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Development of An Interval Chance-Constrained Mixed-Integer Linear Programming Model for Electric Power System Planning — A Case Study for the Province of Alberta, Canada

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ABSTRACT. Reducing carbon emissions from power systems is essential for meeting increasingly stringent decarbonization requirements while maintaining reliable electricity supply and economic performance. This study develops an interval chance-constrained mixed-integer linear programming (ICM) model to maximize total system profit and support capacity expansion and generation planning under uncertainty. The proposed ICM framework integrates mixed-integer programming, chance-constrained programming, and interval linear programming to represent both risk preferences and interval-type uncertainties in key inputs, and it considers eight planned power generation technologies. The model generates optimal technology-specific capacity expansion plans and electricity generation strategies that satisfy end-user demand while complying with carbon dioxide (CO_2) emission targets under three risk levels. The approach is demonstrated through a provincial-scale case study in Alberta, Canada, where uncertainties and risks are quantified and trade-offs among multiple system criteria are examined. Results indicate that the share of installed capacity for small modular reactors (SMRs) will increase rapidly, clean energy generation will rise to 66% of total electricity production, and total CO_2 emissions will decrease by approximately 34%. The proposed framework provides decision-makers with a practical tool for optimizing provincial power systems and advancing long-term environmental and economic sustainability.

Keywords: SMRs, system optimization, uncertainty, power system planning, carbon emission, clean energy

1. Introduction

Climate warming, also known as global warming, has caused widespread impacts and threats to the Earth's environment and human society, including increased frequency of extreme weather event, rising sea levels, threats to ecosystems and species, increased human health risk, economic losses, and so on. These impacts collectively present a broad and profound challenge to the global community due to climate warming (Haines et al., 2006; Stern, 2006; IPCC, 2018a; UNSD, 2021; Zhang et al., 2022). Carbon emissions are one of the main causes of climate change. From the data of global carbon emission contribution by sector, around 30% of carbon dioxide emissions are due to fossil fuel combustion in energy systems in the past 20 years (Song et al., 2012). Therefore, reducing greenhouse gas (GHG) emissions and increasing carbon absorption of electricity power system are crucial measures to address global warming (IPCC, 2018b).

Nowadays, on the one hand, as one of the significant contributors to GHG emissions, the electricity sector is currently facing strict emission regulations and this will bring substantial structural adjustment to electricity systems. For instance, many countries around the world have been making great efforts to achieve long-term goals to transit their electricity system towards a low-carbon, resource-efficient, reliable, and secure one (Government of Canada, 2020; O'Meara, 2020; World Nuclear News, 2020; Beyond Fossil Fuels, 2021). On the other hand, 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). Therefore, in order to meet the growing energy consumption demands and GHG emissions reduction target, it is crucial to conduct optimal planning of global, national, and regional electricity power systems for their sustainable development.

Due to rapid population and economic growth, energy consumption and demands have been increasing globally (Ahmad and Zhang, 2020; Cook, 2021). Therefore, in order to meet the growing energy consumption demands and GHG emissions reduction target, it is crucial to conduct optimal planning of global, national, and regional electricity power systems for their sustainable development.

In Canada, accelerating power-system decarbonization is

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a key pathway to achieving economy-wide emission-reduction commitments. However, Alberta faces particularly strong mitigation pressure because its electricity supply remains relatively carbon-intensive and still relies heavily on fossil-fuel generation. Up to now, the total available generating capacity in Alberta province is around 18,000 megawatts (MW), with natural gas-fired power accounting for 10,000 MW (60%), wind power accounting for 3,600 MW (20%), coal-fired power accounting for 1,500 MW (9%), solar power accounting for 1,100MW (7%), hydroelectricity accounting for 900 MW (5%), waste heat power accounting for 300 MW (2%). The gross electricity supplied in Alberta in 2022 was 55.5 TWh, about 84% of which is produced from fossil fuels — approximately 44% from natural gas, 40% from coal (SaskPower, 2020; IGDP, 2021). Overall, the installed-capacity mix and generation profile indicate that Alberta's power system remains highly dependent on fossil fuels, highlighting the urgency of developing cost-effective decarbonization pathways.

According to the environmental policies of Canada and Alberta, all the conventional coal-fired electricity should be phased out to later than 2030 (Ali, 2017; Rahmanifard and Plaksina, 2019; Ganesh et al., 2020a; Sara et al., 2022; Chen et al., 2023). The Alberta province also should increase investments in clean energy technology, support carbon capture and storage, etc. (CER, 2024). In addition, the province hope that up to 30% of electricity is produced from renewable resources by 2030 (SaskPower, 2023). In addition, the Alberta province will support the Small Modular Reactors (SMRs) development with some positive policies (Rahmanifard and Plaksina, 2019; Ganesh et al., 2020b). The most significant milestone is to reduce emissions by 200 million tonnes (Mt) by 2050 (SaskPower, 2023). To determine effective pathways of power system transition, standard practice is to conduct power system modeling that involves the characterization of various components and activities in the system through an appropriate simulation model. The system optimization model, which allows for the consideration of trade-offs between system costs and GHG emissions, is beneficial for the formulation of regional energy and relevant socio-economic and environmental policies (Chen et al., 2018).

Despite the growing body of work on low-carbon power-system planning, important methodological gaps remain when decisions must be made under multiple sources of uncertainty and explicit risk considerations. Many existing studies either use deterministic optimization or scenario-based analyses that lack a clear probabilistic interpretation of constraint satisfaction, making it difficult to quantify the likelihood of meeting demand and emission limits. In addition, uncertainty is often represented by a single distributional assumption or a limited set of scenarios, while key inputs such as technology costs, fuel prices, and renewable availability may be better described by bounded (interval) information, especially when data are incomplete or highly variable. Furthermore, risk management is rarely integrated with discrete capacity-expansion decisions and operational dispatch in a single optimization framework, limiting the ability to produce implementable transition plans and to reveal robust economic-environmental trade-offs under different risk tolerances.

Therefore, the objective of this study is to propose an interval chance-constrained mixed-integer linear programming (ICM) framework that simultaneously incorporates (i) interval representations for uncertain parameters, (ii) chance constraints to control the probability of constraint violation under specified risk levels, and (iii) mixed-integer decisions for technology expansion planning, thereby enabling a systematic evaluation of cost-emission trade-offs and robust decarbonization pathways at the provincial scale. This study can improve the conventional energy modeling method with a capacity 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 the optimization plan for regional electric power systems to maintain sustainable social and economic development.

2. Methodology

Mixed-integer programming, chance-constrained programming, and interval programming were integrated and applied to electric power systems planning to address input uncertainties. Mixed-integer programming is used to deal with integer variables. Chance-constrained programming is applied to solve the problem of uncertainties described as probability distributions. The primary energy source availability in a specific region, such as hydro, wind and solar power, highly corresponds with the regional weather conditions and can be input as random numbers displayed as probability distributions. Interval programming is used to do with interval parameters.

A Mixed Integer Linear Programming (MILP) model can be formulated as follows:

$$\mathrm{Max}\, f(x) = \sum_{j=1}^{n} C(j) * X(j) \tag{1a}$$

Subject to:

$$\sum_{j=1}^{n} A(i,j) * X(j) \le B(i),\ i = 1,2,...,m \tag{1b}$$

$$X(j) \ge 0,\ j = 1,2,...,n \tag{1c}$$

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

A Chance Constrained Programming (CCP) model can be formulated as follows:

$$\mathrm{Max}\, f(x) = \sum_{i=1}^{m} \sum_{j=1}^{n} C(i,j) * X(i,j) \tag{2a}$$

Subject to:

$$\Pr\left\{ \sum_{j=1}^{n} A(i,j) * X(i,j) \le B(i) \right\} \ge 1 - P_i,\ \forall i \tag{2b}$$

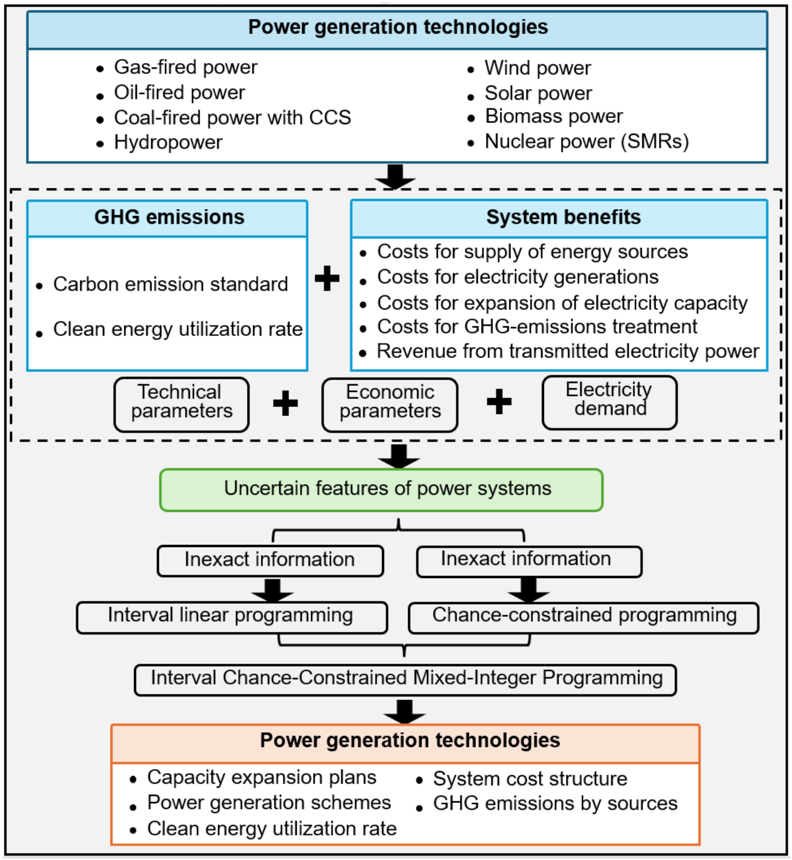

Figure 1. Research framework.

where $X(i, j)$ ($i = 1, 2, \ldots, m$; $j = 1, 2, \ldots, n$) are non-negative continuous decision variables, $A(i, j)$ are constants, B_i, $C(i, j)$ are random variables, $P(i)$ is significance level or risk level.

Based on MILP, CCP and interval linear programming (ILP) methods, an interval chance-constrained mixed-integer programming (ICM) model is introduced into an energy planning framework. In this framework, we can take some uncertainties into consideration. More accurate analysis results for electricity power system planning through dealing with existing uncertainties by integrating MILP, CCP, and ILP methods can be obtained. For instance, for expansion problem of facilities in energy system planning, the need to determine whether existing electricity generation facilities should be expanded can be addressed using a mixed-integer linear programming (MILP) model. As for the uncertainties of the availability of renewable energy sources in a specific region in the future, such as hydropower, wind power, and solar power, caused by weather conditions, these uncertainties can be addressed using a chance-constrained programming (CCP) model. In this single model, these uncertainties are represented using probability distributions (Zhu and Huang, 2013) and probability distributions can be applied to some parameters in CCP model. Due to limitations in data availability and the nature of the data sources, some model parameters are only known within lower and upper bounds. Such bounded uncertainty can be represented using interval analysis, and incorporated into an interval linear programming (ILP) framework. Through integrated MILP, CCP, and ILP models, an interval chance-constrained mixed-integer programming model (ICM) can be formulated as follows:

$$\text{Max} f(x)^{\pm} = \sum_{j=1}^{n} C(j)^{\pm} * X(j)^{\pm} \tag{3a}$$

Subject to:

$$\Pr\left\{\sum_{j=1}^{n} A(i,j)^{\pm} * X(j)^{\pm} \leq B(i)^{\pm}(t)\right\} \geq 1 - P_i,\ i = 1,2,\ldots,\beta \tag{3b}$$

$$A(i,j)^{\pm} * X(j)^{\pm} \leq B(i)^{\pm},\ i = \beta+1, \beta+2, \ldots, m \tag{3c}$$

$$X(j)^{\pm} \geq 0,\ j = 1,2,\ldots,n \tag{3d}$$

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, 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 $\Pr\{\sum_{j=1}^{n} A(i, j) * X(j) \leq B_i\} \geq p_i$ can be converted as:

$$A(i,j) * X(j) \le B_i(t)^{(pi)} \quad (4)$$

where $B_i(t)^{(p_i)} = F_i^{-1}(p_i)$, considering the cumulative distribution function of B_i and the probability of breaking constraint i (p_i). Constraint (4) is linear and the CCP approach can be applied to resolve the ICM model (3) 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 ICM 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 $B_i(t)p_i$.

Step 3: Resolve the ICM 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 ICM model is employed with a case study of Alberta electric power system management problems with real world data (Cai et al., 2009). Figure 1 displays a research framework of this study. There are four non-renewable resources (natural gas, oil, coal and uranium) and four renewable resources (hydro, wind, solar, and biomass) in Alberta 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 increase considerably and power generation capacity will require expansion when the supply of electricity is 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, four five-year periods (2031-2050, 5 years each) 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). On the contrary, the majority of clean energy sources, such as hydro, wind, solar power, and biomass have much lower GHG emissions. These clean 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. Input data of economic and technological parameters for the proposed model, such as the operating expenses for electricity-producing facilities, the typical market prices for fossil fuels, the capital investment costs for every electricity-producing facility, the energy resource availability, and so on, were obtained from government reports, statistical yearbooks, and literatures.

The objective is to maximize the system cost while taking into account the CO_2 emission constraints. The total system costs in the ICM 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:

$$f_1^{\pm} = \sum_{i=1}^{4}\sum_{t=1}^{4} X_{i,t}^{\pm} * CE_{i,t}^{\pm} \quad (5a)$$

(b) Cost of electricity generation:

$$f_2^{\pm} = \sum_{j=1}^{8}\sum_{t=1}^{4} Y_{j,t}^{\pm} * CP_{j,t}^{\pm} \quad (5b)$$

(c) Costs for expansion of electricity capacity:

$$f_3^{\pm} = \sum_{j=1}^{8}\sum_{k=1}^{3}\sum_{t=1}^{4} Z_{j,k,t} * EP_{j,k,t} * CCE_{j,k,t}^{\pm} \quad (5c)$$

(d) Costs for GHG-emissions treatment:

$$f_4^{\pm} = \sum_{j=1}^{8}\sum_{t=1}^{4} Y_{j,t}^{\pm} * ECD_{j,t} * CCT_t^{\pm} \quad (5d)$$

(e) Total system cost:

$$\text{Cost}_{(\text{total})} = f_1^{\pm} + f_2^{\pm} + f_3^{\pm} + f_4^{\pm} \quad (5e)$$

(f) Revenue from transmitted electricity power:

$$f_5^{\pm} = \sum_{j=1}^{8}\sum_{t=1}^{4} Y_{j,t}^{\pm} * SR^{\pm} \quad (5f)$$

Max system profit = Revenue – total cost

$$\begin{aligned} &= f_5^{\pm} - (f_1^{\pm} + f_2^{\pm} + f_3^{\pm} + f_4^{\pm}) \\ &= \sum_{j=1}^{8}\sum_{t=1}^{4} Y_{j,t}^{\pm} * SR^{\pm} - \Bigg[\sum_{i=1}^{4}\sum_{t=1}^{4} X_{i,t}^{\pm} * CE_{i,t}^{\pm} \\ &+ \sum_{j=1}^{8}\sum_{t=1}^{4} Y_{j,t}^{\pm} * CP_{j,t}^{\pm} + \sum_{j=1}^{8}\sum_{k=1}^{3}\sum_{t=1}^{4} Z_{j,k,t} * EP_{j,k,t} * CCE_{j,k,t}^{\pm} \\ &+ \sum_{j=1}^{8}\sum_{t=1}^{4} Y_{j,t}^{\pm} * ECD_{j,t} * CCT_t^{\pm}\Bigg] \end{aligned} \quad (6a)$$

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 primary energy source; (2) the constraints of electricity capacity; (3) capacity constraints for electricity generation; (4) carbon dioxide emissions constraint; (5) non-negativity constraints.

(1) Mass balance constraints:

The input of primary energy ≥ the generated electricity

Table 1. Capacity Expansion Results of the ICM Model (p_i = 0.01 Upper Bound)

Technologies	Options	Period 1	Period 2	Period 3	Period 4
	k_1	0	0	0	0
NG	k_2	0	0	0	0
	k_3	0	0	0	0
	k_1	0	0	0	0
Oil	k_2	0	0	0	0
	k_3	0	0	0	0
	k_1	0	*	0	0
Coal + CCS	k_2	*	0	0	0
	k_3	0	0	*	*
	k_1	0	0	0	0
Hydro	k_2	*	0	0	*
	k_3	0	0	*	0
	k_1	0	0	0	0
Wind	k_2	*	*	0	0
	k_3	0	0	*	*
	k_1	0	*	0	0
Solar	k_2	0	0	0	0
	k_3	0	0	*	*
	k_1	0	0	0	0
Biomass	k_2	0	0	0	0
	k_3	*	*	*	*
	k_1	0	0	0	0
SMRs	k_2	0	0	0	0
	k_3	*	*	*	*

“*” for expansion, “0” for no expansion

Table 2. Capacity Expansion Results of the ICM Model (p_i = 0.01 Lower Bound)

Technologies	Options	Period 1	Period 2	Period 3	Period 4
	k_1	0	0	0	0
NG	k_2	0	0	0	0
	k_3	0	0	0	0
	k_1	0	0	0	0
Oil	k_2	0	0	0	0
	k_3	0	0	0	0
	k_1	0	*	0	0
Coal + CCS	k_2	*	0	0	0
	k_3	0	0	*	*
	k_1	0	0	0	0
Hydro	k_2	*	0	0	*
	k_3	0	0	*	0
	k_1	0	0	0	0
Wind	k_2	*	*	0	0
	k_3	0	0	*	*
	k_1	0	*	0	0
Solar	k_2	0	0	0	0
	k_3	0	0	*	*
	k_1	0	*	0	0
Biomass	k_2	*	0	*	0
	k_3	0	0	0	0
	k_1	0	0	0	0
SMRs	k_2	0	0	0	0
	k_3	*	*	*	*

“*” for expansion, “0” for no expansion

For natural gas ⇨ electricity ($i = 1, j = 1$)

$$X_{1,t}^{\pm} \geq Y_{1,t}^{\pm} * FEG_{1,t}, \ \forall t \tag{6b}$$

For oil ⇨ electricity ($i = 2, j = 2$)

$$X_{2,t}^{\pm} \geq Y_{2,t}^{\pm} * FEG_{2,t}, \ \forall t \tag{6c}$$

For coal ⇨ electricity ($i = 3, j = 3$)

$$X_{3,t}^{\pm} \geq Y_{3,t}^{\pm} * FEG_{3,t}, \ \forall t \tag{6d}$$

For uranium ⇨ electricity ($i = 8, j = 8$)

$$X_{4,t}^{\pm} \geq Y_{8,t}^{\pm} * FEG_{8,t}, \ \forall t \tag{6e}$$

For the renewable energy sources availability

$$\Pr\left\{Y_{4,t}^{\pm} * FEG_{4,t} \leq UPR_{4,t}\right\} \geq 1-q, \ \forall t \text{ Hydro} \tag{6f}$$

$$\Pr\left\{Y_{5,t}^{\pm} * FEG_{5,t} \leq UPR_{5,t}\right\} \geq 1-q, \ \forall t \text{ Wind} \tag{6g}$$

$$\Pr\left\{Y_{6,t}^{\pm} * FEG_{6,t} \leq UPR_{6,t}\right\} \geq 1-q, \ \forall t \text{ Solar} \tag{6h}$$

(2) Capacity constraints: (for electricity generation)

The maximum possible output of facility ≥ the actual electricity produced by the facility

(Existing capacity + Expansion capacity ≥ generated electricity)

$$\left(ECP_j + \sum_{k=1}^{3} Z_{j,k,t} * EP_{j,k,t}\right) * AOT_{j,t} * 5 * PCAP_{j,t} \geq Y_{j,t}^{\pm}, \ \forall j,t \tag{6i}$$

(3) Supply and demand constraints:

The energy supply ≥ the demand of end users

$$\sum_{j=1}^{8} Y_{j,t}^{\pm} \geq ED_t^{\pm}, \ \forall t \tag{6j}$$

(4) Carbon dioxide emissions constraints:

Electricity generated (j = 1, 2, 3, 7) * emission parameter ≤ emission standard

$$\sum_{j=1}^{3} Y_{j,t}^{\pm} * ECD_{j,t} + Y_{7,t}^{\pm} * ECD_{7,t} \leq LEC_t^{\pm}, \ \forall t \tag{6k}$$

(5) Technical constraints: non-negativity

Table 3. Capacity Expansion Results of the ICM Model (p_i = 0.05 Upper Bound)

Technologies	Options	Period 1	Period 2	Period 3	Period 4
	k_1	0	0	0	0
NG	k_2	0	0	0	0
	k_3	0	0	0	0
	k_1	0	0	0	0
Oil	k_2	0	0	0	0
	k_3	0	0	0	0
	k_1	0	0	0	0
Coal + CCS	k_2	*	0	*	0
	k_3	0	0	0	*
	k_1	0	0	0	0
Hydro	k_2	0	0	*	*
	k_3	0	*	0	0
	k_1	0	0	0	0
Wind	k_2	*	0	0	0
	k_3	0	*	*	*
	k_1	0	0	0	0
Solar	k_2	*	0	0	0
	k_3	0	*	*	*
	k_1	0	0	0	0
Biomass	k_2	0	0	0	0
	k_3	*	*	*	*
	k_1	0	0	0	0
SMRs	k_2	0	0	0	0
	k_3	*	*	*	*

"*" for expansion, "0" for no expansion

Table 4. Capacity Expansion Results of the ICM Model (p_i = 0.05 Lower Bound)

Technologies	Options	Period 1	Period 2	Period 3	Period 4
	k_1	0	0	0	0
NG	k_2	0	0	0	0
	k_3	0	0	0	0
	k_1	0	0	0	0
Oil	k_2	0	0	0	0
	k_3	0	0	0	0
	k_1	0	*	0	0
Coal + CCS	k_2	*	0	0	0
	k_3	0	0	*	*
	k_1	0	0	0	0
Hydro	k_2	*	0	0	*
	k_3	0	0	*	0
	k_1	0	0	0	0
Wind	k_2	*	*	0	0
	k_3	0	0	*	*
	k_1	0	*	0	0
Solar	k_2	0	0	0	0
	k_3	0	0	*	*
	k_1	0	*	0	0
Biomass	k_2	0	0	*	0
	k_3	0	0	0	0
	k_1	0	0	0	0
SMRs	k_2	0	0	0	0
	k_3	*	*	*	*

"*" for expansion, "0" for no expansion

$$X_{i,t}^{\pm} \geq 0, \ \forall i,t \tag{6l}$$

$$Y_{j,t}^{\pm} \geq 0, \ \forall j,t \tag{6m}$$

$$0 \leq \sum_{k=1}^{3} Z_{j,k,t} \leq 1, \ Z_{j,k,t} = \text{integer } (0,1), \ \forall j,t \tag{6n}$$

$Z_{j,k,t}$ = 1, capacity expansion for facility j with option k in period t is installed; $Z_{j,k,t}$ = 0, otherwise.

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

3. Results and Discussion

As shown in Table 1, the capacity expansion plan results obtained from the ICM model under the upper bound, with the p_i level set to 0.01, will be observed. Natural gas and oil electricity generation technologies will not be expanded in all four periods, mainly due to carbon-emission limits and/or limited expandable capacities. Coal + CCS electricity generation technologies will be expanded in all four periods by selecting medium, low, high, and high expansion capacities, respectively, which will contribute to meeting total electricity demand while satisfying carbon-emission requirements. For hydropower, medium, high, and medium expansion levels will be selected in periods 1, 3, and 4, respectively, which will likely reflect the need to balance profit maximization, overall electricity supply, and emission constraints within the generation mix. In period 2, hydropower capacity that can be developed relative to other generation technologies will be comparatively small; therefore, expansion will not be selected, as other technologies will be expected to expand to meet demand and system requirements. For wind power, medium, medium, high, and high expansion levels will be chosen across the four periods, respectively, because wind power will remain relatively cost-effective for capacity expansion and electricity generation. For solar power, low, high, and high expansion levels will be selected in periods 2, 3, and 4, respectively, in order to meet electricity demand, reduce carbon emissions, and achieve related targets. For biomass power generation, expansion will be implemented in all four periods, with a high expansion level selected throughout, mainly because biomass power will be supported by government policies for biomass-waste utilization and will contribute to emission reductions as a clean energy source. For SMRs, Alberta will need to continue reducing carbon emissions to achieve the net-zero target while phasing out coal plants; consequently, only a substantial expansion of SMRs will ultimately satisfy these conditions, including growing electricity demand, carbon-emission reduction, and profit maximization.

As shown in Table 2, the capacity expansion plan results obtained from the ICM model under the lower bound with p_i = 0.01 will be presented. Compared with the upper-bound case,

Table 5. Capacity Expansion Results of the ICM Model (p_i = 0.1 Upper Bound)

Technologies	Options	Period 1	Period 2	Period 3	Period 4
	k_1	0	0	0	0
NG	k_2	0	0	0	0
	k_3	0	0	0	0
	k_1	0	0	0	0
Oil	k_2	0	0	0	0
	k_3	0	0	0	0
	k_1	*	0	0	0
Coal + CCS	k_2	0	0	*	0
	k_3	0	0	0	*
	k_1	0	0	0	0
Hydro	k_2	*	0	*	*
	k_3	0	0	0	0
	k_1	0	0	0	0
Wind	k_2	*	0	0	0
	k_3	0	*	*	*
	k_1	0	0	0	0
Solar	k_2	0	0	0	0
	k_3	*	*	*	*
	k_1	0	0	0	0
Biomass	k_2	0	0	0	0
	k_3	*	*	*	*
	k_1	0	0	0	0
SMRs	k_2	0	0	0	0
	k_3	*	*	*	*

"*" for expansion, "0" for no expansion

Table 6. Capacity Expansion Results of the ICM Model (p_i = 0.1 Lower Bound)

Technologies	Options	Period 1	Period 2	Period 3	Period 4
	k_1	0	0	0	0
NG	k_2	0	0	0	0
	k_3	0	0	0	0
	k_1	0	0	0	0
Oil	k_2	0	0	0	0
	k_3	0	0	0	0
	k_1	*	0	0	0
Coal + CCS	k_2	0	0	*	0
	k_3	0	0	0	*
	k_1	0	0	0	0
Hydro	k_2	*	0	*	*
	k_3	0	0	0	0
	k_1	0	0	0	0
Wind	k_2	*	0	0	0
	k_3	0	*	*	*
	k_1	0	0	0	0
Solar	k_2	0	0	0	0
	k_3	*	*	*	*
	k_1	0	*	0	0
Biomass	k_2	*	0	*	0
	k_3	0	0	0	0
	k_1	0	0	0	0
SMRs	k_2	0	0	0	0
	k_3	*	*	*	*

"*" for expansion, "0" for no expansion

only the expansion capacity of the biomass technology will differ, while the expansion decisions for all other technologies will remain the same as those under the upper bound.

Table 3 shows the capacity expansion plan results obtained from the ICM model under the upper bound with $p_i = 0.05$. Compared with the case of $p_i = 0.01$, no changes will be observed in the selected expansion levels for natural gas-, oil-, biomass-, and SMR-based generation technologies. In contrast, the selected expansion levels for hydropower, wind power, and solar power will tend to shift from lower to higher capacity-expansion levels, whereas the selected expansion levels for coal + CCS generation will tend to shift from higher to lower capacity-expansion levels.

As shown in Table 4, the capacity expansion plan results obtained from the ICM model under the lower bound with p_i = 0.05 are presented. Compared with the upper-bound case, only the expansion capacity of the biomass technology will differ, while the expansion decisions for all other technologies will remain the same as those under the upper bound.

Table 5 shows the capacity expansion plan results obtained from the ICM model under the upper bound with $p_i = 0.1$. Compared with the case of $p_i = 0.05$, no changes will be observed in the selected expansion levels for natural gas-, oil-, biomass-, and SMR-based generation technologies. The selected expansion level for solar power will tend to shift from a lower to a higher capacity-expansion level. In contrast, the selected expansion levels for hydropower and wind power will remain unchanged, whereas the selected expansion levels for coal + CCS generation will tend to shift from higher to lower capacity-expansion levels.

As shown in Table 6, the capacity expansion plan results obtained from the ICM model under the lower bound with p_i = 0.1 are presented. Compared with the upper-bound case, only the expansion capacity of the biomass technology will differ, while the expansion decisions for all other technologies will remain the same as those under the upper bound.

As shown in Figure 2, the installed-capacity shares of different generation technologies, together with the total installed capacity, are reported for the ICM solutions under different p_i levels. For $p_i = 0.01$ under the upper bound, the installed-capacity shares in 2030 for Gas, Oil, Coal + CCS, Hydro, Wind, Solar, Biomass, and SMRs will be 67.17, 0.04, 0.00, 5.02, 23.13, 2.89, 1.76, and 0.00%, respectively. In period 1, the corresponding shares will be 52.87, 0.03, 2.63, 4.61, 26.11, 2.27, 1.60, and 9.88%, respectively. In period 2, the installed-capacity percentages will be 41.24, 0.03, 3.34, 3.59, 26.54, 2.02, 1.42, and 21.83%, respectively. In period 3, the shares will be 31.91, 0.02, 4.57, 3.58, 26.57, 2.31, 1.23, and 29.81%, respectively. In period 4, Gas, Oil, Coal + CCS, Hydro, Wind, Solar, Biomass, and SMRs will account for 25.40, 0.02, 5.22, 3.48, 25.95, 2.47, 1.09, and 36.38% of total installed capacity, respectively.

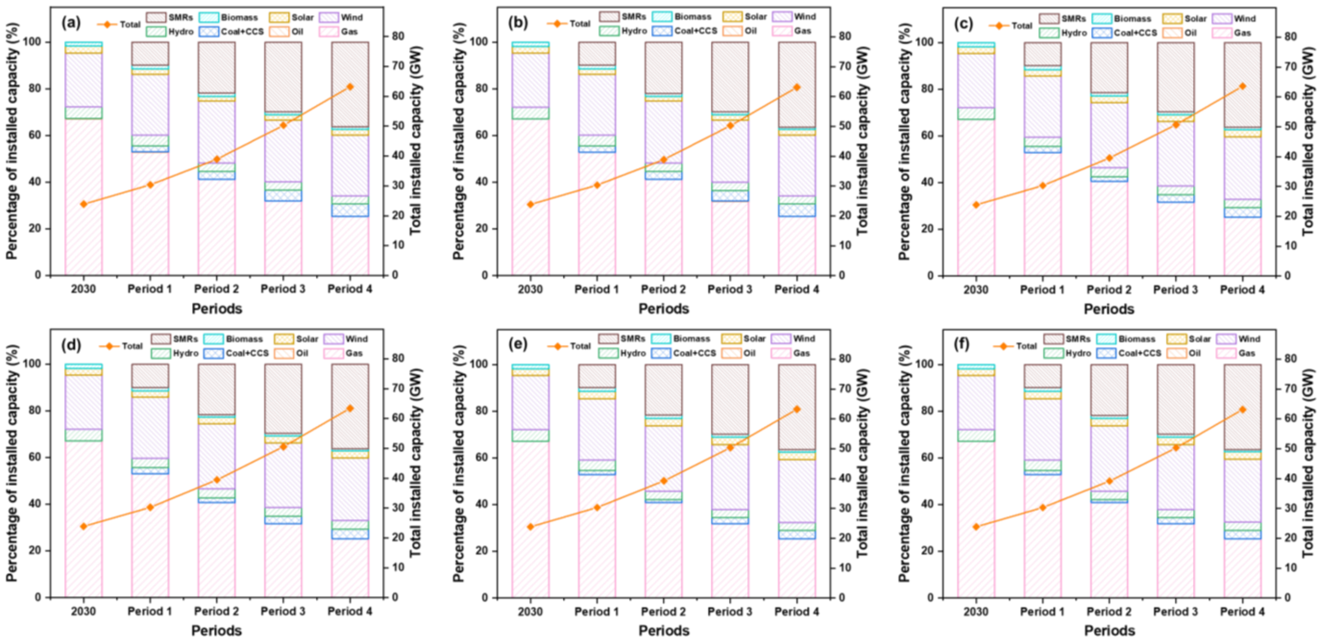

Figure 2. Percentage of installed capacity of different technologies and total installed capacity for $p_i = 0.01$ level under the (a) upper and (b) lower bound, for $p_i = 0.05$ level under the (c) upper and (d) lower bound, and for $p_i = 0.1$ level under the (e) upper and (f) lower bound.

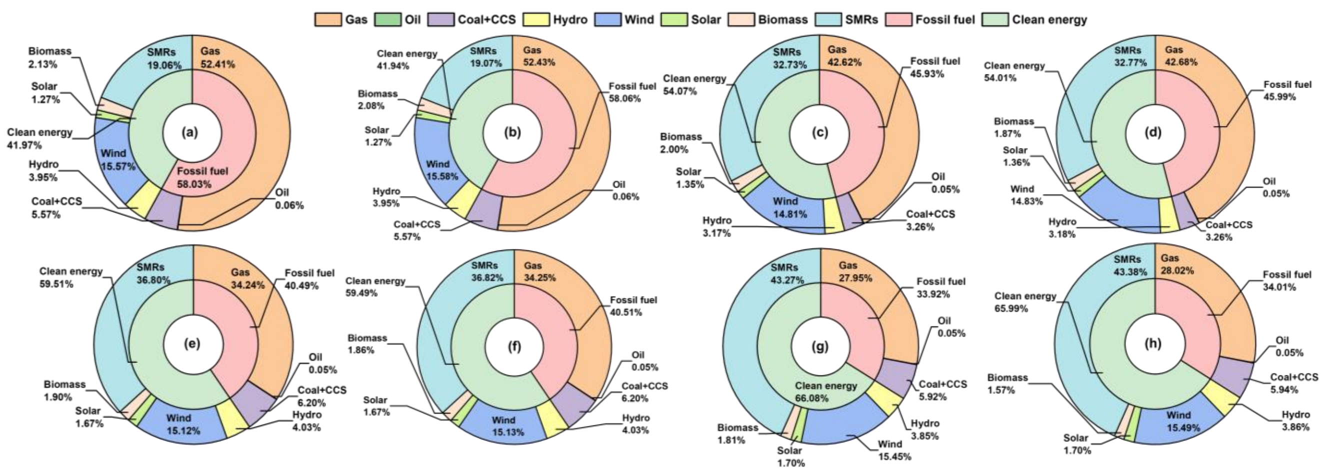

Figure 3. Percentage of electricity generation of different technologies for $p_i = 0.01$ level under the (a) upper and (b) lower bound during period 1, for $p_i = 0.01$ level under the (c) upper and (d) lower bound during period 2, for $p_i = 0.01$ level under the (e) upper and (f) lower bound during period 3, and for $p_i = 0.01$ level under the (g) upper and (h) lower bound during period 4.

For $p_i = 0.01$ under the lower bound, the installed-capacity composition across periods will remain similar. When p_i increases to 0.05 and 0.1, only minor variations will be observed in the installed-capacity shares under both upper and lower bounds. Overall, the total installed capacity will increase from 23.91 GW in 2030 to approximately 63 GW in period 4 across all p_i levels and bound settings.

Figure 3 shows the electricity generation shares of different technologies for $p_i = 0.01$. Under the upper bound, in period 1, Gas, Oil, Coal + CCS, Hydro, Wind, Solar, Biomass, and SMRs will contribute 52.41, 0.06, 5.57, 3.95, 15.57, 1.27, 2.13, and 19.06% of total electricity production, respectively, while clean-energy and fossil-fuel generation will account for 41.97 and 58.03%, respectively. In period 2, the corresponding generation shares will be 42.62, 0.05, 3.26, 3.17, 14.81, 1.35, 2.00, and 32.73%, respectively, whereas clean-energy and fossil-fuel generation will account for 54.07 and 45.93%, respectively. In period 3, Gas, Oil, Coal + CCS, Hydro, Wind, Solar, Biomass, and SMRs will account for 34.24, 0.05, 6.20, 4.03, 15.12, 1.67, 1.90, and 36.80% of electricity production, respectively, and clean-energy and fossil-fuel generation will represent 59.51 and 40.49%, respectively. In period 4, the generation shares from

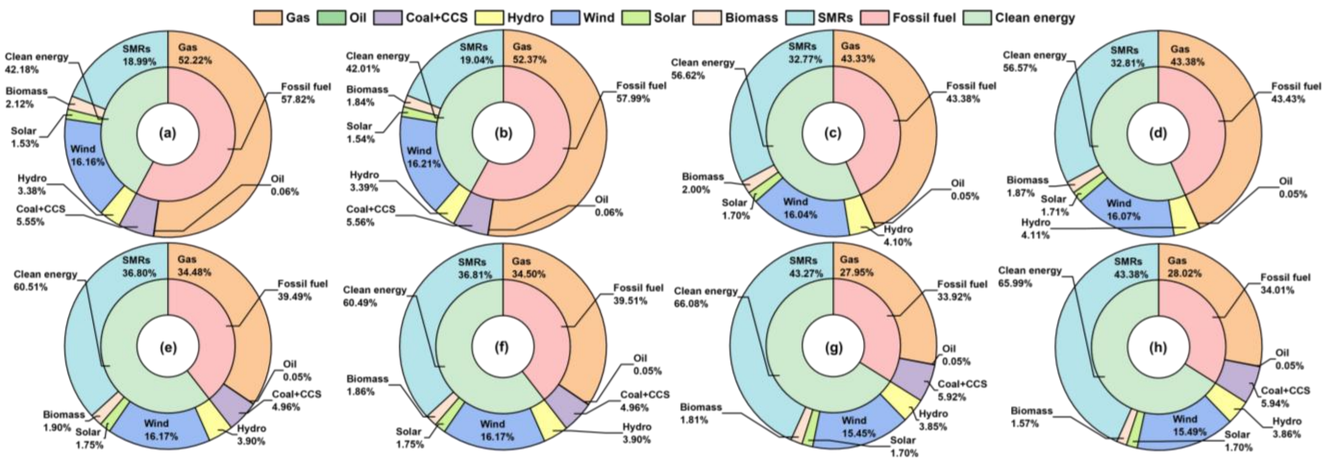

Figure 4. Percentage of electricity generation of different technologies for $p_i = 0.05$ level under the (a) upper and (b) lower bound during period 1, for $p_i = 0.05$ level under the (c) upper and (d) lower bound during period 2, for $p_i = 0.05$ level under the (e) upper and (f) lower bound during period 3, and for $p_i = 0.05$ level under the (g) upper and (h) lower bound during period 4.

Gas, Oil, Coal + CCS, Hydro, Wind, Solar, Biomass, and SMRs will be 27.95, 0.05, 5.92, 3.85, 15.45, 1.70, 1.81, and 43.27%, respectively, while clean-energy and fossil-fuel generation will account for 66.08 and 33.92%, respectively.

It can be seen that the electricity generation share from clean-energy technologies increases, while the share from fossil-fuel power plants decreases. The total electricity generations of all technologies are roughly 128.92×10^6 megawatt-hour (MWh), 132.55×10^6 MWh, 136.17×10^6 MWh, and 139.76×10^6 MWh, respectively.

As shown in Figure 4, compared with the case of $p_i = 0.01$, only slight changes will be observed in the electricity generation shares of each technology across the four periods when $p_i = 0.05$. As shown in Figure 5, compared with the case of $p_i = 0.05$, only slight changes will be observed in the electricity generation shares of each technology across the four periods when $p_i = 0.1$. Figure 6 shows the technology-wise carbon-emission shares for different p_i levels. For $p_i = 0.01$ under the upper bound, the carbon-emission shares of Gas, Oil, Coal + CCS, and Biomass will be 97.25, 0.06, 2.06, and 0.63% in period 1, respectively. The corresponding shares will be 97.71, 0.07, 1.49, and 0.73% in period 2; 95.62, 0.08, 3.45, and 0.84% in period 3; and 94.91, 0.10, 4.01, and 0.98% in period 4. For $p_i = 0.01$ under the lower bound, the carbon-emission shares of these technologies will remain very similar to those under the upper bound. When p_i increases to 0.05 or 0.10, only small changes will be observed across the four periods. Overall, total carbon emissions will decrease from 12.1×10^7 t in period 1 to approximately 8.0×10^7 t in period 4, representing an overall reduction of about 34%.

4. Conclusions

This study proposed an interval chance-constrained mixed-integer programming (ICM) model to support low-carbon power-system planning under uncertainty. By integrating mixed-integer linear programming (MILP), chance-constrained programming (CCP), and interval linear programming (ILP), the proposed framework simultaneously addresses discrete capacity-expansion decisions, operational generation planning, and uncertain input information represented by risk levels and interval bounds. In particular, the objective function incorporates both economic performance and environmental outcomes (i.e., system profit/cost and clean-energy development), enabling an explicit evaluation of cost-emission trade-offs under different constraint-violation tolerances.

The modeling results provide several important insights. First, a clear structural transition in the installed-capacity mix is indicated over the planning horizon: the share of SMRs increases markedly, rising from approximately 0% to above 36% by the final period under representative settings. This pattern suggests that firm, low-carbon capacity becomes increasingly important when stringent emission constraints and growing demand are jointly imposed. Second, the generation portfolio shifts toward cleaner resources over time. By the last period, clean-energy generation reaches roughly 66% of total electricity production, reflecting the combined effects of emission limits, capacity-expansion choices, and the evolving mix of available technologies. Third, total CO_2 emissions decrease substantially across the study periods — dropping from about 12.1×10^7 tonnes to approximately 8.0×10^7 tonnes — corresponding to an overall reduction of around 34%. Moreover, changes across different p_i levels and bound settings are generally modest in many technology shares, implying that the obtained transition pathways exhibit a degree of robustness to the examined uncertainty and risk configurations.

The findings have several policy implications for provincial-scale decarbonization. (1) Firm low-carbon capacity planning should be prioritized to maintain reliability while meeting emission targets; this includes clear long-term signals for SMRs (or other firm clean options) and timely regulatory pathways for deployment. (2) Renewable expansion should be paired with enabling infrastructure, including transmission upgrades, grid flexibility measures, and complementary resources (e.g., storage,

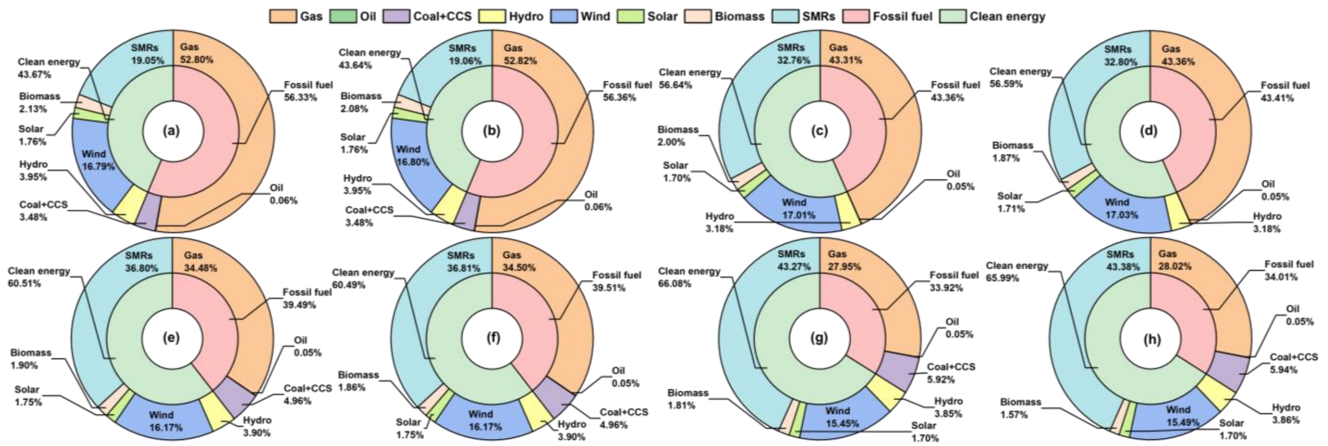

Figure 5. Percentage of electricity generation of different technologies for $p_i = 0.1$ level under the (a) upper and (b) lower bound during period 1, for $p_i = 0.1$ level under the (c) upper and (d) lower bound during period 2, for $p_i = 0.1$ level under the (e) upper and (f) lower bound during period 3, and for $p_i = 0.1$ level under the (g) upper and (h) lower bound during period 4.

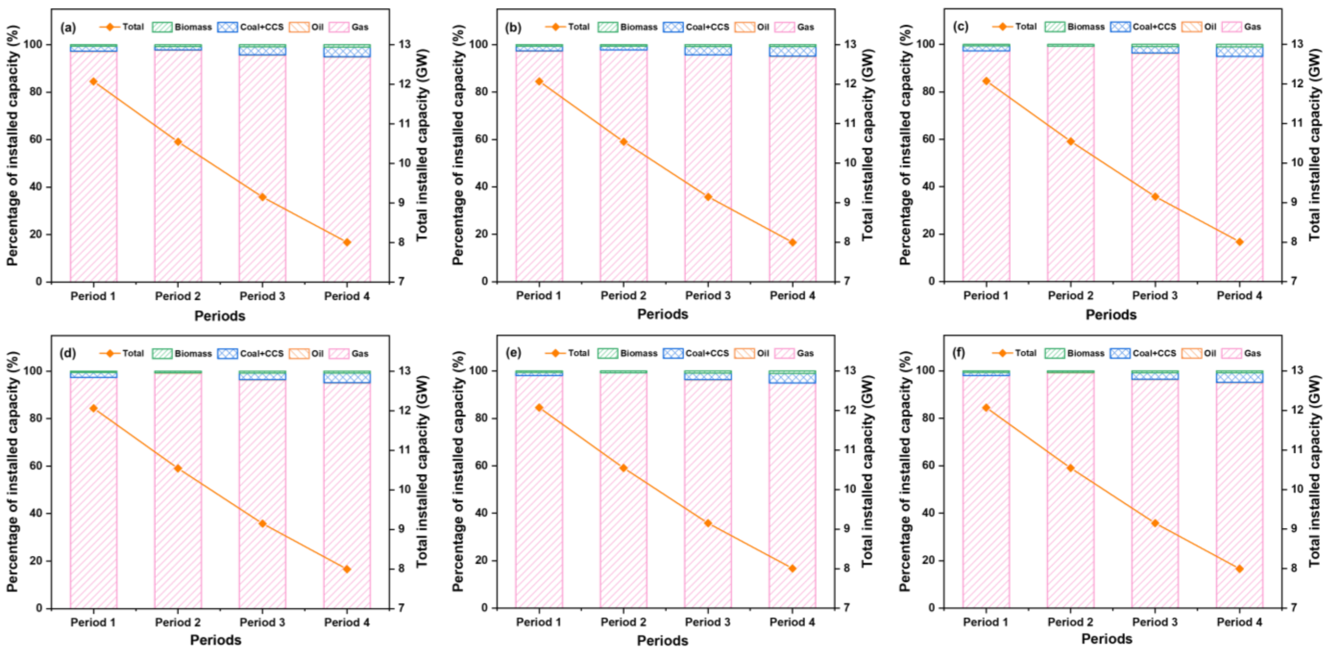

Figure 6. Percentage of CO_2 emission of different technologies and total CO_2 emission for $p_i = 0.01$ level under the (a) upper and (b) lower bound, for $p_i = 0.05$ level under the (c) upper and (d) lower bound, and for $p_i = 0.1$ level under the (e) upper and (f) lower bound.

demand response, and flexible generation) to support higher penetrations of wind and solar. (3) Targeted support for abatement technologies (e.g., CCS where appropriate, and biomass utilization with sustainable feedstock governance) can help manage near-term emission reductions while longer-term clean capacity scales up. (4) Risk-informed planning is recommended: decision-makers can use solutions under different p_i levels to select portfolios that best match acceptable environmental risk and feasibility trade-offs.

Several limitations should be acknowledged. The current model is based on a simplified, aggregated representation of the power system and does not explicitly capture transmission constraints, unit commitment details, chronological (hourly/seasonal) renewable variability, or detailed reliability metrics. Uncertainty is represented through interval bounds and chance constraints, but the quality of results still depends on the credibility of input ranges and probabilistic assumptions used for CCP. In addition, the technology set and cost/emission parameters are assumed exogenous; learning-by-doing, endogenous cost declines, and market/price-feedback effects are not fully modeled.

Future work can extend the ICM framework in multiple directions. Multi-stage or rolling-horizon formulations can be incorporated to better represent sequential decision-making and adaptive investment under evolving uncertainties. More detailed operational constraints (e.g., reserve requirements, ramping, storage dynamics, and hourly dispatch) and transmission expansion options can be integrated to improve realism and implementability. Uncertainty treatment can be strengthened by combining interval/chance constraints with robust or distributionally robust optimization, and by introducing endogenous technology learning and policy-driven market mechanisms. Finally, broader sustainability considerations — such as lifecycle emissions, environmental justice, and regional economic impacts — can be embedded to support more comprehensive decision-making.

Appendix A. Nomenclature

A.1. Indices:

i: Primary energy/non-renewable energy resources (i = 1, 2, 3, and 4); i = 1 (Natural gas); i = 2 (Oil); i = 3 (Coal); i = 4 (Uranium)

j: Power generation technology/electricity-generation facilities (j = 1, 2, 3, 4, 5, 6, 7, and 8); j = 1 (Natural gas); j = 2 (Oil); j = 3 (Coal + CCS); j = 4 (Hydropower); j = 5 (Wind power); j = 6 (Solar power); j = 7 (Biomass); j = 8 (SMR)

k: Capacity expansion options of power generation facilities j (1 = Low, 2 = Medium, 3 = High)

t: Planning periods (t = 1, 2, 3, and 4) (2031-2050, 5 years each)

±: Interval value with lower and upper bounds.

A.2. Decision variables:

$X_{i,t}$: Supply amount of non-renewable energy source i during period t (PJ)

$Y_{j,t}$: Electricity generation amount from technology facility j during period t (MWh)

$Z_{j,k,t}$: Binary variable (0-1) representing capacity for facility j with option k during period t will be expanded or not

A.3. Parameters:

(1) Revenue Parameters

SR: System revenue per unit of electricity generation ($/MWh)

(2) Economic parameters

$CE_{i,t}$: Cost of primary energy source i supplied in period t ($/KWh)

$CP_{j,t}$: Cost of power generation/electricity generation from facility j in period t ($/MWh)

$CCE_{j,k,t}$: Cost of capacity expansion for facility j with option k in period t ($/MW)

CCT_t: Carbon dioxide (CO_2) emission treatment cost during period t ($/tone)

(3) Capacity parameters

$EP_{j,k,t}$: Capacity expansion amount for facility j with option k in period t (MW)

ECP_j: Existing capacity amount of power generation facility j before planning period (MW)

(4) Demand parameters

ED_t: Total electricity demand from end users in period t (MWh)

(5) GHG emission parameters

$ECD_{j,t}$: Emission amount of CO_2 for electricity generation from facility j in period t (tone/PJ) (tone/MWh)

LEC_t: Emission standard/upper limit of CO_2 emissions in period t (tone)

(6) Other parameters

$UPR_{j,t}$: Renewable energy resource availability for power generation for facility j in period t (j = 4 ~ 6) (PJ)

— Hydro, Wind, Solar have alternating and temporally variable properties

— Renewable energy uncertainty

p_i: constraint-violation probability of hydro, wind, and solar mass balance constraints (0.01, 0.05, and 0.1)

Coefficient:

$FEG_{j,t}$: Conversion coefficient of facility j from primary energy to electricity generation in period t (PJ/MWh) (PJ primary energy/1 MWh power-electricity j)

$PCAP_{j,t}$: Capacity factor of power generation for facility j in period t (actual output/Maximum output) (%)

$AOT_{j,t}$: Annual operation time per year for facility j in period t (h/year)

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