound	Upper bound
Z_{11}	Coal (domestic production)	1	42.01	116.40
Z_{12}	Coal (domestic production)	2	74.18	74.18
Z_{13}	Coal (domestic production)	3	18.81	90.52
Z_{21}	Coal (import)	1	0	0
Z_{22}	Coal (import)	2	42.50	42.50
Z_{23}	Coal (import)	3	0	0
Z_{31}	NGA (domestic production)	1	45.58	58.52
Z_{32}	NGA (domestic production)	2	21.19	34.74
Z_{33}	NGA (domestic production)	3	48.24	61.03
Z_{41}	NGA (import)	1	0	0
Z_{42}	NGA (import)	2	25.50	25.50
Z_{43}	NGA (import)	3	0	0
Z_{51}	Diesel (domestic production)	1	0	7.68
Z_{52}	Diesel (domestic production)	2	25.19	34.32
Z_{53}	Diesel (domestic production)	3	25.14	33.54
Z_{61}	Diesel (import)	1	22.89	22.89
Z_{62}	Diesel (import)	2	0	0
Z_{63}	Diesel (import)	3	2.61	2.61
Z_{71}	Gasoline (domestic production)	1	30.84	54.25
Z_{72}	Gasoline (domestic production)	2	77.15	101.68
Z_{73}	Gasoline (domestic production)	3	79.90	105.24
Z_{81}	Gasoline (import)	1	42.50	42.50
Z_{82}	Gasoline (import)	2	0	0
Z_{83}	Gasoline (import)	3	0	0
Z_{91}	Electricity (import)	1	18.43	20.43
Z_{92}	Electricity (import)	2	1.21	11.25
Z_{93}	Electricity (import)	3	17.86	29.93
Objective	function values ($\$10^6$)			2,375.67
4,319.53				

Table 8
Solutions of the electricity generation (PJ)

Variables	Facility	Period	Lower bound	Upper bound
X_{11}	Coal	1	31.40	37.39
X_{12}	Coal	2	44.57	44.57
X_{13}	Coal	3	18.78	18.78
X_{21}	NGA	1	4.80	4.80
X_{22}	NGA	2	4.06	4.06
X_{23}	NGA	3	4.06	4.06
X_{31}	Hydropower	1	0.02	0.02
X_{32}	Hydropower	2	0.02	0.02
X_{33}	Hydropower	3	13.89	13.89
X_{41}	Solar energy	1	0	0
X_{42}	Solar energy	2	9.39	9.39
X_{43}	Solar energy	3	0	0
X_{51}	Wind energy	1	0	0
X_{52}	Wind energy	2	1.07	1.07
X_{53}	Wind energy	3	0	0
X_{61}	Nuclear	1	0	0
X_{62}	Nuclear	2	1.28	1.28
X_{63}	Nuclear	3	13.88	13.88

Table 9
Solutions of the binary variables and the corresponding capacity expansion options

Variables	Facility	Period	Option scheme	Capacity expansion	
Y_{131}	Coal thermal	1	3	$p = 0.15$	(0.30, 0.1, 0.1)
				$p = 0.7$	(0.40, 0.1, 0.1)
				$p = 0.15$	(0.52, 0.1, 0.1)
Y_{221}	NGA thermal	1	2	$p = 0.15$	(0.07, 0.1, 0.1)
				$p = 0.7$	(0.10, 0.1, 0.1)
				$p = 0.15$	(0.12, 0.1, 0.1)
Y_{313}	Hydro station	3	1	$p = 0.15$	(0.23, 0.1, 0.1)
				$p = 0.7$	(0.30, 0.1, 0.1)
				$p = 0.15$	(0.39, 0.1, 0.1)
Y_{613}	Nuclear plant	3	1	$p = 0.15$	(0.23, 0.1, 0.1)
				$p = 0.7$	(0.30, 0.1, 0.1)
				$p = 0.15$	(0.39, 0.1, 0.1)

mary factor for determining the structure and pattern of energy importation. Natural gas, diesel, gasoline and electricity would be imported in all of the three periods. Particularly, electricity would be imported in the cases of (a) electricity demand can hardly be met by domestic production and (b) imported electricity is more competitive in economic costs and availabilities compared that produced domestically.

It is indicated from the results that interval solutions can be generated from the developed FRIP model. As displayed in Tables 7 and 8, the majority of the obtained solutions can be presented with interval values, implying that a variety of decision alternatives within such interval ranges could be used for providing support to relevant decision making. Also, such intervals reflect (a) any changes in energy availabilities and end-user demands and (b) multiple uncertainties (expressed as fuzzy-random variables) of the related parameters, reflecting varied fuzzy sets under different probability levels (i.e., fuzzy-random variables). Although energy supply and demand would response sensitively to energy availabilities and related economic and technical parameters, allocation patterns of energy resources would be stable over the planning horizon. For example, within the 15-year planning horizon, the majority of coal, natural gas and RPP would be jointly used as primary energy resources since they are basically needed for meeting municipal, commercial, industrial and agricultural demands. Meanwhile, part of these energies would be adopted for electricity generation.

In the study system, a variety of energy resources and the associated technologies would compete with each other for providing energies to end-users under different economic costs, availabilities and other relevant performance factors such as efficiencies. Most of RPP would be utilized for transportation activities. In detail, in period 1, [42.01, 116. 40] and 0 PJ of coal would be supplied by domestic production and import. Such intervals of the domestic coal production mean the supply of coal would respond sensitively to the variations of the end-user demands and other relevant factors, which are mainly expressed as fuzzy-random variables. Also, the deterministic value obtained for the coal import in period 1 represents that coal import would be merely a minor adjustment to the entire coal supply due to the raised prices of energy import compared with those of domestic production. Over the planning horizon, the total amount of coal supply would be [177.50, 281.10] PJ. Among this amount, coal importation would be 0, 42.50 and 0 PJ over periods 1–3. The variations of coal supply are mainly caused by: (a) the growth of end-user demands on coal and (b) the raised price for energy import. Moreover, the system automatically chooses to generate a raised proportion of electricity from other energy resources such as hydropower, solar and wind energies, as well as nuclear, leading to the declination of the total coal demands over a specific period. The patterns of natural gas supply would be similar to those of coal supply over the 3 planning period. Domestic production of natural gas would be [45.58, 58.52], [21.19, 34.74], and [48.24, 61.03] PJ, respectively, reflecting an increasing trend over the three period due to the increment of end-user demands in municipal, commercial and agricultural sectors. However, the importation of natural gas would be significantly different compared with that produced domestically. Natural gas would be merely imported in period 2 (25.50 PJ). This is probably because most of the coal in the period 2 would be supplied to direct end-user consumption instead of electricity generation, which correspondingly reduce the demands for natural gas since coal and natural gas are mainly competitive with each other for heat generation in municipal, commercial and industrial sectors. Diesel and gasoline are the two major energy sources of RPP. Most of the diesel consumed in the region would be supplied by domestic production, i.e., [0, 7.68], [25.19, 34.32] and [25.14, 33.54] PJ, respectively. The imported diesel would contribute a minor part to the total natural gas consumption, i.e., 22.89, 0 and 2.61 PJ in periods 1–3. Supply patterns of gasoline would be more stable compared with those of diesel supply. The results indicate that almost all of the gasoline demands from transportational, municipal and industrial sectors could be satisfactorily met by domestic production except in period 1. Over the planning horizon, domestic production of gasoline would be [30.84, 54.25], [77.15, 101.68], and [79.90, 105.24] PJ, respectively. The imported gasoline would be 42.50 PJ in period 1, as well as 0 PJ over the next two periods. Generally, supply patterns of RPP (diesel and gasoline) would be comparatively stable compared with most of other major energy resources (coal and natural gas). This is because that almost all of RPP would be used for transportation activities and would be hardly employed for secondary energy generation such as electricity.

Furthermore, over the 15-year planning period, most of energy supply plans (in both domestic and imported ones) indicate an increasing trend except coal supply. For example, total supplies of diesel would be [22.89, 30.57], [25.19, 34.32] and [27.75, 36.15] PJ over the three periods, respectively. Similarly, in the same periods, gasoline supply would be [73.34, 96.75], [77.15, 101.68] and [79.90, 105.24] PJ, respectively. Such an increasing tendency might be primarily caused by the increment of end-user demands in the transportational sector. Comparatively, the supply of coal would vary slightly over the 15-year period. In period 1, the total supply of coal would be [42.01, 116.40] PJ.

In the following period, this value would increase greatly to 116.68 PJ. This is because that some of the electricity-generating facilities would be expanded after period 1, resulting in a raised capacity in electricity generation from resources besides coal. Thus, the total demand for coal would increase greatly, coupling with an increasing trend of demand for heating in municipal, commercial and industrial sectors.

Over the planning horizon, electricity generation patterns would be comparatively stable compared with those of primary energy supply. This is mainly because (a) capacities of electricity-generating facilities can be expanded within the planning period, improving flexibility of their capabilities in meeting end-user demands, (b) limits of electricity import are too high to be exceeded, (c) electricity can be generated from conventional energy resources, such as coal and natural gas, (d) availabilities of local renewable energy resources are sufficient to meet the demand for power production, (e) the mixture of electricity generation options is diverse, leading to a relatively stable electricity-generating structure, and (f) electricity can be imported as a stable adjustment to that generated domestically. Specifically, in period 1, most of the electricity would be generated from the facilities based on coal, natural gas and hydropower, as well as importation. A minor part of electricity would be produced from wind energy (approximately 0 PJ). In detail, [31.40, 37.39], 4.80, 0.02, and [18.43, 20.43] PJ of electricity would be generated from coal, natural gas, hydropower and importation, respectively. However, the patterns of electricity supply would vary greatly in the next two periods because of capacity expansion in period 1.Capacities of relevant facilities (those utilize coal, natural gas, hydropower and nuclear) would be expanded in periods 1 and 3. Since most of the expanded capacities could be available as residual capacities in the following periods, the total capacities of the related facilities would be sufficient for meeting the electricity demand in the study region in period 2. In period 3, the existing capacities might be insufficient to meet end-user demands, invoking capacity expansion of relevant facilities, i.e., hydropower stations and nuclear plants. For all of the capacity expansion options, the ones in period 1 would be options 2 and 3. In periods 3, only option 1 would be adopted. Overall, electricity would be mainly generated from hydropower, nuclear, solar and wind energies. For example, in period 3, the main contributors to electricity production would be coal (18.78 PJ), natural gas (4.06 PJ), hydropower (13.89 PJ), nuclear plants (13.88 PJ) and importation ([17.86, 29.93] PJ). Such patterns of power generation could be mainly dependent on: (a) availability limits of nuclear and wind energy, (b) price competitiveness of related facilities after capacity expansion, and (c) price is comparatively high for electricity import.

Under multiple uncertainties in the related factors and parameters, solution of the objective function values ($f_{\text{opt}}^{\pm} = \$[2,375.67, 4,319.53] \times 10^6$) represents two extremes of net system cost over the planning horizon. Conventionally, as the actual value of each continuous variable varies within its lower and upper bounds, the net system cost would change correspondingly between f_{opt}^{-} and f_{opt}^{+} with a variety of system-reliability level. In the FRIP model, most uncertain parameters are expressed as intervals with known lower and upper bounds, which can be further presented as a series of fuzzy sets with known probability distributions. These parameters are expressed as fuzzy-random variables, reflecting hybrid uncertainties of fuzziness and randomness in determining related factors for the planning of energy management systems. Given different energy-availability conditions and the underlying competitions in the associated accessibility and economic costs, the obtained plans of the net system cost would vary progressively within its relevant solution interval. Normally, a plan with a lower system cost would correspond to a lower end-user demand and a lower level of projection to economic development and population growth in the study region; however, it would result in a higher risk of violating the system constraints. Besides, the upper bounds of cost coefficients correspond to f_{opt}^{+}, implying that the decision maker has an extremely conservative attitude for estimating the system cost and end-user demand, leading to a low system-failure risk and high reliability level for energy production and supply. Conversely, a plan with a lower system cost would correspond to an optimistic estimation towards energy demand projection and relevant costs (i.e., lower-bound system cost, lower energy demand and lower cost coefficients), which also means that conservative prediction of economic development and population growth over the planning horizon. Thus, a decision with lower system cost could lead to a higher risk of system failure and lower system reliability for meeting energy needs in the study region. This demonstrates that there is a tradeoff between system cost and reliability level for energy resources management.

The FRIP model can deal with multiple uncertainties expressed as fuzzy-random variables, discrete intervals, as well as their combinations through a two-step interactive procedure based on the analysis of a series of superiority and inferiority degrees. Variations both in the cost coefficients and the end-user demands would correspond to different energy management policies and strategies under uncertainty. Tables 7–9 provide various energy allotment schemes with the consideration of uncertain parameters which are expressed as fuzzy sets under different probability levels. The results indicate that, when the energy demands reaches the lower bounds, the corresponding plans would be in a reliable status and result in a lower system cost. Conversely, a policy corresponding to the upper bounds of energy demand would lead to an enhanced system cost. Since energy activities are closely related to policies at the regional context, solutions of the FRIP model can also be interpreted to clarify the interactions among various system components and the associated tradeoffs between energy security and economic objectives.

5. Conclusions

In this study, a fuzzy-random interval programming (FRIP) model has been developed for supporting effective planning of energy management systems at the regional scale under multiple uncertainties. This method represents an extension of the existing interval linear programming (ILP) and superiority–inferiority-based fuzzy-stochastic programming (SI-FSP) and mixed integer programming (MILP) techniques. FRIP is capable of reflecting multiple formats of uncertainties in both objective function and system constraints which are presented as interval values, possibilistic and/or probabilistic distributions, as well as their combinations. Particularly, uncertainties expressed as fuzzy-random variables are allowed to be modeling inputs in both of the objective function and the constraints. Moreover, the lower and upper bounds of interval parameters are allowed to be expressed as fuzzy-random variables, further improving the robustness of optimization efforts.

The developed method has then been applied to a case of long-term regional EMS planning. The obtained interval solutions can be used for generating decision alternatives and thus help decision makers identify desired policies under various economic and system-reliability constraints. The generated solutions can provide optimal patterns of energy resource/service allocation and facility capacity expansion options with a minimized system cost, maximized system reliability and a maximized energy security. Tradeoffs between system costs and reliability can also be tackled. Higher costs would increase system stability, while a desire for lower system costs would run into a risk of potential instability of the management system. The obtained solutions can also be used for examining the relations between system cost and resources availability.

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