Journal of Environmental Informatics Letters 10(1) 23-31 (2023)

Journal of Environmental Informatics Letters

www.iseis.org/jeil

A Linear Chance-Constrained Mixed-Integer Programming Model for Optimizing Regional Electric Power Systems under Carbon Constraints

Y. Xu[1], C. Z. Huang[2 *], J. P. Chen[1], B. Luo[1], and Y. Y. Liu[1]

[1] *Faculty of Engineering and Applied Science, University of Regina, Regina, Saskatchewan S4S0A2, Canada*
[2] *Department of Chemical and Materials Engineering, University of Alberta, Edmonton, Alberta T6G2R3, Canada*

Received 16 July 2023; revised 18 August 2023; accepted 10 September 2023; published online 25 Spetember 2023

ABSTRACT. In view of increasing population size and energy consumption, greenhouse gas (GHG) emissions are increasing and are one of the main causes of climate change. Typically, electric power generation is one of the main sources of carbon emissions, so there is an urgent need to optimize regional electric power systems to meet the Paris Agreement's long-term temperature goal. Therefore, this study provides a linear chance-constrained mixed-integer programming (LCMI) model with the objective of maximizing total system profit and applying it to the regional electric power system. Chance-constrained programming and mixed-integer programming were integrated into the LCMI model to address input uncertainties, including five commonly used power generation technologies, namely coal-fired, natural gas-fired, hydropower, wind power, and solar power. The model can provide optimal electricity generation schemes and capacity expansion plans for different technologies at the regional level to meet the end-user's needs while meeting the carbon dioxide emission targets under different risk levels. The outcomes of the research will offer decision-makers a framework for optimizing conventional regional electric power systems for their long-term sustainability in environmental and economic development.

Keywords: chance-constrained programming, uncertainty, system planning, capacity expansion, renewable energy

1. Introduction

The production and utilization of energy supplies are essential to the development of human society and economy. Due to rapid population and economic growth, energy consumption and demands have been increasing globally (Ahmad and Zhang, 2020; Cook, 2021). Nowadays, non-renewable energies, including coal and natural gas, are the primary energy resources for electricity generation and also the main source of greenhouse gas (GHG) emissions (Agrawal et al., 2014; Karmaker et al., 2020). The increased GHG emisons can result in temperatures rising and climate change (Limeechokchai and Chungpaibulpatana, 2001). According to IPCC Sixth Assessment Report (Pörtner et al., 2022), the past 2,000 years have seen the greatest increase in temperature on Earth because of human activities in recent years. More than 30% of carbon dioxide emissions are due to fossil fuel combustion in energy systems in the past 20 years (Song et al., 2012). In order to meet the growing energy consumption demands and GHG emissions reduction target, it is crucial to conduct optimal planning of regional electric power systems for their sustainable development.

Previously, many researchers proposed a number of different models that have been applied in environmental management (Tabors and Monroe, 1991; Malik, 2001; Nilsson and Mårtensson, 2003; Rong and Lahdelma, 2005; Rong and Lahdelma, 2007; Li et al., 2009; Ren et al., 2010; Li et al., 2013; Zhou et al., 2016). Some linear programming (LP) models were applied to minimize total cost under different environmental requirements (Li et al., 2011). For instance, Groscurth et al. (1989) introduced a linear approach to assess possible reductions in energy consumption from industries in various industrialized nations. Zhu et al. (2011) proposed an energy model for Beijing China on a municipal scale, which aimed to minimize the total system cost. Tiris et al. (1994) suggested a linear model in Turkey, which aims to plan for the future relationships among energy, the environment, and the economy. Smith (1980) developed a linear approach for the optimization of energy distribution and provision systems in New Zealand. However, the single objective can be undiversified if environmental factors are not considered, and the optimal solution may not be achieved if environmental factors are only placed in constraints. Thus, numerous researchers developed multi-objective programming models for energy systems optimization because of the conflict between economic development and environmental conservation. For example, Rekik et al. (2015) constructed an optimization model with multiple objectives to improve the quality of energy systems. Quaddus and Goh (1985) proposed a linear MOP model for energy system planning in Singapore. However, it is difficult for conventional multi-objective programming models to merge multiple conflicting objectives into a single one with weighting factors, which are usually subjective

* Corresponding author. Tel.: 1-778-858-0870.
E-mail address: charleyhuang33@gmail.com (C. Z. Huang).

ISSN: 2663-6859 print/2663-6867 online
 doi:10.3808/jeil.202300115

or even inaccurate (Lara and Stancu-Minasian, 1999). Thus, optimal mathematical programming models for planning regional electric power systems under conflict between economic development and environmental conservation are desired.

Therefore, in order to fill the gap between the singularity of traditional linear optimization models and the inaccuracy of multi-objective optimization models of most previous related studies as well as to consider the capacity expansion for technologies and uncertainties from input data in the planning process at the regional level, this study converts renewable energy generation into system benefits and compares it to the total system cost to obtain an objective function that maximizes the total system profit.

In this study, a linear chance-constrained mixed-integer programming approach for planning regional electric power systems was developed and the trade-offs between the economy and the environment were taken into consideration. Chance-constrained programming and mixed-integer programming were integrated and applied to electric power systems planning to address input uncertainties. Chance-constrained programming is applied to solve the problem of uncertainties described as probability distributions. The energy source availability in a specific region, such as wind and solar power, highly corresponds with the regional weather conditions and can be input as random numbers displayed as probability distributions (Zhu and Huang, 2013). Mixed-integer programming is used to deal with integer variables. This study can improve the conventional energy modeling method with a capability of addressing uncertain information, and it is well-considered for managing GHG emissions and obtaining renewable energy amounts to the maximum simultaneously. The modeling results will provide decision-makers with an optimization plan for regional electric power systems to maintain sustainable social and economic development.

2. Methodology

A linear mixed-integer programming approach can be expressed as follows:

$$Max\ f(x) = \sum\nolimits_{(j=1)}^{n} C_j X_j + \infty \tag{1a}$$

Subject to:

$$\sum\nolimits_{(j=1)}^{n} A_i j X_j \leq B_i,\ i = 1,\ 2,\ ...,\ m \tag{1b}$$

$$X_j \geq 0,\ j = 1,\ 2,\ ...,\ n \tag{1c}$$

where X_j (j = 1, 2, …, s) are non-negative continuous decision variables and X_j (j = s + 1, …, n) are non-negative integer decision variables, A_{ij}, B_i, $C_j \in R$, and ∞ is scalar constant.

In order to obtain more accurate analysis results for energy system planning, input uncertainties need to be taken into consideration. For instance, the availability of renewable energy sources, such as wind and solar power, in a specific region in the future can be uncertain, as they are highly correlated with the weather conditions. These uncertainties can be represented using probability distributions (Zhu and Huang, 2013). When probability distributions are applied to some parameters in the model (1), a linear chance-constrained mixed-integer programming model (LCMI) can be formulated as follows:

$$Max\ f(x) = \sum\nolimits_{(j=1)}^{n} C_j X_j + \infty \tag{2a}$$

Subject to:

$$\Pr[\sum\nolimits_{(j=1)}^{n} A_{ij} X_j \leq B_i(t)] \geq 1 - p_i,\ i = 1,\ 2,\ ...,\ \beta \tag{2b}$$

$$A_{ij} X_i \leq B_i,\ i = \beta + 1,\ \beta + 2,\ ...,\ m \tag{2c}$$

$$X_j \geq 0,\ j = 1,\ 2,\ ...,\ n \tag{2d}$$

where $t \in T$, $B_i(t)$ is a right-hand-side parameter based on a probability space T; p_i ($p_i \in [0, 1]$) is a given level of probability of constraint i, which indicates the allowable risk of breaking constraints.

According to the CCP approach (Charnes et al., 1971), when the right-hand-side coefficients [B_j] are random and the left-hand-side coefficients [A_i] are deterministic (for all p_i levels), the constraint $\Pr[\sum^{n}_{j=1} A_{ij} \times X_j \leq B_i(t)] \geq 1 - p_i$ can be converted as:

$$A_{ij} X_j \leq B_i(t)^{(p_i)} \tag{3}$$

where $B_i(t)^{pi} = F_i^{-1}(p_i)$, considering the cumulative distribution function of B_i and the probability of breaking constraint i (p_i). Constraint (3) is linear and the CCP approach can be applied to resolve the LCMI model (2) through transferring it into deterministic form (Zhu and Huang, 2013).

In general, the steps of this algorithm can be distilled into the following:

Step 1: Formulate the initial LCMI model.

Step 2: Choose a group of p_i values for the constraints and determine the distribution information $B_i(t)$ first. And the matching value can be calculated using $B_i(t)^{pi}$.

Step 3: Resolve the LCMI model through the approach above.

Step 4: Rerun steps 2 and 3 under various p_i levels.

To better illustrate the application of this model, the developed LCMI model is employed with a case study of regional electric power system management problems with exemplary data in a Chinese setting (Cai et al., 2009). Figure 1 displays a schematic of the regional electric power system. There are two non-renewable resources (coal and natural gas) and three renewable resources (hydro, wind, and solar) in the regional electricity grid, which can be used for electricity generation.

With the development of the economy, the electricity demands of residential, commercial, and industrial end-users also

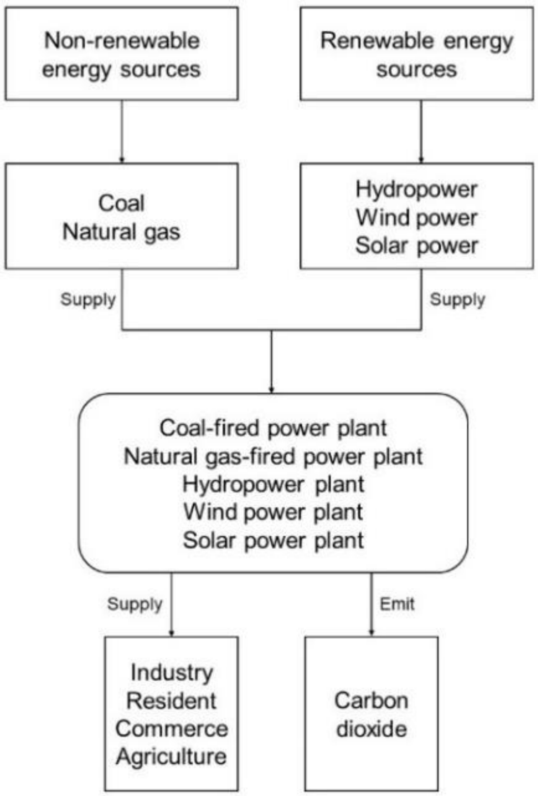

Figure 1. The research system.

Table 1. Energy Supply and Operation Cost

Non-Renewable Energy Supply Cost, PC_{it} (10^6\$/PJ*)	Time Period $t = 1$	$t = 2$	$t = 3$
$i = 1$ (Coal)	2.57	2.77	2.97
$i = 2$ (Natural gas)	4.88	5.08	5.28
Operating Costs, OC_{jt} (10^6\$/PJ)			
$j = 1$ (Coal-fired)	0.15	0.15	0.15
$j = 2$ (Natural gas-fired)	0.58	0.58	0.58
$j = 3$ (Hydropower)	0.48	0.48	0.48
$j = 4$ (Wind)	1.37	1.37	1.37
$j = 5$ (Solar)	0.01	0.01	0.01

Note: PJ* stands for petajoule.

increase considerably and power generation capacity will require expansion when the supply of electricity insufficient to meet the rising demand (Kim and Ahu, 1993). Each power-generation facility capacity can be expanded at most once in each period, where there are three expansion levels that can be chosen (Zhang et al., 2012). The present and subsequent periods would see the implementation of the capacity expansions after they had been decided. In order to take into account the dynamic aspects of the research system, three five-year periods are considered in the planning period (Zhu and Huang, 2013).

At present, the generated electricity in the research system mainly comes from non-renewable fossil fuels, which is a major contributor to greenhouse gas emissions (GHG) and also has an impact on climate change and global warming (Zhou et al., 2011). Besides carbon dioxide emissions, other pollutants like volatile organic compounds (VOCs), sulfur dioxide (SO_2), and nitrogen oxides (NO_x) can also be emitted by using non-renewable energy during electricity generation (Zhu and Huang, 2013). On the contrary, the majority of renewable energy sources, such as hydro, wind, and solar power, have much lower GHG emissions.

Table 2. Capital Cost for Electricity Generation Facilities, Capacity Expansion Options and Electricity Demand from End-Users for Each Period

		Time Period $t = 1$	$t = 2$	$t = 3$
Capital Cost, EC_{jt} (10^6 \$/GW*)				
$j = 1$ (Coal-fired)		767	716	667
$j = 2$ (Natural gas-fired)		824	773	724
$j = 3$ (Hydropower)		3229	3029	2829
$j = 4$ (Wind)		1459	1354	1259
$j = 5$ (Solar)		4509	4319	4119
Capacity Expansion Options, CE_{jkt} (GW)				
$j = 1$ (Coal-fired)	$k = 1$	0.030	0.030	0.030
	$k = 2$	0.040	0.040	0.040
	$k = 3$	0.020	0.020	0.020
$j = 2$ (Natural gas-fired)	$k = 1$	0.011	0.011	0.011
	$k = 2$	0.024	0.024	0.024
	$k = 3$	0.037	0.037	0.037
$j = 3$ (Hydropower)	$k = 1$	0.007	0.007	0.007
	$k = 2$	0.008	0.008	0.008
	$k = 3$	0.011	0.011	0.011
$j = 4$ (Wind)	$k = 1$	0.006	0.006	0.006
	$k = 2$	0.011	0.011	0.011
	$k = 3$	0.016	0.016	0.016
$j = 5$ (Solar)	$k = 1$	0.005	0.005	0.005
	$k = 2$	0.009	0.009	0.009
	$k = 3$	0.013	0.013	0.013
Electricity Demand Average, ED_t (PJ)		20	28	35
Standard Deviation		4	4	4

Note: GW* stands for gigawatt.

Table 3. Capacities of Electricity Production Facilities and Availabilities of Energy Resources

Power Production Facilities	Residual (GW)	Allowable (GW)	Availability (PJ)
$j = 1$ (Coal-fired)	0.06	0.11	100
$j = 2$ (Natural gas-fired)	0.05	0.07	40
$j = 3$ (Hydropower)	0.03	0.04	
$j = 4$ (Wind)	0.02	0.05	
$j = 5$ (Solar)	0.02	0.04	

Table 4. Allowable Capacities for Solar and Wind Power Facilities under Different p_i Levels (Unit: GW)

p_i level	0.01	0.05	0.1	0.25	0.5
$j = 4$ (Wind), AC_4	0.05117	0.05661	0.05950	0.06443	0.06987
$j = 5$ (Solar), AC_5	0.03864	0.04008	0.04080	0.04200	0.04344

These renewable energy resources should be encouraged in order to face the escalating needs for the preservation of the environment and conservation of natural resources. Therefore, optimal resource allocations and strategies for capacity expansion are required by the decision-makers. The operating expenses for electricity-producing facilities and the typical market prices for fossil fuels for the three planned periods are shown in Table 1. Table 2 gives the capital investment costs and capacity expansion options for every electricity-producing facility. The residual and allowable capacity of each facility, as well as the energy resource availability, are listed in Table 3. Given that renewable energy sources vary naturally, the probability distributions of maximum capacities of solar and wind power facilities under various levels of constraint violation (p_i) are provided in Table 4 (Zhu and Huang, 2013).

The objective is to maximize the system cost while taking into account the CO_2 emission constraints. The total system costs in the LCMI method consist of costs of the non-renewable energy supply, electricity generation, capital investments for facility expansions, and carbon dioxide emissions treatment:

(a) Costs for non-renewable energy supply:

$$f_1 = \sum_{i=1}^{2}\sum_{t=1}^{3} PC_{it} \times XS_{it} \tag{4a}$$

(b) Cost of electricity generation:

$$f_2 = \sum_{j=1}^{5}\sum_{t=1}^{3} OC_{jt} \times XE_{jt} \tag{4b}$$

(c) Capital investments for facility expansions:

$$f_3 = \sum_{j=1}^{5}\sum_{k=1}^{3}\sum_{t=1}^{3} EC_{jt} \times CE_{jkt} \tag{4c}$$

(d) Cost of the carbon dioxide emissions treatment:

$$f_4 = \sum_{j=1}^{5}\sum_{t=1}^{3} XE_{jt} \times EA_{jt} \times CT_t \tag{4d}$$

Total system cost:

$$C_{total} = f_1 + f_2 + f_3 + f_4 \tag{4e}$$

Revenue of renewable energy source:

$$f_5 = \sum_{j=3}^{5}\sum_{t=1}^{3} XE_{jt} \times BE_{jt} \tag{4f}$$

$$\begin{aligned} &Max\ (system\ profit) = Revenue - total\ cost \\ &= f_5 - (f_1 + f_2 + f_3 + f_4) = \sum_{j=3}^{5}\sum_{t=1}^{3} XE_{jt} \times SR \\ &- [\sum_{i=1}^{2}\sum_{t=1}^{3} PC_{it} \times XS_{it} + \sum_{j=1}^{5}\sum_{t=1}^{3} OC_{jt} \times XE_{jt} \\ &+ \sum_{j=1}^{5}\sum_{t=1}^{3}\sum_{k=1}^{3} EC_{jt} \times CE_{jkt} Y_{jkt} \\ &+ \sum_{j=1}^{5}\sum_{t=1}^{3} XE_{jt} \times EA_{jt} \times CT_t] \end{aligned} \tag{5a}$$

A number of constraints specify how the decision variables and system circumstances interact with one another. Constraints fall into six groups: (1) the mass balance of electricity; (2) the mass balance of primary energy source; (3) capacity constraints for electricity generation; (4) carbon dioxide emissions constraint; (5) expansion option constraints; (6) non-negativity constraints. Equations are as follows:

(1) Mass balance of electricity:

$$\sum_{j=1}^{5} XE_{jt} \times ED_t,\ \forall t \tag{5b}$$

(2) Mass balance of energy source:

$$XS_{it} \geq XE_{jt},\ j = 1 \text{ and } 2,\ \forall t \tag{5c}$$

$$\sum_{t=1}^{3} XS_{it} \times UP_i,\ \forall i \tag{5d}$$

(3) Capacity constraints for electricity generation:

$$(REC_j + \sum_{k=1}^{3}\sum_{q=1}^{t} Y_{jkq} \times CE_{jkq}) \times U_{cap,j} \geq XE_{jt},\ \forall j,\ t \tag{5e}$$

$$REC_j + \sum_{t=1}^{3}\sum_{k=1}^{3} Y_{jkt} \times CE_{jkt} \leq AC_j,\ j = 1,\ 2, \text{ and } 3 \tag{5f}$$

$$REC_j + \sum_{t=1}^{3}\sum_{k=1}^{3} Y_{jkt} \times CE_{jkt} \leq (AC_j)^{p_i},\ j = 4\ (Wind) \tag{5g}$$

$$REC_j + \sum_{t=1}^{3}\sum_{k=1}^{3} Y_{jkt} \times CE_{jkt} \leq (AC_j)^{p_i},\ j = 5\ (Solar) \tag{5h}$$

(4) Carbon dioxide emissions constraint:

$$\sum_{j=1}^{5} XE_{jt} \times EA_{jt} \leq ULE_t,\ \forall t \tag{5i}$$

(5) Expansion option constraints:

$$\begin{aligned} &\sum_{k=1}^{3} Y_{jkt} \leq 1,\ \forall j,\ k,\ t \\ &Y_{jkt} = 1,\ capacity\ expansion\ for\ facility\ j \\ &\qquad with\ option\ k\ in\ period\ t\ is\ installed; \\ &Y_{jkt} = 0,\ otherwise \end{aligned} \tag{5j}$$

(6) Non-negativity constraints:

$$0 \leq Y_{jkt} \leq 1,\ Y_{jkt} = \text{integer},\ \forall j,\ k,\ t \tag{5k}$$

$$XS_{it} \geq 0,\ XE \geq 0,\ \forall j,\ k,\ t \tag{5l}$$

Description of subscripts, parameters, and decision variables can be seen in Appendix A.

3. Results

Table 5 shows the results of electricity generation XE_{it}, primary energy supply XS_{it}, and capacity expansion plans under different p_i levels obtained from the LCMI model. For example, when p_i equals 0.1, the power generation of coal-fired technol-

Table 5. Results of the LCMI Model

Power Generation, XE_{jt} (PJ)	Period	$p_i = 0$	$p_i = 0.01$	$p_i = 0.05$	$p_i = 0.1$	$p_i = 0.25$	$p_i = 0.5$
$j = 1$ (Coal-fired)	$k = 1$	2.7344	2.5000	1.9336	1.9336	1.6992	1.6992
	$k = 2$	10.7344	10.5000	9.9336	9.3672	8.6608	8.1888
	$k = 3$	17.7344	17.5000	16.9336	16.3672	15.6608	15.1888
$j = 2$ (Natural gas-fired)	$k = 1$	6.1244	6.1244	6.1244	6.1244	6.1244	6.1244
	$k = 2$	6.1244	6.1244	6.1244	6.1244	6.1244	6.1244
	$k = 3$	6.1244	6.1244	6.1244	6.1244	6.1244	6.1244
$j = 3$ (Hydropower)	$k = 1$	4.7120	4.7120	4.7120	4.7120	4.7120	4.7120
	$k = 2$	4.7120	4.7120	4.7120	4.7120	4.7120	4.7120
	$k = 3$	4.7120	4.7120	4.7120	4.7120	4.7120	4.7120
$j = 4$ (Wind)	$k = 1$	4.4368	4.4368	5.0032	5.0032	5.0032	5.0032
	$k = 2$	4.4368	4.4368	5.0032	5.5696	6.0416	6.5136
	$k = 3$	4.4368	4.4368	5.0032	5.5696	6.0416	6.5136
$j = 5$ (Solar)	$k = 1$	1.9924	2.2268	2.2268	2.2268	2.4612	2.4612
	$k = 2$	1.9924	2.2268	2.2268	2.2268	2.4612	2.4612
	$k = 3$	1.9924	2.2268	2.2268	2.2268	2.4612	2.4612
Primary Energy Supply, XS_{it} (PJ)	Period	$p_i = 0$	$p_i = 0.01$	$p_i = 0.05$	$p_i = 0.1$	$p_i = 0.25$	$p_i = 0.5$
i = 1 (Coal)	$k = 1$	2.7344	2.5000	1.9336	1.9336	1.6992	1.6992
	$k = 2$	10.7344	10.5000	9.9336	9.3672	8.6608	8.1888
	$k = 3$	17.7344	17.5000	16.9336	16.3672	15.6608	15.1888
i = 2 (Natural gas)	$k = 1$	6.1244	6.1244	6.1244	6.1244	6.1244	6.1244
	$k = 2$	6.1244	6.1244	6.1244	6.1244	6.1244	6.1244
	$k = 3$	6.1244	6.1244	6.1244	6.1244	6.1244	6.1244
Capacity Expansion (GW)	Period	$p_i = 0$	$p_i = 0.01$	$p_i = 0.05$	$p_i = 0.1$	$p_i = 0.25$	$p_i = 0.5$
$j = 1$ (Coal-fired)	$k = 1$	0	0	0	0	0	0
	$k = 2$	0	0	0	0	0	0
	$k = 3$	0.040	0.040	0.040	0.030	0.030	0.030
$j = 2$ (Natural gas-fired)	$k = 1$	0.011	0.011	0.011	0.011	0.011	0.011
	$k = 2$	0	0	0	0	0	0
	$k = 3$	0	0	0	0	0	0
$j = 3$ (Hydropower)	$k = 1$	0.008	0.008	0.008	0.008	0.008	0.008
	$k = 2$	0	0	0	0	0	0
	$k = 3$	0	0	0	0	0	0
$j = 4$ (Wind)	$k = 1$	0.027	0.027	0.033	0.033	0.033	0.033
	$k = 2$	0	0	0	0.006	0.011	0.016
	$k = 3$	0	0	0	0	0	0
$j = 5$ (Solar)	$k = 1$	0.014	0.018	0.018	0.018	0.022	0.022
	$k = 2$	0	0	0	0	0	0
	$k = 3$	0	0	0	0	0	0

ogies over three periods would be 1.9336, 9.3672, and 16.3672 PJ respectively; natural gas-fired technologies over the three periods would be 6.1244, 6.1244, and 6.1244 PJ; hydropower technologies over the three periods would be 4.7120, 4.7120, and 4.7120 PJ respectively; wind energy technologies over the three periods would be 5.0032, 6.0416, and 6.0416 PJ; solar energy technologies over the three periods would be 2.4612, 2.4612, and 2.4612 PJ, respectively. When p_i equals 0.25, the primary energy supplies of coal in 3 periods would respectively be 1.6992, 8.6608, and 15.6608 PJ; and natural gas would respectively be 6.1244, 6.1244, and 6.1244 PJ. As for the capacity expansion plans for coal-fired facility, natural gas-fired facility, hydropower plant, wind power facility, and solar power facility in the first period would respectively be 0, 0.011, 0.008, 0.027, and 0.018 GW when p_i equals 0.1. Similar to that, the outcomes for the three planning periods at various p_i levels can be understood. In addition, the results of system profit, renewable electricity amount, and carbon dioxide emission amount were given in Figure 2 to Figure 4. When p_i equals to 0, 0.01, 0.05, 0.1, 0.25, and 0.5, system profit would be \$2301.673, 2306.016, 2350.642, 2396.230, 2433.005, and 2465.437 million respectively; the system renewable electricity would be 33.4236, 34.1268, 35.8260, 36.9588, 38.6060, and 39.5500 PJ respectively; and carbon dioxide emission amount would be 11.3714, 11.1787, 10.6970, 10.3744, 9.9131, and 9.6444 Mt respectively. As p_i level increases, the system profit and renewable electricity amount will raise while the carbon dioxide emission amount will decrease.

Figure 5 presents capacity expansion schemes of five facilities under different p_i levels. As for coal-fired facility, capacity would only be expanded at the third period, which would be 0.040, 0.040, 0.040, 0.030, 0.030, and 0.030 GW respectively. Different from coal-fired facility, natural gas-fired facility, hydropower facility, and solar power facility will only expand the capacity at the first period. When p_i equals to 0, 0.01, 0.05, 0.1, 0.25, and 0.5, the capacity expansion option of natural gas-fired facility would always be 0.011 GW while hydropower facility is always 0.008 GW; the capacity expansion of solar energy would be 0.014, 0.018, 0.018, 0.022, and 0.022 GW respectively. And as for wind energy, it will be expanded both in the first and second periods, which is 0.027, 0.027, 0.033, 0.033, 0.033, 0.033 GW in the first period and 0, 0, 0, 0.006, 0.011, 0.016 GW in the second period. The largest expansion of capacity is the wind energy facility, which is 0.219 GW in total, while the smallest is the natural gas-fired facility, which is 0.066 GW in total.

Furthermore, system power-generation patterns under different p_i levels were provided in Figure 6. As the p_i level increases, the power generation percentage of natural gas and hydropower remain the same, which is 22 and 17%. The power generation percentage of solar energy will raise from 7 ~ 9%. And the biggest increase of power generation percentage is wind energy, which would be 16% raise to 22%. Contrary to this, the power production percentage of coal-fired will drop from 38 ~ 30%.

4. Discussion

Over the 15-year planning period, electricity from coal-fired facilities increases firmly and remains a major source in energy systems because of its large supply and competitive price, which reflects that relying solely on renewable energy generation would be insufficient for the increased energy demands in the future. Electricity generation from natural gas-fired facilities remains the same during all 3 periods, which means the supply of natural gas stays quite steady in the future. As for renewable energy facilities, capacity expansion plans are similar and applied in the initial two periods for the application of electricity generation. Under different p_i levels, the hydropower facility has the smallest capacity expansion of 0.008 GW in the first period. By contrast, the outcomes of wind and solar power are very sensitive because of the random availabilities and natural variations in these resources.

The LCMI results in Figure 2, and Figure 4 show that a higher system profit and lower carbon dioxide emissions can be obtained as the p_i level increases. For example, system profit will increase from \$2301.673 to 2465.437 million when p_i is increased from 0 to 0.05, and the carbon dioxide emissions will decrease from 11.3714 to 9.6444 Mt. The p_i level stands for the probability of constraint violation. A smaller decision space results from a smaller admissible risk of breaching the constraints caused by a lower p_i level, which also causes the constraints to be more stringent. As shown in Figure 3, the amount of renewable energy will increase with an increase in p_i level. When the availability of renewable energy resources is under higher p_i levels, the system will allow more electricity to be gen-

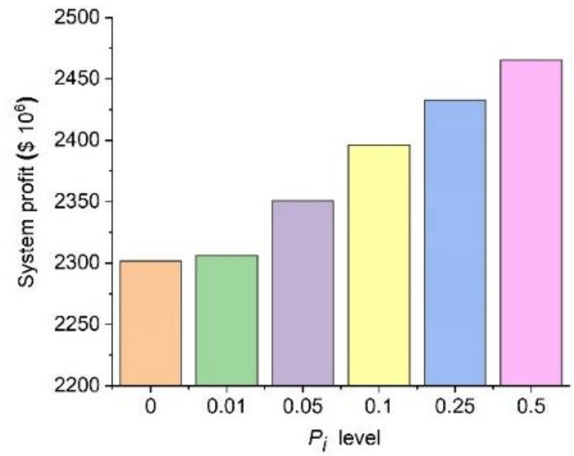

Figure 2. System profit under different p_i levels.

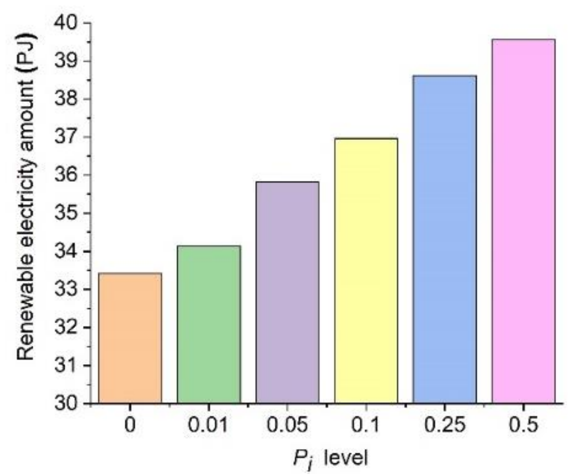

Figure 3. System renewable electricity amount under different p_i levels.

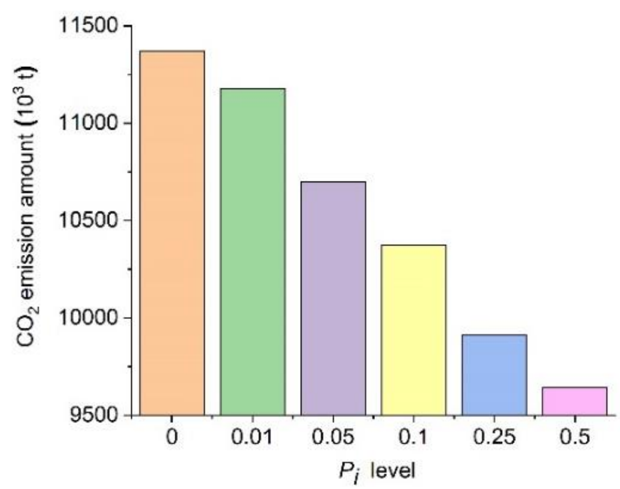

Figure 4. System carbon dioxide emission amount under different p_i levels.

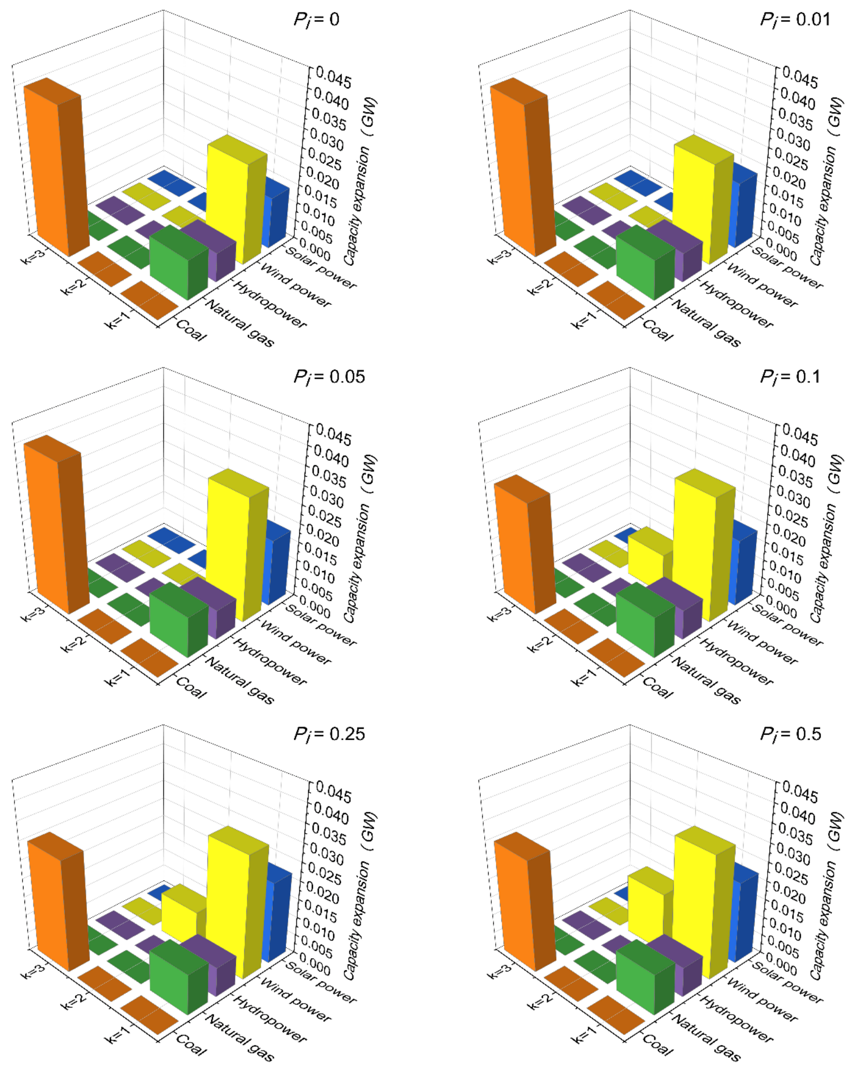

Figure 5. Comparative analysis of capacity-expansion plans of facilities under p_i levels.

erated from renewable sources to satisfy the increasing energy demands, which can obtain a plan of higher system efficiency with lower reliability. Therefore, the LCMI method can provide valuable plans under different constraint violation levels, which will offer a reference for decision-makers to choose ideal electricity generation and capacity expansion schemes under various system conditions. When the decision-makers aim to increase system profits and renewable energy generation while maintaining relatively low carbon dioxide emissions, the LCMI approach can be effective for achieving optimal system efficiency with different constraint violation levels.

However, the LCMI model still has some shortcomings: (a) insufficient processing of uncertain information. This study only took the right-hand side parameters in constraints into consideration, but there are some other uncertainties in input information, like fuzzy and interval numbers, which can be enhanced by combining other optimization techniques in the future; (b) insufficient innovation of method. There are some methods like machine learning and the Monte Carlo that can be further considered to make a combination with the LCMI model to make it more general, applicable, and accurate; (3) insufficient application of real cases. It is quite different for system planning when it comes to real cases, which will be more complicated and specific. The LCMI model can be improved by applying it to a real region in the future.

5. Conclusions

A linear chance-constrained mixed-integer programming (LCMI) approach has been proposed for optimizing regional electric power systems. The chance-constrained programming (CCP) and mixed integer linear programming (MILP) approaches are employed in the LCMI approach for resolving optimization problems, including those involving capacity expansion and uncertain data. The developed LCMI method has advantages in (1) integrating the total system cost and renewable energy generation amount in the objective function, which takes into account both economic benefits and environmental impacts;

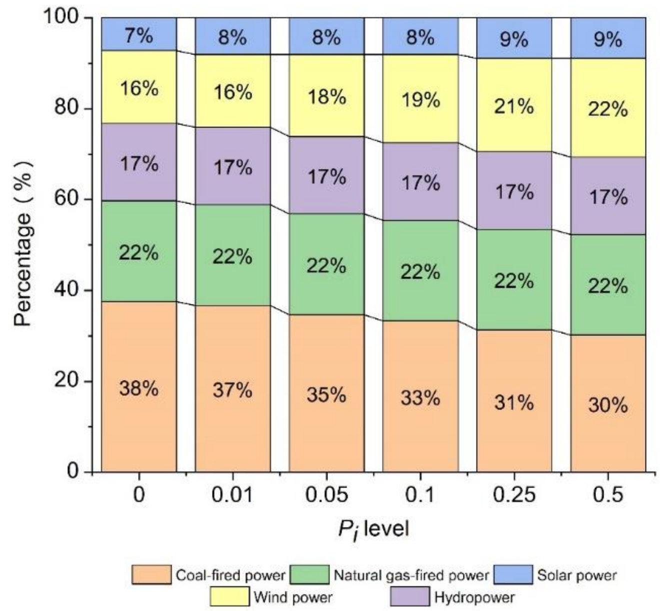

Figure 6. System power-generation patterns under different p_i levels.

(2) simplifying the calculation of multi-objective optimization and making the results more accurate; (3) handling the problem of input data uncertainty well by applying the CCP and MILP methods; (4) providing optimal capacity expansion plans under different constraint violation levels, which is conducive to the decision makers to make the best judgments for different environmental risks. It is revealed that the LCMI model is supportive in providing sustainable electricity generation and capacity expansion plans with maximized system profit and minimized carbon dioxide emissions under different risk levels through its application in a regional electric power system. Furthermore, the LCMI method would be a useful tool and has good potential for future applications in solving optimization problems such as air pollution control, water resource allocation, etc. Also, the LCMI model can be improved by further integrating other optimization methods (interval programming, multi-stage programming, etc.) to deal with data uncertainties.

Appendix A. Nomenclature

Subscripts:

i: Non-renewable energy resources (i = 1, 2); i = 1 (Coal); i = 2 (Natural gas)

j: Electricity-generation facilities (j = 1, 2, 3, 4, 5); j = 1 (Coal); j = 2 (Natural gas); j = 3 (Hydropower); j = 4 (wind); j = 5 (Solar)

t: Planning periods (t = 1, 2, and 3)

k: Capacity expansion options (k = 1, 2, and 3)

Decision variables:

XS_{it}: Supply amount of non-renewable energy source i during period t (PJ)

XE_{jt}: Electricity generation amount from technology facility j during period t (PJ)

Y_{jkt}: Binary variable representing capacity for facility j with option k during period t will be expanded or not

Parameters:

PC_{it}: Purchase cost for non-renewable energy source i during period t (10^6 $/PJ)

OC_{jt}: Operating costs for electricity generation from facility j during period t (10^6 $/PJ)

EC_{jt}: Expansion cost for electricity generation technology j during period t (10^6 $/GW)

CE_{jkt}: Capacity expansion amount for facility j with option k during period t (GW)

EA_{jt}: Emission amount of CO_2 for electricity generation facility j during period t (10^3 t/PJ)

CT_t: Carbon dioxide emission treatment cost during period t (10^3 $/t)

SR: System revenue per unit of electricity generation (10^6 $/PJ)

ED_t: Total electricity demand from end-users during period t (PJ)

REC_j: Residual capacity amount of electricity generation facility j (GW)

U_j: Conversion coefficient of facility j from electricity generation capacity to energy (GW to PJ)

AC_j: Allowable capacity for electricity generation facility j (GW)

ULE_t: Upper limit of CO_2 emissions during period t (10^3 t)

UP_i: the available resource for non-renewable energy resources i (PJ)

References

Agrawal, K.K., Jain, S., Jain, A.K. and Dahiya, S. (2014). Assessment of greenhouse gas emissions from coal and natural gas thermal power plants using life cycle approach. *International Journal of Environmental Science and Technology,* 11, 1157-1164. https://doi.org/10.1007/s13762-013-0420-z

Ahmad, T. and Zhang, D. (2020). A critical review of comparative global historical energy consumption and future demand: The story told so far. *Energy Reports,* 6, 1973-1991. https://doi.org/10.1016/j.egyr.2020.07.020

Cai, Y., Huang, G., Yang, Z., Lin, Q. and Tan, Q. (2009). Community-scale renewable energy systems planning under uncertainty-An interval chance-constrained programming approach. *Renewable and Sustainable Energy Reviews*, 13(4), 721-735. https://doi.org/10.1016/j.rser.2008.01.008

Charnes, A., Cooper, W.W. and Kirby, M.J.L. (1971). Chance-constrained programming: An extension of statistical method. *Optimizing Methods in Statistics*. Elsevier Inc., pp 391-402. https://doi.org/10.1016/B978-0-12-604550-5.50022-5

Cook, M. (2021). Trends in global energy supply and demand. In *Developments in Petroleum Science*, 71, 15-42. https://doi.org/10.1016/B978-0-12-821190-8.00002-2

IPCC (2007). *Climate Change 2007: Synthesis Report. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Intergovernmental Panel on Climate Change.

IPCC (2022). *Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Intergovernmental Panel on Climate Change.

Groscurth, H.M., Kümmel, R. and Van Gool, W. (1989). Thermodynamic limits to energy optimization. *Energy*, 14(5), 241-258. https://doi.org/10.1016/0360-5442(89)90097-2

Karmaker, A.K., Rahman, M.M., Hossain, M.A. and Ahmed, M.R. (2020). Exploration and corrective measures of greenhouse gas emission from fossil fuel power stations for Bangladesh. *Journal of Cleaner Production, 244*, 118645. https://doi.org/10.1016/j.jclepro.2019.118645

Kim, Y.C. and Ahu, B.-H. (1993). Multicriteria generation-expansion planning with global environmental considerations. *IEEE Transactions on Engineering Management*, 40(2), 154-161. https://doi.org/10.1109/17.277407

Lara, P. and Stancu-Minasian, I. (1999). Fractional programming: a tool for the assessment of sustainability. *Agricultural Systems*, 62 (2), 131-141. https://doi.org/10.1016/S0308-521X(99)00062-1

Li, Y., Huang, G. and Chen, X. (2011). Planning regional energy system in association with greenhouse gas mitigation under uncertainty. *Applied Energy*, 88(3), 599-611. https://doi.org/10.1016/j.apenergy.2010.07.037

Li, Y.P., Huang, G.H., Huang, Y.F. and Zhou, H.D. (2009). A multistage fuzzy-stochastic programming model for supporting sustainable water-resources allocation and management. *Environmental Modelling & Software*, 24(7), 786-797. https://doi.org/10.1016/j.envsoft.2008.11.008

Li, Z., Huang, G., Zhang, Y.M. and Li, Y.P. (2013). Inexact two-stage stochastic credibility constrained programming for water quality management. *Resources, Conservation and Recycling*, 73, 122-132. https://doi.org/10.1016/j.resconrec.2013.01.008

Limmeechokchai, B. and Chungpaibulpatana, S. (2001). Application of cool storage air-conditioning in the commercial sector: An integrated resource planning approach for power capacity expansion planning and emission reduction. *Applied Energy*, 68(3), 289-300. https://doi.org/10.1016/S0306-2619(00)00060-X

Malik, A. (2001). Modelling and economic analysis of DSM programs in generation planning. *International Journal of Electrical Power & Energy Systems*, 23(5), 413-419. https://doi.org/10.1016/S0142-0615(00)00077-6

Nilsson, J.S. and Mårtensson, A. (2003). Municipal energy-planning and development of local energy-systems. *Applied Energy*, 76(1-3), 179-187. https://doi.org/10.1016/S0306-2619(03)00062-X

Quaddus, M.A. and Goh, T.N. (1985). Electric power generation expansion: Planning with multiple objectives. *Applied Energy*, 19(4), 301-319. https://doi.org/10.1016/0306-2619(85)90004-2

Rekik, M., Abdelkafi, A. and Krichen, L. (2015). A micro-grid ensuring multi-objective control strategy of a power electrical system for quality improvement. *Energy*, 88, 351-363. https://doi.org/10.1016/j.energy.2015.05.050

Ren, H., Zhou, W., Nakagami, K., Gao, W. and Wu, Q. (2010). Multi-objective optimization for the operation of distributed energy systems considering economic and environmental aspects. *Applied Energy*, 87(12), 3642-3651. https://doi.org/10.1016/j.apenergy.2010.06.013

Rong, A. and Lahdelma, R. (2005). An efficient linear programming model and optimization algorithm for trigeneration. *Applied Energy*, 82(1), 40-63. https://doi.org/10.1016/j.apenergy.2004.07.013

Rong, A. and Lahdelma, R. (2007). An effective heuristic for combined heat-and-power production planning with power ramp con-straints. *Applied Energy*, 84(3), 307-325. https://doi.org/10.1016/j.apenergy.2006.07.005

Smith, B. (1980). Modelling New Zealand's energy system. *European Journal of Operational Research*, 4(3), 173-184. https://doi.org/10.1016/0377-2217(80)90003-X

Song, H., Dotzauer, E., Thorin, E., Guziana, B., Huopana, T. and Yan, J. (2012). A dynamic model to optimize a regional energy system with waste and crops as energy resources for greenhouse gases mitigation. *Energy*, 46(1), 522-532. https://doi.org/10.1016/j.energy.2012.07.060

Tabors, R.D. and Monroe, B.L. (1991). Planning for future uncertainties in electric power generation: An analysis of transitional strategies for reduction of carbon and sulfur emissions. *IEEE Transactions on Power Systems*, 6(4), 1500-1507. https://doi.org/10.1109/59.116996

Tiris, M., Atagunduz, G. and Dincer, I. (1994). Energy, economy and environment modelling: Applications for Turkey. *Energy*, 19(9), 1005-1009. https://doi.org/10.1016/0360-5442(94)90087-6

Zhang, Y., Huang, G., Lin, Q. and Lu, H. (2012). Integer fuzzy credibility constrained programming for power system management. *Energy*, 38(1), 398-405. https://doi.org/10.1016/j.energy.2011.11.0 35

Zhou, Q., Chan, C. and Tontiwachiwuthikul, P. (2011). Development of an intelligent system for monitoring and diagnosis of the carbon dioxide capture process. *Journal of Environmental Informatics*, 18(2). https://doi.org/10.3808/jei.201100201

Zhou, Y., Huang, G., Zhu, H., Li, Z. and Chen, J. (2016). A factorial dual-objective rural environmental management model. *Journal of Cleaner Production*, 124, 204-216. https://doi.org/10.1016/j.jclepro.2016.02.081

Zhu, H. and Huang, G. (2013). Dynamic stochastic fractional programming for sustainable management of electric power systems. *International Journal of Electrical Power & Energy Systems*, 53, 553-563. https://doi.org/10.1016/j.ijepes.2013.05.022

Zhu, Y., Huang, G., Li, Y., He, L. and Zhang, X. (2011). An interval full-infinite mixed-integer programming method for planning municipal energy systems-A case study of Beijing. *Applied Energy*, 88(8), 2846-2862. https://doi.org/10.1016/j.apenergy.2011.01.058