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Development of a Chance-Constrained Dual-Objective Fractional Programming for Shandong's Clean Power Transition

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ABSTRACT. In this study, an inexact mixed-integer interval stochastic fractional model (IMSFP) is developed for Shandong's sustainable power system management under uncertainties. Shandong has a high proportion of fossil-fuel power, which has resulted in significant greenhouse gas emissions. Future is an essential period for energy structure transition. Developed IMSFP can effectively tackle dual objective, system efficiency represented as output/input ratios, as well as uncertainties described as interval values and probability distributions in the constraints and objectives. The results indicate that the clean power transition and capacity expansion scheme are sensitive to different constraint-violation risk levels. Obtained interval solutions can provide flexible strategies for resource allocation and expansion capacities under multiple complexities. An economic single objective model (IMCLP) is also developed, which aims at minimizing the system cost. The comparative results illustrate that the IMSFP model can better characterize the real-world power system problems through optimizing a ratio between clean energy utilization and system cost. Biomass and wind power would be major developed electricity forms in the future, and solar energy has great development potential. In short, the proposed IMSFP model is advantageous in balancing conflicting dual objectives and reflecting complicated interactions among system efficiency, economic cost, system reliability, and constraint-violation scenarios.

Keywords: dual-objective linear programming; interval linear programming; constraint-violation risk; power system planning; clean power transition

1. Introduction

Sustainable management of the energy system is essential to regional social and economic development, as well as environmental protection throughout the world (Dubreuil et al., 2013; Xie et al., 2014). At present, the major consumptive energy resource for electricity generation and heating systems are concentrated on fossil fuels (e.g., coal, natural gas, and oil), especially in developing countries, which are the largest producers for air-pollution contaminants (Noailly and Smeets, 2015; Khosravani et al., 2016). For example, in China, the fossil-fuel power generation was 4923.1 TW, accounting for 70.39% of total power generation in 2018. The total discharged pollutant for sulfur dioxide (SO_2) reached 821.1 million tonnes; nitric dioxide (NO_2) reached 4516.05 million tonnes, and particulate matter (PM) reached 666.4 million tonnes. It worth mentioning that the concerned factor resulted in 9.3 trillion tonnes of carbon dioxide (CO_2). Coupled with the growing electricity demand, global warming, and climate change, high-ratio fossil fuel utilization energy structure poses a threat to human health, social sustainability, economic development, and environmental protection. The unprecedented situation process alleviates actions to promote the previous shortage. Consequently, clean energy is putting into the calendar these days, which including nuclear power, biomass, wind power, solar energy, and hydropower. Such clean technologies are regarded as optimal alleviations to energy generation and environmental protection. Decision-makers have committed to increasing the utilization of clean energy through articulated energy system planning and technical improvement. In previous studies, numerous of optimization methods have been applied to power system management; however, a variety of challenges for sustainable management of hybrid electrical systems are still existing in current research progress (Zhu and Huang, 2013; Zhu et al., 2014). Firstly, the uncertainties hiding in the trade-off between environmental protection and economic development for decision-makers to identify (Zhou et al., 2015). Secondly, unexpectable uncertainties associated with the input parameters, such as future electricity demand, resource availabilities, and technological capital costs, as well as their interrelationships have to be addressed properly (Chen et al., 2019). Thirdly, the increasing energy demand should be satisfied by power generation, which often implies that the dynamic features of facility capacities and capacity expansion problems should be taken into consideration. Therefore, an efficient integrated model that can systematically satisfy complexities related to environmental, social, and economic aspect is desired for energy system planning under uncertainties.

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Over the past decades, a large number of hybrid optimization models were proposed in system optimization and energy management (Li et al., 2013; Zhu and Huang, 2013; Xu et al., 2016; Zhou et al., 2016; Carvalho et al., 2018; Du et al., 2018; Li et al., 2018). Classically, a great many models were single-objective linear programming (LP), which aims to identify the most economic solutions with minimized of the total system cost. Interval possibilistic-stochastic programming (IPSP) was proposed for regional mixed energy system planning (Yu et al., 2019). An interval fuzzy programming was established to evaluate the system risk with carbon capture technology (Xie et al., 2019). Obviously, the single-objective programming models roughly convert environmental factors into economic factors or simply transform environmental elements into one of the constraints, thus such models may not achieve the sustainable development of both economic and environment. For better uncovering the multi-dimensionality of the sustainability target, an increasing number of multiple objective programming models have been applied to tackle energy management problems (Martins et al., 1996; Mavrotas et al., 1999). Among them, goal programming (Ramanathan and Ganesh, 1995), weighted sum (Martins et al., 1996; Jeganathan et al., 2011), and fuzzy multi-objective models (Nasiri and Huang, 2008) have been widely employed to identify satisfactory compromise solutions. In general, there are two major approaches to address multi-objective problems: compromise programming and aspiration analysis approaches (Zhu and Huang, 2013). In compromise programming, the importance of each objective was expressed by weighting factors based on unrealistic or subjective assumptions, thus the determined solutions are highly dependent on the preference of decision-makers. For instance, Ren and Zhou (2010) solved the multi-objective goal programming by compromise programming, which based on the preferenced criteria of planners. Subsequently, the aspiration-analysis approaches are to form a single-objective model by optimizing one objecttive and transforming others into constraints under certain aspiration levels. A short-term multi-objective economic environmental hydrothermal scheduling (MEEHS) model (Zhang et al., 2012) was formulated for optimizing energy cost and the pollutant emission effects, which was solved by constraint handling method. This method is combined objectives of multiple aspects into a single measure on the basis of subjective assumptions as well. Moreover, none of them could analyze the system efficiencies represented as output/input ratio.

Fractional programming (FP) is an effective approach to deal with multi-objective problems and address system efficiency without subjective assumptions (Stancu-Minasian, 1999; Gómez et al., 2006; Tofallis, 1998; Zhu and Huang, 2013). It was diffusely used in ratio optimal problems between two quantities, such as cost/time, output/input, and output/cost, and solutions only with better performance of per unit of inputs (e.g., resource, time, and cost) would be chosen. It has been applied in the domain of economic analysis, solid waste management, and water resource allocation (Li et al., 2011; Zhu and Huang, 2011, 2013; Zhu et al., 2014). For instance, a dynamic stochastic fractional programming (DSFP) was developed for capacity-expansion planning of electricity systems, which targeted at a maximized ratio of renewable energy generation of total system cost (Zhu and Huang, 2013). Zhou et al. (2015) proposed a chance-constrained two-stage fractional regional energy model (CTFO-REM) for British Columbia regional energy system planning under stochastic uncertainties, in order to minimize the system cost of per unit renewable energy utilization. Furthermore, an inexact two-stage fractional energy systems planning model (ITF-ESP) was devised in 2018 to address dual-objective energy system planning problems under interval featured uncertainties (Song et al., 2018). Both CTFO-REM and ITF-ESP models are practical methods to deal with conflicting issues (e.g., renewable energy utilization and system cost), however, the CTFO-REM cannot address interval uncertainties in input parameters, and the ITF-ESP was unable to analyze management schemes under different constraint-violation risk levels. In real-world energy system, renewable energy resource is limited to spatial and/or temporal fluctuations, the availability of wind and solar energies can be expressed as probability distributions. In addition, resource prices and power demand are barely estimated imprecisely and also lack of distribution information, and only can be converted as interval information.

Therefore, the objective of this study is to develop a dynamic chance-constrained interval fractional programming (IMSFP) for sustainable management of regional power system and environmental management under uncertainties through incorporating CCP (chance-constrained programming), ILP (interval linear programming), and MILP (mixed-integer linear programming) techniques into an FP optimization framework. The integrated IMSFP model can not only address the multi-objective trade-off between environment and economy, but also reflect dynamic variations under uncertainties presented as interval and stochastic variables in the objective and constraints. Then the developed model will be applied to a real-world case study to demonstrate its flexibility in supporting power system planning and environmental management. Desired regional power system management schemes under different constraint-violation risks will be obtained by solving this model. These results will provide planners to analyze (a) sophisticated interrelationships within renewable energy utilization efficiency and subsystems (i.e., resource availabilities) under different system violation levels; (b) conflicts between economic and environmental objectives in regional power system planning; (c) dynamic facilities' capacity-expansion decisions; (d) input parameters described as interval and probability distribution; (e) energy allocation patterns of generating technologies.

2. Methodology

2.1. Inexact Linear Fractional Programming (ILFP)

As the aforementioned energy system complexities and uncertainties in system planning, an inexact mixed-integer interval stochastic fractional programming (IMSFP) is introduced into the energy planning system. According to Zhu and Huang (2013), inexact linear fractional programming (ILFP) is a high-efficiency tool to transform dual objective optimization problems into ratio optimal problems and to tackle with these parameters which only upper and lower bounds are available, without distribution information:

$$Max\ f^{\pm} = \frac{\sum_{j=1}^{n} c_j^{\pm} x_j^{\pm} + \alpha^{\pm}}{\sum_{j=1}^{n} d_j^{\pm} x_j^{\pm} + \beta^{\pm}} \tag{1a}$$

subject to:

$$\sum_{j=1}^{n} a_{ij}^{\pm} x_j^{\pm} \le b_i^{\pm},\ i = 1, 2, \ldots, m \tag{1b}$$

$$x_j^{\pm} \ge 0,\ j = 1, 2, \ldots, n \tag{1c}$$

where $x_j^{\pm}$ (j = 1, 2, ..., n) are interval decision variables, $c_j^{\pm}$ and $d_j^{\pm}$ are coefficients in numerator and denominator of the objecttive function, and $\alpha^{\pm}$ are $\beta^{\pm}$ scalar constants, $a_{ij}^{\pm}$ are technical coefficients, and $b_i^{\pm}$ are right-hand side parameters. All or some of these parameters can be described as interval numbers.

2.2. Inexact Mixed-Integer Fractional Programming

In practical energy system planning, some of the decision variables should be considered as integers. An inexact mixed-integer fractional programming (IMIFP) (Zhu et al., 2014) is formulated by incorporating mixed-integer programming techniques into the ILFP. Then the Equation (1) can be converted to:

$$Max\ f^{\pm} = \frac{\sum_{j=1}^{l} c_j^{\pm} x_j^{\pm} + \sum_{j=l+1}^{n} c_j^{\pm} y_j^{\pm} + \alpha^{\pm}}{\sum_{j=1}^{l} d_j^{\pm} x_j^{\pm} + \sum_{j=l+1}^{n} d_j^{\pm} y_j^{\pm} + \beta^{\pm}} \tag{2a}$$

subject to:

$$\sum_{j=1}^{l} a_{ij}^{\pm} x_j^{\pm} + \sum_{j=l+1}^{n} a_{ij}^{\pm} y_j^{\pm} \le b_i^{\pm},\ i = 1, 2, \ldots, m \tag{2b}$$

$$x_j^{\pm} \ge 0,\ j = 1, 2, \ldots, l\ \ (l < n) \tag{2c}$$

$$y_j^{\pm} \ge 0,\ y_j^{\pm} \text{ are integer variables, } j = l+1, l+2, \cdots, n \tag{2d}$$

where $y_j^{\pm}$ are interval-integer decision variables, it is defined as $y_j^{\pm} = \{y_j \mid y_j^- \le y_j \le y_j^+$, and y_j^-, y_j, y_j^+ are all integers$\}$. Specifically, when $y_j^{\pm}$ are interval-binary variables, it can be defined as $y_j^{\pm} = \{y_j \mid 0 \le y_j \le 1$, and y_j are all integers$\}$.

2.3. Inexact Mixed-Integer Interval Stochastic Fractional Programming Method

When some of the right-hand-side parameters ($b_{ij}^{\pm}$) in the model (2) are stochastics, IMIFP model is transformed into an inexact mixed-integer interval stochastic fractional IMSFP which can be formulated as follows:

$$Max\ f^{\pm} = \frac{\sum_{j=1}^{l} c_j^{\pm} x_j^{\pm} + \sum_{j=l+1}^{n} c_j^{\pm} y_j^{\pm} + \alpha^{\pm}}{\sum_{j=1}^{l} d_j^{\pm} x_j^{\pm} + \sum_{j=l+1}^{n} d_j^{\pm} y_j^{\pm} + \beta^{\pm}} \tag{3a}$$

subject to:

$$\Pr\left[\sum_{j=1}^{l} a_{ij}^{\pm} x_j^{\pm} + \sum_{j=l+1}^{n} a_{ij}^{\pm} y_j^{\pm} \le b_i^{\pm}(t)\right] \ge 1 - p_i,\ i = 1, 2, \ldots, m \tag{3b}$$

$$x_j^{\pm} \ge 0,\ j = 1, 2, \ldots, l\ \ (l < n) \tag{3c}$$

$$y_j^{\pm} \ge 0,\ y_j^{\pm} \text{ are integer variables, } j = l+1, l+2, \cdots, n \tag{3d}$$

where $b_i(t)$ are random right-hand-side parameters, it is defined on a possibility space T ($t \in T$), p_i is a given level of probability for constraint.

Since coefficients in both constraints and objective are intervals, this model could not be solved directly (Zhu et al., 2014). It should be converted into two interactive sub-models corresponding to f^- and f^+ (Hladík, 2010). For the purpose of improving calculating accuracy, the sub-model corresponding to f^- is calculated first (Fan and Huang, 2012). According to Charnes et al. (1971), when the left-hand-side coefficients a_{ij} are deterministic and $b_i(t)$ are random at all p_i values, the constraint $\Pr\left[A_i X \le b_i(t)\right] \ge 1 - p^i$ can be linearized as $A_i X \le b_i(t)^{(p_i)}$, where $b_i(t)^{(p_i)} = F_i^{-1}(t)$ was calculated from the cumulative distribution function of b_i and the probability of violating constraint p_i. Thus, the abovementioned model can be formulated as follows:

$$Max\ f^{+} = \frac{\begin{array}{c}\sum_{j=1}^{k} c_j^{-} x_j^{-} + \sum_{j=k+1}^{l} c_j^{-} y_j^{+} + \\ \sum_{j=l+1}^{l+t} c_j^{-} y_j^{-} + \sum_{j=l+t+1}^{n} c_j^{-} y_j^{+} + \alpha^{-}\end{array}}{\begin{array}{c}\sum_{j=1}^{k} d_j^{+} x_j^{-} + \sum_{j=k+1}^{l} d_j^{+} x_j^{+} + \\ \sum_{j=l+1}^{l+t} d_j^{+} y_j^{-} + \sum_{j=l+t+1}^{n} d_j^{+} y_j^{+} + \beta^{+}\end{array}} \tag{4a}$$

subject to:

$$\begin{aligned}&\sum_{j=1}^{k} \left|a_{ij}^{\pm}\right|^{+} Sign\left(a_{ij}^{\pm}\right) x_j^{-} + \sum_{j=k+1}^{l} \left|a_{ij}^{\pm}\right|^{-} Sign\left(a_{ij}^{\pm}\right) x_j^{+} \\ &+ \sum_{j=l+1}^{l+t} \left|a_{ij}^{\pm}\right|^{+} Sign\left(a_{ij}^{\pm}\right) y_j^{-} + \sum_{j=l+t+1}^{n} \left|a_{ij}^{\pm}\right|^{-} Sign\left(a_{ij}^{\pm}\right) y_j^{+} \\ &\le \left(b_i^{-}\right)^{p_i},\ i = 1, 2, \ldots, m\end{aligned} \tag{4b}$$

$$x_j^{-} \ge 0,\ j = 1, 2, \ldots, k \tag{4c}$$

$$x_j^{+} \ge 0,\ j = k+1, k+2, \ldots, l \tag{4d}$$

$$y_j^{-} \ge 0,\ y_j^{-} \text{ are integer variables, } j = l+1, l+2, \ldots, n \tag{4e}$$

$$y_j^+ \ge 0\,,\ y_j^+ \ \text{ are integer variables, } j = t+1, t+2, \ldots, n \tag{4f}$$

where $Sign\left(a_{ij}^\pm\right)$ is defined as:

$$Sign\left(a_{ij}^\pm\right) = \begin{cases} 1 & if\ \ a_{ij}^\pm \ge 0 \\ -1 & if\ \ a_{ij}^\pm \le 0 \end{cases} \tag{4g}$$

The solutions of $x_{jopt}^-\left(j = 1, 2, \ldots, k\right)$, x_{jopt}^+ (j = k + 1, k + 2, ..., l), y_{jopt}^- ($j = l + 1$, $l + 2$, …, $l + t$) and y_{jopt}^+ ($j = l + t + 1$, $l + t + 2$, ..., n) can be obtained from sub-model f^-. Then the interactive sub-model corresponding to f^+ can be expressed as follows:

$$Max\ f^+ = \frac{\sum_{j=1}^{k} c_j^+ x_j^+ + \sum_{j=k+1}^{l} c_j^+ y_j^- + \sum_{j=l+1}^{l+t} c_j^+ y_j^+ + \sum_{j=l+t+1}^{n} c_j^+ y_j^- + \alpha^+}{\sum_{j=1}^{k} d_j^- x_j^+ + \sum_{j=k+1}^{l} d_j^- x_j^- + \sum_{j=l+1}^{l+t} d_j^- y_j^+ + \sum_{j=l+t+1}^{n} d_j^- y_j^- + \beta^-} \tag{5a}$$

subject to:

$$\sum_{j=1}^{k} \left|a_{ij}^\pm\right|^- Sign\left(a_{ij}^\pm\right) x_j^+ + \sum_{j=k+1}^{l} \left|a_{ij}^\pm\right|^+ Sign\left(a_{ij}^\pm\right) x_j^- + \sum_{j=l+1}^{l+t} \left|a_{ij}^\pm\right|^- Sign\left(a_{ij}^\pm\right) y_j^+ + \sum_{j=l+t+1}^{n} \left|a_{ij}^\pm\right|^+ Sign\left(a_{ij}^\pm\right) y_j^- \le \left(b_i^+\right)^{p_i},\ i = 1, 2, \ldots, m \tag{5b}$$

$$x_j^+ \ge x_{jopt}^-,\ j = 1, 2, \ldots, k \tag{5c}$$

$$x_j^- \ge x_{jopt}^+,\ j = k+1, k+2, \ldots, l \tag{5d}$$

$$y_j^+ \ge y_{jopt}^-,\ j = l+1, l+2, \cdots, l+t \tag{5e}$$

$$y_j^- \ge y_{jopt}^+,\ j = t+1, t+2, \ldots, n \tag{5f}$$

$$\sum_{j=1}^{oi} a_{ij}^- x_j^+ + \sum_{j=oi+1}^{k} a_{ij}^- x_{jopt}^- + \sum_{j=k+1}^{k+qi} a_{ij}^- y_{jopt}^+ + \sum_{j=k+qi+1}^{l} a_{ij}^- x_j^- + \sum_{j=l+1}^{l+ui} a_{ij}^- x_j^+ + \sum_{j=l+ui+1}^{l+t} a_{ij}^- y_{jopt}^- + \sum_{j=l+t+1}^{l+t+vi} a_{ij}^- y_{jopt}^+ + \sum_{j=l+t+vi+1}^{n} a_{ij}^- y_j^- \le \left(b_i^+\right)^{p_i},\ i = 1, 2, \ldots, m \tag{5g}$$

$$x_j^+ \ge 0,\ j = 1, 2, \ldots, k \tag{5h}$$

$$x_j^- \ge 0,\ j = k+1, k+2, \ldots, l \tag{5i}$$

$$y_j^+ \ge 0\,,\ y_j^+ \ \text{ are integer variables, } j = l+1, l+2, \ldots, l+t \tag{5j}$$

$$y_j^- \ge 0\,,\ y_j^- \ \text{ are integer variables, } j = t+1, t+2, \ldots, n \tag{5k}$$

where o_i ($o_i \le k$) and q_i ($q_i \le 1 - k$) stands for the numbers of decision variables $x_j^\pm$ (j = 1, 2, ..., k) and $x_j^\pm$ ($j = k + 1$, $k + 2$, ..., l) with $a_{ij}^- \ge 0$ in constant i. Similarly, u_i ($u_i \le t$) and v_i ($v_i \le n - l - t$) represents for the numbers of integer decision variables $y_j^\pm$ ($j = l + 1$, $l + 2$, …, $l + t$) and $y_j^\pm$ ($j = l + t + 1$, $l + t + 2$, …, n) with $a_{ij}^- \le 0$ in constant i. The solutions of x_{jopt}^+ (j = 1, 2, …, k), x_{jopt}^- ($j = k + 1$, $k + 2$, …, l), y_{jopt}^+ ($j = l + 1$, $l + 2$, …, $l + t$), and x_{jopt}^- ($j = l + t + 1$, $l + t + 2$, …, n) can be obtained from sub-model f^+.

The above interactive sub-models can be solved by mixed-integer linear fractional programming method (MILFP) and branch-and-bound algorithm as follows (Swarup, 1965). Finally, the solutions of $f_{opt}^\pm = \left[f_{opt}^-, f_{opt}^+\right]$, $x_{jopt}^\pm = \left[x_{jopt}^-, x_{jopt}^+\right]$, ($j$ = 1, 2, …, l) and $y_{jopt}^\pm = \left[y_{jopt}^-, y_{jopt}^+\right]$, ($j = l + 1$, $l + 2$, …, n) can be obtained. Figure 1 shows the framework of the IMSFP model.

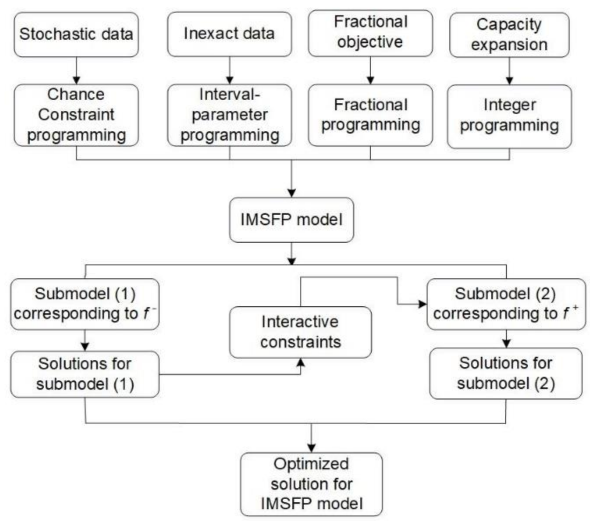

Figure 1. Schematic diagram of the IMSFP model.

An inexact mixed-integer stochastic fractional (MSFP) programming model can be formulated as:

$$Max\ f = \frac{\sum_{j=1}^{l} c_j x_j + \sum_{j=l+1}^{n} c_j y_j + \alpha}{\sum_{j=1}^{l} d_j x_j + \sum_{j=l+1}^{n} d_j y_j + \beta} \tag{6a}$$

subject to:

$$\sum_{j=1}^{l} a_{ij} x_j + \sum_{j=l+1}^{n} a_{ij} y_j \le b_i\left(t\right)^{p_i},\ i = 1, 2, \ldots, m \tag{6b}$$

$$x_j \ge 0,\ j = 1, 2, \ldots, l\ \ \left(l < n\right) \tag{6c}$$

$$y_j \ge 0\,,\ y_j \ \text{ are integer variables, } j = l+1, l+2, \ldots, n \tag{6d}$$

If the denominator is constant and is strictly positive within the feasible region, the MSFP model can be transformed to:

$$Max\ g = \sum_{j=1}^{l} c_j x_j^* + \sum_{j=l+1}^{n} a_j y_j^* + \alpha \cdot r \tag{7a}$$

subject to:

$$\sum_{j=1}^{l} a_{ij} x_j^* + \sum_{j=l+1}^{n} a_{ij} y_j^* \le b_i(t)^{p_i} \cdot r \tag{7b}$$

$$\sum_{j=1}^{l} d_j x_j^* + \sum_{j=l+1}^{n} d_j y_j^* + \beta \cdot r = 1 \tag{7c}$$

$$x_j^* = x_j \cdot r,\ j = 1, 2, \ldots, l\ \ (l < n) \tag{7d}$$

$$y_j^* = y_j \cdot \gamma \tag{7e}$$

$$y_j \ge 0\ ,\ y_j \ \text{ are integer variables, } j = l+1, l+2, \ldots, n \tag{7f}$$

$$r \ge 0 \tag{7g}$$

The above model can be solved through the branch-and-bound algorithm. The solution of integer variables y_j ($j = l + 1$, $l + 2$, …, n) can be obtained directly, and the optimal solution of x_j ($j = 1, 2, \ldots, l$) can be obtained through $x_j = x_j^*/r$.

Compared with the existing optimization models, the proposed IMSFP model is advantageous in four aspects: (i) it can balance the trade-offs between environmental protection and economic development; (ii) it can address uncertainties which are described as interval parameters and probability distributions; (iii) it supports dynamic analysis of capacity expansion problems; (iv) it analyzes various p_i levels, generates a range of operational schemes, and provides planning options for decision-makers under varying conditions.

3. Case Study

3.1. Statement of the Problem

Shandong is a coastal province and is located on the eastern edge of the North China Plain and in the lower reaches of the Yellow River. As shown in Figure 2, it borders the Bohai Sea to the north, Hebei to the northwest, Henan to the west, Jiangsu to the south, and the Yellow Sea to the southeast; it also shares a very short border with Anhui, between Henan and Jiangsu. The total area of Shandong Province is 0.157 million square kilometers, and it governs 16 cities. Until the end of 2018, the amount of permanent residence is 100.47 million, accounting for approximately 7.2% of China's population; it produces GDP of 11,555.6 billion dollars, responsible for 8.5% of the national domestic product.

Shandong has independent electricity grid, and 85.3% of electricity is generated by coal-fired in 2015, 19% higher than the national average level. Renewable energy, including wind power, solar power, hydropower, and biomass, only contribute 11.5% power generation by the end of 2015. The specific energy structure is shown in Figure 3. The GHG emission of Shandong Province is mainly due to the coal-fired power plant. Moreover, with the population growth and economic development, there is an increasing electricity demand, which means the amount of GHG and other pollutant emissions (e.g., nitrogen oxides, sulfur dioxide, and particulate matter) will rise continuously. In order to balance the increased demand and emission reductive target, the percentage of clean energy utilization to the total power resource is expected to grow. By the end of 2018, there are seven types of electricity-generation facilities, including fossil fuel (e.g., coal- and natural gas-fired) and clean energy (e.g., nuclear power, biomass power, wind power, solar power, and hydropower). Clean energy, such as nuclear power, wind power, solar power, and hydropower do not have GHG and pollutant emission. GHG emission of biomass power is assumed as a natural carbon cycle, and pollutant emissions are approximately one-tenth of coal power. Therefore, enhancement of clean energy utilization will reduce energy-related GHG and pollutant emission.

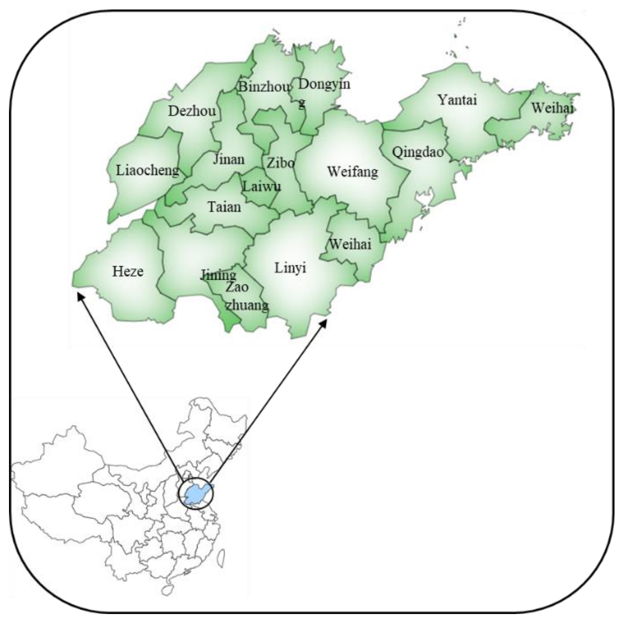

Figure 2. The study area —Shandong Province.

The potential of clean energy is not fully utilized due to conversion technology limitation, instability, and relatively high capital cost. Therefore, clean energy receives great attention to satisfy the increasing power demand and pollution control target. An effective energy management system can maximize energy efficiency at the lowest unit cost. While in the EMS, there are many complex processes, such as energy supply, power conversion, economic development, and pollution emission mitigation. Moreover, uncertainties in the real-world energy system intensifies the complexities. Various uncertainties exist in multiple parameters in both the objective and constraints (e.g., power demand, energy availability, technological efficiency, and utilization factors) as well as their interrelationships. Therefore, it is desired to develop a practical long-term energy planning system to address these complexities and uncertainties comprehensively. The major problem is the optimal allocation of energy resource and capacity expansion options to meet the increasing energy demand. Decision-makers are facing complexities as follows: (a) energy allocation to power generation plants; (b) reasonable facility capacity expansion schemes; (c) effectively maximize the utilization of renewable energy resource; (d) rational planning imported electricity; (e) methods of dealing with uncertainties in objective and constraints; (f) balancing the trade-off between system economy and pollution control.

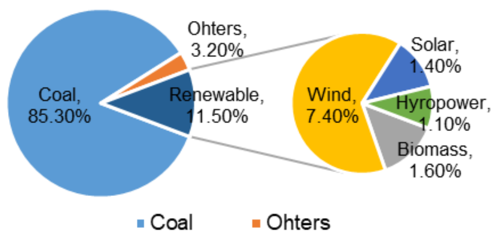

Figure 3. Composition of electricity generation of Shandong Province in 2015.

3.2. Development of IMSFP Model

The proposed IMSFP model is applied to support the power system management of Shandong province. The model consists of several parts, such as resource supply, power conversion, power transmission, capacity expansion, and pollutant emissions. The objective is to maximize the clean energy utilization of per-unit system cost which mainly involves primary energy purchase cost, power generation cost, as well as environmental cost:

$$Max\ f^{\pm} = \frac{\sum_{j=3}^{7} Y_{j,t}^{\pm}}{f_1^{\pm}+f_2^{\pm}+f_3^{\pm}+f_4^{\pm}+f_5^{\pm}+f_6^{\pm}+f_7^{\pm}+f_8^{\pm}+f_9^{\pm}} \tag{8a}$$

(1) Cost for primary energy supply:

$$f_1^{\pm} = \sum_{i=1}^{4}\sum_{t=1}^{4} X_{i,t}^{\pm} \cdot CP_{i,t}^{\pm} \tag{8a-1}$$

(2) Cost for electricity generation:

$$f_2^{\pm} = \sum_{j=1}^{7}\sum_{t=1}^{4} Y_{i,t}^{\pm} \cdot \left(CP_{j,t}^{\pm} + CPV_{j,t}^{\pm}\right) \tag{8a-2}$$

(3) Cost for import electricity:

$$f_3^{\pm} = \sum_{t=1}^{4} IE_t^{\pm} \cdot CIE_t^{\pm} \tag{8a-3}$$

(4) Cost of electricity transmission:

$$f_4^{\pm} = \sum_{j=1}^{7}\sum_{t=1}^{4} Y_{j,t}^{\pm} \cdot CT_t^{\pm} \tag{8a-4}$$

(5) Cost of capacity expansion:

$$f_5^{\pm} = \sum_{j=1}^{7}\sum_{t=1}^{4} EP_{j,t}^{\pm} \cdot CEP_{j,t}^{\pm} \tag{8a-5}$$

(6) Cost for emission treatment:

$$f_6^{\pm} = \sum_{j=1}^{7}\sum_{e=1}^{3}\sum_{t=1}^{4} Y_{j,t}^{\pm} \cdot EF_{j,e,t}^{\pm} \cdot RE_{e,t}^{\pm} \cdot CPM_{e,t}^{\pm} \tag{8a-6}$$

(7) Cost for CO_2 treatment:

$$f_7^{\pm} = \sum_{j=1}^{7}\sum_{t=1}^{4} Y_{j,t}^{\pm} \cdot ECO_{j,t}^{\pm} \cdot RECO_t^{\pm} \cdot CTCO_t^{\pm} \tag{8a-7}$$

(8) Penalty for excess CO_2 emission:

$$f_8^{\pm} = \sum_{j=1}^{7}\sum_{t=1}^{4} \begin{bmatrix} Y_{j,t}^{\pm} \cdot ECO_{j,t}^{\pm} \cdot \left(1 - RECO_t^{\pm}\right) \\ -UPCO_t^{\pm} \end{bmatrix} \cdot CPCO_t^{\pm} \tag{8a-8}$$

(9) Penalty for excess pollution emission:

$$f_9^{\pm} = \sum_{j=1}^{7}\sum_{e=1}^{3}\sum_{t=1}^{4} Y_{j,t}^{\pm} \cdot EF_{j,e,t}^{\pm} \cdot \left(1 - RE_{e,t}^{\pm}\right) \cdot CPE_{e,t}^{\pm} \tag{8a-9}$$

This optimization problem is subjected to the following constraints:

(1) Mass balance:

$$Y_{j,t}^{\pm} \cdot TEF_{j,t}^{\pm} \le X_{i,t}^{\pm},\ j = 1 \sim 4,\ i = 1 \sim 4,\ \forall t \tag{8b}$$

$$X_{i,t}^{\pm} \le UPAV_{i,t}^{\pm}, \forall i, t \tag{8c}$$

(2) Availabilities of renewable energy resource:

$$Y_{j,t}^{\pm} / TF_{j,t}^{\pm} \le AREN_{j,t}^{p_i \pm},\ j = 5 \text{ and } 6,\ \forall t \tag{8d}$$

$$Y_{7,t}^{\pm} / TF_{7,t}^{\pm} \le AREN_{7,t}^{\pm}, \forall t \tag{8e}$$

(3) Electricity demand:

$$\left(\sum_{j=1}^{7} Y_{j,t}^{\pm} + IE_t^{\pm}\right) \cdot \left(1 - LF_t^{\pm}\right) \ge ED_t^{\pm} \tag{8f}$$

(4) Capacity of electricity generation:

$$RES_t^{\pm} + \sum_{t=1}^{m} EPN_{j,t}^{\pm} \ge Y_{j,t}^{\pm}, 0 \le m \le 4, 0 \le t \le m, \forall j, t \tag{8g}$$

(5) Capacity expansion constraints:

$$Z_{j,t}^{\pm} \cdot EPN_{j,t}^{\pm} \le EP_{j,t}^{\pm} \le Z_{j,t}^{\pm} \cdot EPM_{j,t}^{\pm}, \forall j,t \tag{8h}$$

$$Z_{j,t}^{\pm} = \begin{cases} 1, \text{ if the capacity expansion is undertaken} \\ 0, \text{ otherwise} \end{cases} \forall t \tag{8i}$$

(6) Transmission capacity constraints:

$$\sum_{j=1}^{7} Y_{j,t}^{\pm} + IE_t^{\pm} \le ETC_t^{\pm}, \forall t \tag{8j}$$

(7) Policy target constraint:

$$\sum_{j=3}^{7} Y_{j,t}^{\pm} / \sum_{j=1}^{7} Y_{j,t}^{\pm} \ge 22\%, \forall t \tag{8k}$$

$$\sum_{j=4}^{6} Y_{j,t}^{\pm} / ED_t^{\pm} \ge 10\%, \forall t \tag{8l}$$

$$IE_t^{\pm} / ED_t^{\pm} \ge 22\%, \forall t \tag{8m}$$

(8) Technology constraints:

$$X_{i,t}^{\pm} \ge 0, \forall i,t \tag{8n}$$

$$Y_{j,t}^{\pm} \ge 0, \forall j,t \tag{8o}$$

$$EP_{j,t}^{\pm} \ge 0, \forall j,t \tag{8p}$$

$$IE_t^{\pm} \ge 0, \forall t \tag{8q}$$

3.3. Data Allocation

The planning horizon is 20 years (2021 ~ 2040) which is divided into four periods with each representing a 5-year span. Facilities of coal-fired power plant, natural gas power plant, nuclear power plant, biomass power plant, wind power plant, solar power plant, and hydropower plant are available for power generation. The related economic data of the power generation system were obtained through analyses for a number of representative reports of the regional power system. Tables 1 to 4 depicts the cost for primary energy supply, electricity generation and capacity expansion cost, wind and solar energy availability under different constraint-violation risk levels.

4. Result Analysis

The results of the IMSFP model under different p_i levels are shown in Tables 5 and 6, which mainly include the primary resource allocation patterns, the amount of imported electricity, total system cost, and clean energy generation strategies. For example, when $p_i = 0.01$, the primary energy supplies of coal, natural gas, uranium, and biomass in period 1 would be [833.45, 852.53] million tonnes, [48,383.43, 61,422.39] million m^3, [4,251.29, 4,337.29] million grams, and [152.04, 174.10] million tonnes, respectively. Meanwhile, in period 1, the imported electricity would be [4,325.84, 4,607.66] TW; the total system cost would be [933.60, 935.64] billion dollars, and electricity generated by clean energy would be [5,827.01, 7,008.84] TW at $p_i = 0.01$ violation value. Similarly, the energy supply schemes for each technology under different p_i levels over the four periods can be interpreted.

Table 1. Cost for Primary Energy Supply

Energy supply cost, $CP_{i,t}$	Time period			
	$t = 1$	$t = 2$	$t = 3$	$t = 4$
Coal ($i = 1$) \$/tonne	[86.77, 98.23]	[86.77, 98.23]	[86.77, 98.23]	[86.77, 98.23]
Natural gas ($i = 2$) \$/m^3	[0.44, 0.57]	[0.43, 0.56]	[0.43, 0.56]	[0.42, 0.55]
Uranium ($i = 3$) \$/g	[0.06, 0.07]	[0.06, 0.07]	[0.06, 0.07]	[0.06, 0.06]
Biomass ($i = 4$) \$/tonne	[59.61, 74.52]	[58.72, 73.4]	[57.85, 72.31]	[56.99, 71.23]

Furthermore, as shown in Table 6, the utilization of total imported electricity would drop stably as the violation level risks. For instance, imported power would decrease from [4,325.84, 4,607.66] TW in $p_i = 0.01$ to [3,412.34, 3,654.23] TW in $p_i = 0.99$. The primary reason for this result is that the price of imported electricity would progressively climb, while the cost of clean energy power would decrease gradually. Therefore, supplying power by clean energy generation instead of imported electricity can not only reduce system costs, but also meet the pollutant emission control targets. In addition, the ratio objective implies the system efficiency, which means clean energy power generation per unit of the system cost. Obviously, a higher ratio objective would be obtained under a higher p_i level. For example, the ratio objective would rise from

Table 2. Availabilities of Wind Power and Solar Energy under Different p_i Values

p_i level	$p_i = 0.01$	$p_i = 0.05$	$p_i = 0.10$	$p_i = 0.25$	$p_i = 0.50$	$p_i = 0.75$	$p_i = 0.90$	$p_i = 0.95$	$p_i = 0.99$
Wind power (GW)									
Upper bound	193.72	195.59	196.58	198.24	200.09	201.93	203.59	204.59	206.45
Lower bound	184.65	186.51	187.51	189.17	191.01	192.86	194.52	195.51	197.38
Solar energy (GW)									
Upper bound	41.74	42.64	43.12	43.92	44.81	45.70	46.51	46.99	47.88
Lower bound	37.37	38.27	38.74	39.55	40.44	41.33	42.13	42.61	43.51

[6.24, 7.49] to [7.79, 8.73] per 10^3\$, when p_i increases from 0.01 to 0.99. Similarly, the system cost would rise with increasing p_i levels as well. Thus, the relationship between different p_i levels and ratio objective reveals the interrelationship among system reliability, economic cost, and system efficiency. A lower p_i level means a lower admissible risk of violating the constraints and higher system reliability, which lead to an increased strictness for the constraints and a shrunk decision space. Specifically, when the availabilities of wind power and solar energy are restricted under a lower p_i level, more electricity would be generated by non-renewable resource to meet the increased electricity demand, which results in a lower system cost, lower system efficiency, but higher system reliability.

Table 3. Total Amount of Power Demand (10^6 MWh)

	Time period			
	t = 1	t = 2	t = 3	t = 4
Upper bound	3,395.88	3,936.76	4,364.44	5,600.81
Lower bound	3,886.75	4,728.83	5,421.55	5,985.83

Figure 4 shows the electricity generation pattern under five chosen risk levels over the planning horizon. As the result showed, clean energy would play an important role at a high p_i level due to a loosen availability of wind power and solar energy constraint, thus there would be higher system efficiency (higher clean energy electricity generation and relative lower system cost) but decreased reliability. Biomass and wind power would be two major clean energy generation forms under all p_i values during the whole planning horizon. Moreover, at higher p_i levels, wind power would develop more quickly, because the constraint for wind power availability is loosen. For instance, the wind power generation would rise [42.74, 47.08]% compared to biomass [8.36, 9.34]%, when p_i increase from 0.01 to 0.95 in period 1. Furthermore, solar energy would grow rapidly as the p_i level increases. Specially, it would be [150.24, 164.52] TWh when p_i = 0.01 and [283.85, 318.36] TWh when p_i = 0.95, which means [89.24, 94.12]% rate of growth. The rapid development of wind power and solar energy results from the loosen energy availability constraint. In addition, the coal-fired electricity would reduce steadily, however, clean energy generated power would be insufficient for the future electricity demand due to rapid economic development and population growth. Thus, there would be an increasing amount of natural gas-fired electricity supply. This result is mainly because the CO_2 and NO_x emitted by natural gas power generation is only 1/3 and 1/10 of the coal power generation respectively, and there is almost no SO_x and PM emission for natural gas power generation. In addition, with the development of power generation technologies, costs of natural gas power will be further reduced. Therefore, in period 4, the coal power and natural gas power generation would reach almost the same level, [1,532.65, 1,601.76] and [1,067.96, 1,104.47] TWh when p_i = 0.01.

The optimal capacity expansion scheme under different p_i levels is represented in Figure 5. There would be no expansion of coal-fired facilities during the whole planning horizon under all p_i levels. Similarly, the hydropower expansion capacity would be nearly zero, because there is less hydropower availability in Shandong Province. In addition, the nuclear-fired facilities would only expand in the first period and the expansion would be almost the same under several p_i levels, which indicates that the nuclear-fired expansion is not sensitive to the system uncertainties. The natural gas expansion capacity would be larger than wind power and solar energy under lower p_i levels, but it would be smaller at higher p_i levels. For example, when p_i = 0.01, the expansion capacity would be [9.53, 10.49], [6.05, 7.66], and [3.75, 5.18] GW for natural gas, wind power, and solar energy, respectively, but this trend would become [9.15, 9.80], [13.99, 16.44], and [17.33, 20.84] when p_i = 0.95 in period 1. This is mainly due to the tighter constraints on the availability of wind power and solar energy at low p_i levels, and other technologies that have relatively less emission and high stability would be developed to meet the growing energy de-

Table 4. Electricity Generation Cost and Capital Cost for Capacity Expansion

	Time period			
	t = 1	t = 2	t = 3	t = 4
Electricity generation cost, $CE_{j,t}$ (\$/MWh)				
Coal (j = 1)	[0.89, 1.2]	[0.88, 1.19]	[0.87, 1.17]	[0.86, 1.16]
Natural gas (j = 3)	[1.48, 1.63]	[1.46, 1.6]	[1.43, 1.58]	[1.41, 1.55]
Uranium (j = 3)	[0.80, 2.00]	[0.80, 2.00]	[0.80, 2.00]	[0.80, 2.00]
Biomass (j = 4)	[4.10, 4.88]	[3.99, 4.76]	[3.90, 4.64]	[3.80, 4.52]
Wind power (j = 5)	[5.71, 6.66]	[5.43, 6.33]	[5.16, 6.02]	[4.91, 5.73]
Solar energy (j = 6)	[4.78, 5.73]	[4.57, 5.48]	[4.35, 5.24]	[4.19, 5.01]
Hydropower (j = 7)	[5.97, 7.53]	[5.94, 7.49]	[5.91, 7.46]	[5.88, 7.42]
Capital cost for capacity expansion, $CEP_{j,t}$ (\$/MW)				
Coal (j = 1)	[479,293, 524,226]	[474,519, 519,005]	[469,793, 513,836]	[465,113, 508,718]
Natural gas (j = 3)	[805,679, 814,312]	[766,193, 774,402.81]	[728,642, 736,449]	[692,931, 700,356]
Uranium (j = 3)	[1,815,431, 2,571,860]	[1,815,431, 2,571,860]	[1,815,431, 2,571,860]	[1,815,431, 2,571,860]
Biomass (j = 4)	[820,502, 857,699]	[741,669, 775,292]	[670,410, 700,802]	[605,998, 633,470]
Wind power (j = 5)	[877,966, 924,791]	[679,353, 715,585]	[525,670, 553,706]	[406,754, 428,447]
Solar energy (j = 6)	[678,449, 740,126]	[553,189, 603,478]	[451,055, 492,060]	[367,778, 401,212]
Hydropower (j = 7)	[1,505,310, 1,956,903]	[1,497,798, 1,947,138]	[1,490,324, 1,937,421]	[1,482,887, 1,927,754]

Table 5. Results of IMSFP Model — Primary Energy Allocation Pattern (10^6 MWh)

p_i	0.01	0.05	0.10	0.25	0.50	0.75	0.90	0.95	0.99
Coal (i = 1) 10^6 tonne									
t = 1	[833, 852]	[795, 839]	[757, 852]	[736, 838]	[718, 828]	[685, 779]	[669, 751]	[660, 755]	[654, 745]
t = 2	[711, 732]	[703, 753]	[673, 759]	[667, 745]	[652, 737]	[631, 693]	[624, 676]	[620, 669]	[616, 658]
t = 3	[634, 671]	[624, 676]	[594, 663]	[586, 651]	[579, 639]	[568, 619]	[573, 613]	[568, 608]	[561, 601]
t = 4	[628, 641]	[608, 635]	[545, 620]	[534, 606]	[528, 597]	[502, 613]	[498, 610]	[495, 605]	[490, 598]
Natural gas (i = 2) 10^6 m^3									
t = 1	[48,383, 61,422]	[51,301, 61,816]	[51,858, 62,337]	[52,398, 62,427]	[52,500, 62,559]	[540,351, 645,211]	[545,351, 650,321]	[549,375, 653,954]	[551,236, 655,762]
t = 2	[82,228, 112,188]	[92,426, 115,540]	[93,169, 11,625]	[111,849, 117,634]	[112,007, 118,088]	[114,596, 120,549]	[119,654, 1,236,954]	[122,945, 239,542]	[124,659, 241,563]
t = 3	[141,397, 176,101]	[149,326, 177,174]	[150,240, 178,607]	[151,644, 179,981]	[151,932, 180,129]	[168,945, 181,954]	[175,036, 187,652]	[178,646, 190,056]	[180,965, 192,365]
t = 4	[158,839, 198,753]	[161,036, 199,046]	[161,534, 199,800]	[162,000, 200,753]	[162,476, 201,288]	[164,956, 203,968]	[170,009, 241,569]	[172,996, 244,631]	[176,354, 246,379]
Uranium (i = 3) 10^6 g									
t = 1	[4,251, 4,337]	[4,249, 4,337]	[4,333, 4,404]	[4,462, 4,540]	[4,662, 4,855]	[5,027, 5,205]	[5,038, 5,252]	[5,067, 5,269]	[5,070, 5,271]
t = 2	[4262, 4,359]	[4,270, 4,364]	[4,355, 4,458]	[4,475, 4,562]	[4,687, 4,982]	[5,052, 5,221]	[5,052, 5,263]	[5,053, 5,285]	[5,053, 5,286]
t = 3	[4,272, 4,380]	[4,274, 4,381]	[4,377, 4,509]	[4,486, 4,585]	[4,712, 5,090]	[5,134, 5,278]	[5,152, 5,286]	[5,198, 5,296]	[5,206, 5,301]
t = 4	[4,283, 4,402]	[4,403, 4,683]	[4,428, 4,540]	[4,497, 4,608]	[4,700, 5,115]	[5,203, 5,305]	[5,206, 5,309]	[5,209, 5,311]	[5,213, 5,313]
Biomass (i = 4) 10^6 tonne									
t = 1	[152, 174]	[150, 209]	[150, 195]	[152, 183]	[161, 195]	[170, 202]	[168, 195]	[165, 191]	[163, 189]
t = 2	[278, 298]	[348, 358]	[272, 328]	[314, 332]	[324, 341]	[315, 352]	[300, 350]	[283, 347]	[279, 341]
t = 3	[437, 466]	[446, 485]	[479, 494]	[498, 509]	[502, 523]	[512, 535]	[498, 500]	[477, 488]	[472, 481]
t = 4	[493, 532]	[498, 532]	[521, 545]	[563, 566]	[572, 577]	[584, 593]	[583, 587]	[582, 584]	[580, 583]

Table 6. Results of IMSFP Models

p_i level	0.01	0.05	0.10	0.25	0.50	0.75	0.90	0.95	0.99
Import Electricity (10^3 GW)									
Lower bound	4,325	4,176	3,938	3,837	3,697	3,572	3,488	3,456	3,412
Upper bound	4,607	4,482	4,266	4,045	3,923	3,785	3,694	3,685	3,654
System Cost ($\$10^9$)									
Lower bound	933	942	951	970	989	1,010	1,015	1,020	1,025
Upper bound	935	944	953	972	992	1,012	1,017	1,022	1,027
Clean Energy Power Generation (10^3 GW)									
Lower bound	5,827	6,557	6,731	7,006	7,113	7,932	8,027	7,861	7,988
Upper bound	7,008	7,067	7,127	7,360	7,427	8,776	8,970	8,754	8,967
Clean Energy Power Generation/System Cost (MWh per $\$10^3$)									
Lower bound	6.24	6.96	7.03	7.22	7.35	7.85	7.91	7.71	7.79
Upper bound	7.49	7.62	7.84	7.96	8.12	8.67	8.82	8.56	8.73

mand, thus natural gas would have larger expansion at low p_i levels.

5. Discussion

Except for the above model, which targeted at maximizing the system efficiency, another scenario of minimizing the system cost is also analyzed to demonstrate the advantages of the developed IMSFP model. The optimal-ratio problem presented in the model (8a) can be converted into a least-cost problem with the following objective:

$$Min\ z^{\pm} = f_1^{\pm} + f_2^{\pm} + f_3^{\pm} + f_4^{\pm} + f_5^{\pm} + f_6^{\pm} + f_7^{\pm} + f_8^{\pm} + f_9^{\pm} \tag{9}$$

Thus, the obtained least-cost model is an integrated interval mixed-integer chance-constraint linear programming problem, which can be solved through the robust two-step method (Fan and Huang, 2012). The submodel corresponding to z^+ will be solved firstly.

The compared results of the optimal-ratio model and the least-cost model under different p_i levels are presented in Figures 5 to 8. As shown in Figure 6, the optimal-ratio model has a higher percentage of clean energy utilization; it would be 45% when p_i = 0.01, and 52% when p_i = 0.95, while the least-cost model would be 28 and 31% under p_i = 0.01 and p_i = 0.95, respectively. Specially, the ratio of nuclear power and wind power would be similar for two scenarios under lower p_i level.

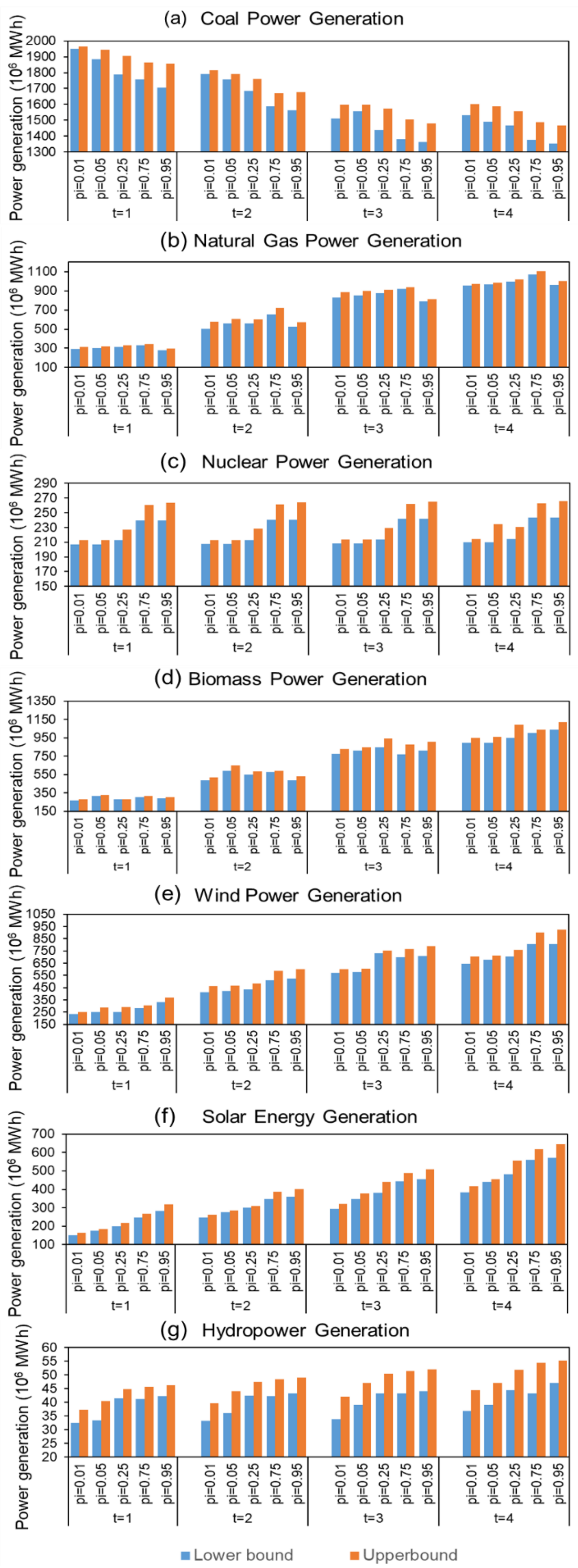

Figure 4. Electricity generation patterns.

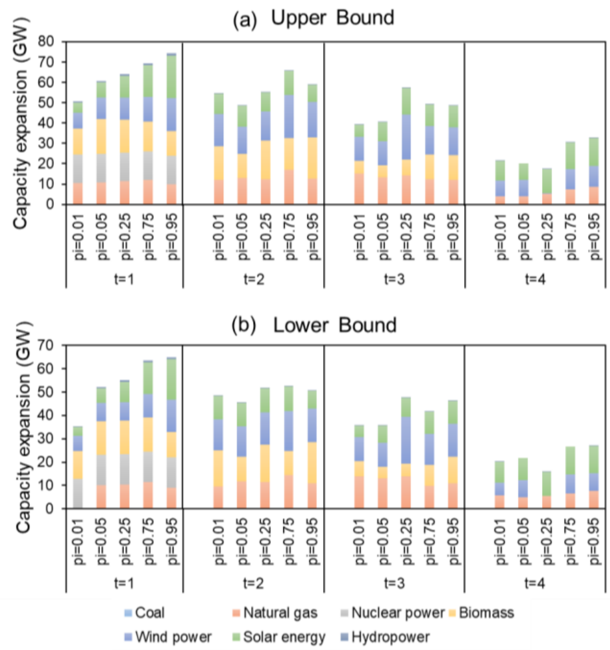

Figure 5. Capacity expansion schemes.

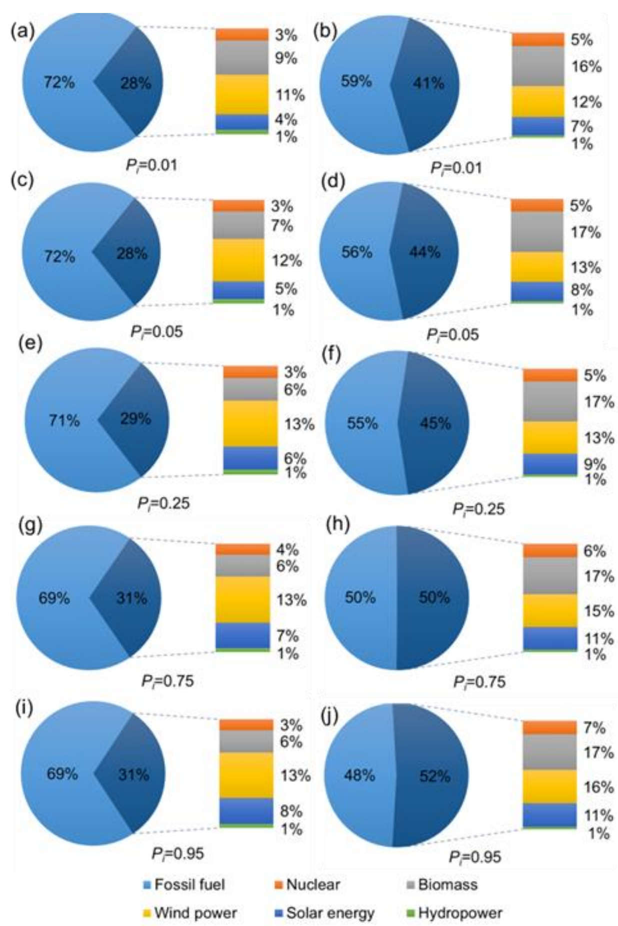

Figure 6. Energy structure comparison of sing- and dual-objective models.

However, the proportion of consumption of biomass and solar energy in the optimal-ratio model would be 1.78 and 1.75 times that of the least-cost model, respectively. This proves that part of the fossil fuel power generation would be compensated by biomass and solar energy in the optimal-ratio scenario. When $p_i = 0.95$, the percentage of nuclear power, biomass, wind power, and solar energy would be 7, 17, 16, and 11% in the optimal-ratio model, and 3, 6, 13, and 18% in the least-cost model. Therefore, the clean energy consumption ratio in the optimal-ratio scenario is significantly higher than that in the least-cost model.

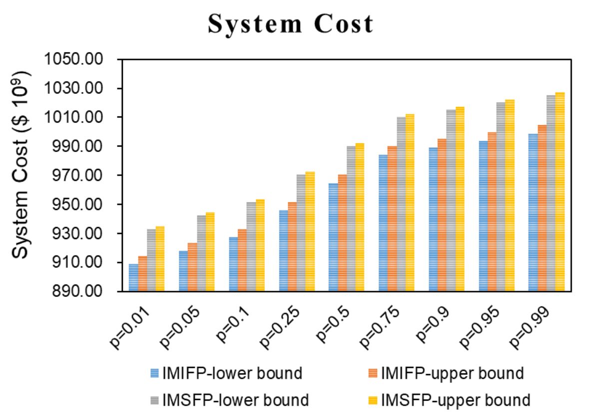

Figure 7. System cost comparison of sing- and dual-objective models.

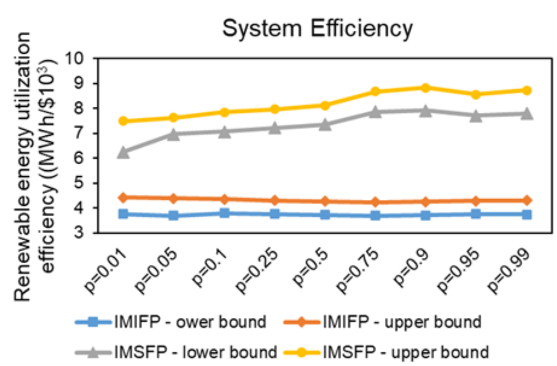

Figure 8. System efficiency comparison of sing- and dual-objective models.

Furthermore, Figure 7 shows the comparison of system costs corresponding to optimal-ratio and least-cost scenarios under various constraint-violation risks. As indicated, the system cost solutions corresponding to the least-cost model are slightly lower than that of the optimal model under a range of constraint violation levels. Particularly, system cost in the least-cost model would be [909.03, 914.51], [918.12, 923.66], [984.06, 990.00], and [993.92, 999.85] × $10^9$$ when $p_i = 0.01$, 0.05, 0.75, and 0.95, and these would be [933.12, 935.52], [942.33, 944.35], [1,010.01, 1,012.17], and [1,020.13, 1,022.32] × $10^9$$ under the above p_i levels in the optimal-ratio model. On the other hand, in practical energy management problems, a comparison of the ratio of two magnitudes can offer more insight into the situation than a simple comparison of each magnitude. As shown in Figure 7, the ratio of clean energy utilization per unit of cost represents a comprehensive measure of system efficiency. As the result showed, the system efficiency of the optimal-ratio model is around [7.2, 7.96] MWh per $10^3$$, which is significantly higher than [3.75, 4.31] MWh per $10^3$$ from the least-cost model.

In summary, the solutions obtained from these two models can provide practical decision alternatives under various energy availabilities. Compared with the single-objective least-cost model, the optimal-ratio IMSFP model can better fit the real-world energy management problems and better reflect the interrelationships among system efficiency, economic cost, and system reliability.

6. Conclusions

In this study, an inexact mixed-integer interval stochastic fractional model (IMSFP) was developed for sustainable power system management under uncertainties. Methods of interval linear programming (ILP), chance-constrained programming (CCP), mix-integer linear programming (MILP) were incorporated into the fractional linear programming (FP) to develop the IMSFP model to tackle uncertainties described as interval values and probability distributions. The developed model could effectively reveal the interrelationship among system reliability, system efficiency, and economic cost. The advantages of IMSFP model involve (a) balancing trade-off objectives of environmental protection and economic cost; (b) providing desired power system planning schemes under a various of constraint violation conditions; (c) identifying reasonable dynamic capacity expansion strategies; (d) dealing with uncertainties described as interval parameters and probability distribution.

The developed IMSFP model was applied to a real-world case study of the Shandong province's power system management, and the adaptability has been demonstrated. The results indicated that the IMSFP model can achieve the maximized system efficiency and provide desired schemes for resource allocation, as well as dynamic capacity expansion strategies over a long-term planning period. Furthermore, the results also demonstrate that the clean energy power generation and capacity expansion scheme are sensitive to different constraint-violation risk conditions.

As comparation, an economical energy management system was also developed with the objective of minimizing the system cost. The scenario-compared results prove that the IMSFP model can better achieve the system efficiency, which means that a higher clean energy utilization per unit system cost can be obtained by IMSFP model. Moreover, the results also demonstrate that the IMSFP model is advantageous in balancing conflicting objectives and reflecting complicated relationships among multiple system factors.

This study attempts to apply an integrated regional power system management model into Shandong province for addressing dual-objective optimization problems involving interval uncertainties and different constraint-violation risk conditions

tions. IMSFP could be an articulated tool for supporting power system management problems; however, there are more impact factors (e.g., climate change impact) and integrated method (e.g., two-stage programming) should be systematically considered in the future studies. In addition, extensions of the single-region IMSFP model to multi-region and incorporation of regional interaction are also deserved future research efforts.

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Appendix A. Parameters

Subscripts

i: primary energy: 1 = coal, 2 = natural gas, 3 = nuclear, and 4 = biomass

j: power generation technology: 1 = coal, 2 = natural gas, 3 = nuclear, 4 = biomass, 5 = wind power, 6 = solar energy, and 7 = hydropower

t: period: t = 1: 2021 ~ 2025, t = 2: 2026 ~ 2030, t = 3: 2031 ~ 2035, and t = 4: 2036 ~ 2040

e: contaminant emission: 1 = SO_x, 2 = NO_x, and 3 = PM

Decision variables

$x_{i,t}^{\pm}$: Amount of primary energy supply i in period t (coal: tonne, natural gas: m^3, uranium: g, biomass: tonne)

$y_{j,t}^{\pm}$: Amount of electricity supply by technology j in period t (10^6 MWh)

$EP_{j,t}^{\pm}$: Capacity expansion of technology j in period t (10^6 MW)

$z_{j,t}^{\pm}$: Integer variable identifying whether expansion of technology j undertaken during period t

$IE_t^{\pm}$: Amount of imported electricity (10^6 MWh)

Parameters

$CP_{i,t}^{\pm}$: Cost of primary energy i supply in period t (\$/MWh)

$CE_{j,t}^{\pm}$: Cost of electricity generated by technology j in period t (\$/MWh)

$CT_{j,t}^{\pm}$: Costs of electricity transmission during period t (\$/MWh)

$CEP_{j,t}^{\pm}$: Cost of capacity expansion of technology j during period t (\$/MW)

$CIE_t^{\pm}$: Cost of imported electricity from other regions (\$/MWh)

$CPM_{e,t}^{\pm}$: Cost of the treatment of pollutant e emission during period t (\$/kg)

$CTCO_t^{\pm}$: Cost of CO_2 treatment during period t (\$/tonne)

$CPCO_t^{\pm}$: Cost for excess CO_2 emission in period t (\$/tonne)

$CPE_{e,t}^{\pm}$: Cost for pollution e emission in period t (\$/kg)

$AREN_{j,t}^{\pm}$: Availabilities of renewable energy j during period t (10^6 MW)

$RES_j^{\pm}$: Residual capacity of electricity generation technology j during period t (10^6 MW)

$ED_t^{\pm}$: Electricity demand during period t (10^6 MWh)

$UPAV_{i,t}^{\pm}$: Maximized availabilities of primary i during period t (10^6 MW)

$UPCO_j^{\pm}$: Maximized allowable CO_2 emission in period t (tonne)

$EF_{j,e,t}^{\pm}$: Emission factors of electricity-generating technology j during period t (kg/MWh)

$TEF_{j,t}^{\pm}$: Efficiency factor of technology j in period t (%), j = 1 ~ 4

$TE_{j,t}^{\pm}$: Efficiency factor of technology j in period t (%), j = 5 ~ 7

$LF_t^{\pm}$: Loss efficiency of electricity-transmission process (%)

$RE_{e,t}^{\pm}$: Pollutant reduction efficiency for contaminant e in period t (%)

$ECO_{j,t}^{\pm}$: CO_2 emission factor of electricity-generating technology j during period t (kg/MWh)

$RECO_t^{\pm}$: CO_2 treatment efficiency in period t (%)

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