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Innovative Applications of O.R.

Optimizing electricity mix for CO2 emissions reduction: A robust input-output linear programming model

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ABSTRACT

Input-Output Linear Programming (IO-LP) model has been recently used to identify a cost-effective strategy for reduction in economy-wide CO2 emissions through a shift in the electricity generation mix. As an extension, this study further develops a robust IO-LP model to address the data uncertainties of technology cost and final demand. Compared to the deterministic IO-LP model which seeks to minimize the levelized cost of electricity (LCOE), the robust IO-LP model aims to maximize the tolerance of data uncertainty under a dynamic uncertainty setting. The modelling results in case study of China show that coal-fired and hydro generation technologies should be greatly developed from 2020 to 2050 in the Business-As-Usual (BAU) scenario with no emissions target set. In order to mitigate accumulated economy-wide CO2 emissions by 30% compared to the BAU emissions level, various types of clean generation technologies, i.e., gas-fired, hydro, nuclear, solar, wind, and biomass, should be introduced into the electricity mix. Along with the decrease in emissions target, the tolerance of data uncertainty will drop to a certain degree. Finally, we compared results of the robust IO-LP model with results of the stochastic and deterministic IO-LP models. The comparative analysis shows that the robust IO-LP model tends to select the generation technologies with smaller uncertainty in LCOE, and is able to improve the robustness of capacity planning solutions compared to the alternative models under data uncertainty.

1. Introduction

Shifting of electricity mix from fossil-based electricity (e.g. coal and oil) to non-fossil electricity (e.g. hydro, wind, solar, and biomass) has been widely considered as a key strategy for the mitigation in carbon dioxide (CO2) emissions (Ang and Su, 2016). For example, in the recent submitted Intended Nationally Determined Contributions (INDC), China set a target to raise the non-fossil fuels in primary energy consumption to around 20% in 2030, and India set a target to increase its share of non-fossil-based power capacity to about 40% by 2030 (UNFCCC, 2015). On the other hand, the development of non-fossil generation technology is constrained by high cost for electricity generation and low capacity utilization rate. According to the Projected Costs of Generating Electricity (IEA, 2015), the fixed costs of wind and solar electricity can be two to three times higher than the fixed cost of coal-fired electricity, and the annual capacity utilization rates of wind and solar electricity are mostly less than 30% at the current stage. Under this circumstance, how to select generation technologies with the consideration of both environmental and economic objectives is a critical issue in electricity system planning.

Optimization model has been widely used to identify the least-cost strategy for reduction in greenhouse gas (GHG) emissions in the electricity system. Most of the optimization models are based on bottom-up data, and can be accordingly called bottom-up optimization models. For instance, Parpas and Webster (2014), Boffino, Conejo, Sioshansi, and Oggioni (2019); Domnguez, Conejo, and Carrin (2015) proposed stochastic bottom-up optimization models for electricity generation capacity expansion. Moret, Babonneau, Bierlaire, and Mar chal (2019); Ruiz and Conejo (2015) developed robust bottom-up optimization models for the planning of generation and transmission expansions in electricity system. Lara, Mallapragada, Papageorgiou, Venkatesh, and Grossmann (2018); Munoz, Hobbs, and Watson (2016) developed bottom-up Mixed-Integer Linear Programming (MILP) models to identify optimal strategies in the planning of electric power infrastructures. Wang et al. (2019) and Wang et al. (2020) developed the bottom-up optimization models for multi-regional electricity generation and trading strategies in China based on power-plant constraints and

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Nomenclature

Index

i	Index of commodity
j	Index of sector/technology
t	Index of time period
k	Index of sampling in SAA approach

Sets

J_e	Set of generation technologies
J_i	Set of technologies for producing commodity i
Ω	Set of possible technology cost scenarios
D	Set of possible final demand scenarios
Π	Set of possible technology cost and final demand
Y	Set of feasible output and capacity

Parameters

n	Number of commodities
m	Number of sectors and technologies
E	Number of generation technologies
T	Number of time periods
K	Sample size in SAA approach
c_j	Capacity of technology j in the base year
$\bar{h}^t_j$	Upper bound of capacity of technology j in year t
α^t_j	Variable cost of technology j in year t
β^t_j	Fixed cost of technology j in year t
$\bar{\alpha}^t_j$	Upper bound of variable cost of technology j in year t
$\underline{\alpha}^t_j$	Lower bound of variable cost of technology j in year t
$\bar{\beta}^t_j$	Upper bound of fixed cost of technology j in year t
$\underline{\beta}^t_j$	Lower bound of fixed cost of technology j in year t
a_{ij}	Input of commodity i to produce one unit output of sector/technology j
b_{ij}	Capital consumption of commodity i to increase one unit capacity of technology j
$\overline{CO2}$	Target set on accumulated CO2 emissions
d^t_i	Final demand of commodity i in year t
$\bar{d}^t_j$	Upper bound of final demand of commodity i in year t
$\underline{d}^t_j$	Lower bound of final demand of commodity i in year t
f^t_j	CO2 emission intensity of sector/technology j in year t
τ_j	Construction period of technology j
q_j	Life time of technology j
c_j	Base year capacity of technology j
η_j	Annual depreciation rate of old capacity of technology j
ρ	maximum annual operation hours of power plant
p_j	Price of electricity generated by technology j
ϵ_j	Capacity utilization rate of technology j
N	Sum of uncertain cost parameters of generation technologies
$\bar{N}$	Upper bound on the sum of uncertain cost parameters of generation technologies
$\underline{N}$	Lower bound on the sum of uncertain cost parameters of generation technologies
Γ	Predefined budget of LCOE

Variables

x^t_j	Output of sector/technology j in year t
Δz^t_j	New capacity installation of technology j in year t
z^t_j	New capacity of technology j in year t
h^t_j	Total capacity of technology j in year t
θ	Tolerance of cost uncertainty
δ	Tolerance of demand uncertainty
$\boldsymbol{\omega}$	Vector of uncertain technology cost
$\boldsymbol{d}$	Vector of uncertain final demand
$\boldsymbol{y}$	Vector of output and capacity
$\boldsymbol{\pi}$	Vector of all uncertain parameters
$LCOE$	Cumulative Levelized cost of electricity generation

renewable portfolio standard targets. The advantages of bottom-up models are that they usually include a great deal of details about electricity system, and are able to identify the very specific technological options and the associated investments and fuel costs. However, a shortcoming of bottom-up models is that they single out electricity system from the entire economic system and fail to take the indirect emissions of electricity (e.g. emissions associated with manufacturing, construction, and maintenance of power plant) into consideration.

To overcome the shortcoming of bottom-up models, Kang, Ng, Su, and Yuan (2020) recently combined a top-down input-output (IO) model and a linear programming (LP) model to identify a cost-effective strategy for reduction in economy-wide CO2 emissions through a shift in electricity generation mix. The combined model can be called input-output linear programming (IO-LP) model. Compared to bottom-up optimization model, IO-LP model is able to account for both the operation-related and capital-related CO2 emissions[1] associated with electricity generation technologies. The study found out that the change in capital-related CO2 emissions associated with electricity generation could account for 7% of the absolute change in operation-related CO2 emissions associated with electricity generation in China. While the capital-related CO2 emissions are relatively small compared to the operation-related CO2 emissions, they could impact the optimal technological path, especially in very low-carbon scenario Pehl et al. (2017). Consequently, the indirect CO2 emissions of electricity technologies should be taken into consideration in electricity system optimization. Besides, IO-LP model is able to easily link the optimization of electricity system to the economy-wide emissions targets (e.g. INDC targets). Those insights generally cannot been directly obtained through applying a bottom-up optimization model to the electricity sector.

As an extension to the work, this study further develops a robust IO-LP model to address the data uncertainties of technology cost and final demand. Compared to the deterministic IO-LP model which seeks the least-cost strategy for emissions mitigation, the robust IO-LP model seeks the strategy that is less susceptible to violation of predefined budget under a dynamic data uncertainty setting. To better illustrate the model, the robust IO-LP model is applied to identify cost-effective choices of generation technologies for the reduction in economy-wide CO2 emissions in China from 2020 to 2050. The contributions of this study are summarized as follows. First, this study develops a tolerance optimization approach to handle data uncertainties of technology cost and final demand simultaneously under an IO-LP framework. Second, the robust IO-LP model is proven to be applicable to a dynamic optimization problem in which the exact values of uncertain parameters (i.e. upper and lower bounds) in each period are only known in that period and not in advance. Third, the dynamic optimiza-

[1] Kang et al. (2020) refer “operation-related CO2 emissions” as the CO2 emissions associated with fuel combustion during the operational phase of electricity generation, and they refer “capital-related CO2 emissions” as the CO2 emissions associated with capacity installation of power plants.

tion problem is transformed into an equivalent static optimization problem, which is further solved using a binary search algorithm. Unlike dynamic programming which in general suffers from the curse of dimensionality, the proposed solving approach only solves a small set of linear optimization models so that the computational effort only increased very modestly. Fourth, a comparison between results of the robust IO-LP model and results of the stochastic and deterministic IO-LP models is conducted.

The remainder of paper is organized as follows. Section 2 gives a literature review of IO-LP model. Section 3 introduces the deterministic IO-LP model, the robust IO-LP model, and the stochastic IO-LP model. Section 4 presents the data and the modelling results in case study of China. Finally, Section 5 concludes the study and discusses the pros and cons of robust IO-LP model and some possible extensions.

2. Literature review

Recently, an increasing number of researches used IO-LP model to explore the optimal technological choices in one specific industry for GHG emissions mitigation. Different from bottom-up optimization model, IO-LP model incorporates detailed alternative technologies into a top-down IO model and expands the boundaries of the analysis to the entire economic system. As such, the model is able to identify the optimal choices of technologies with the consideration of both direct and indirect emissions of technologies. Until today, IO-LP model has been applied to identify the optimal strategies for energy and emissions reduction in various processes and industries, e.g., the housing industry (Henriques, Coelho & Antunes, 2015; Honda, Moriizumi & Sakao, 2006), the advertisement activities (Mc Kenzie & Durango-Cohen, 2010), the cellulosic biofuel production (Dilekli & Duchin, 2015), the bioenergy industry (Carvalho, Antunes & Freire, 2016; Song, Yang, Higano & Wang, 2015a), the electricity system (Kang, Ng, Su & Yuan, 2020), and the entire energy system (He, Ng & Su, 2015, 2017, 2019; Pan, Liu, Li & Wang, 2018; Song, Yang, Higano & Wang, 2015b).

The above mentioned IO-LP models are deterministic optimization models, in which all the parameters are assumed to be exactly known. In reality, there may not be enough information to allow for the accurate estimation of model parameters. Thus, it is needed to consider the extension of IO-LP model to further address the data uncertainty issue. There has been some efforts on data uncertainty handling in IO-LP model. Chang and Juang (1998) developed an IO-LP model with fuzzy parameters of the objective functions for economy-energy-environment planning in Taiwan. Borges and Antunes (2003) proposed a fuzzy multi-objective IO-LP model with fuzzy coefficients in the objective functions and fuzzy right-hand-side of the constraints for economy-energy-environment planning in Portugal. Aviso, Tan, Culaba, and Cruz (2011) proposed a multi-regional fuzzy IO-LP model to optimize supply chains in the presence of multiple stakeholders and under water footprint constraints. The method utilizes a scale-invariant technological coefficients matrix and a max-min aggregation to construct an LP model. Based on a similar approach, Tan, Aviso, Barilea, Culaba, and Cruz (2012); Tan, Ballacillo, Aviso, and Culaba (2009) developed fuzzy IO-LP models to optimize biomass production and trade under resource availability and environmental footprint constraints. Uncertainty was considered on the upper or lower bounds of the constraints. In addition to that, other models allow for the incorporation of uncertainty in the coefficients of IO matrix. For example, Oliveira and Antunes (2011, 2012) updated the early versions of the models proposed by Antunes, Oliveira, and Clmaco (2002); Oliveira and Antunes (2002, 2004), including considering all IO-LP model parameters as intervals, then providing information regarding the robustness of non-dominated solutions under a more optimistic or pessimistic decision maker's stance. More recently, Wen, Xu, Wen, and Lin (2014) proposed an approach to overcome the inexactness and limitations regarding the entries of IO coefficient matrix through the use of polyhedral uncertainty or ellipsoidal uncertainty or cardinality constrained uncertainty in the framework of robust optimization.

While the data uncertainty issue has been widely considered in IO-LP model, few study applies a tolerance optimization approach to address the data uncertainties of technology cost and final demand simultaneously. As a matter of fact, both sets of parameters could be with great data uncertainty. The data uncertainty of technology cost originates from the fact that each technology represents a group of specific technologies which could be possibly used in different locations with different specific designs. For example, the investment cost of commercial PV could range from 1029 USD/kW to 1967 USD/kW, whereas the investment cost of residential PV could range from 1867 USD/kW to 3366 USD/kW (IEA, 2015). In addition to technology cost, final demand could also be with data uncertainty as a result of inaccuracy in demand projection. Under this circumstance, decision-makers may not be confident to specify how large an uncertainty assumption should be made. One possible appoach to address the issue is to optimize the tolerance of data uncertainty (i.e. the largest amount of uncertainty a system can endure) in the system. The tolerance optimization is a commonly used approach in the mechanic engineering system (Cho, 2014; Lee et al., 2017; Lei et al., 2015; Ma et al., 2018; Xiao, Li, Rotaru & Sykulski, 2015), where designers may prefer designs that can tolerate noise as much as possible. However, the application to an IO-LP model for electricity system planning is rare. Besides, another gap in the existing studies is that most uncertainty handling approaches are merely suitable to a single-stage optimization problem, but have never been proven to be applicable to a dynamic optimization problem in which the exact values of uncertain parameters (e.g. upper and lower bounds) in each period are only known in that period and not before that. In fact, the dynamic optimization problem can be more consistent to the real situation compared to the single-stage optimization problem.

3. Methodology

This section first introduces the deterministic IO-LP model for electricity system planning. Subsequently, a robust IO-LP model and a stochastic IO-LP model are developed respectively to address the data uncertainties of technology cost and final demand. The notations used in the entire study are summarized in Nomenclatures.

3.1. Deterministic IO-LP model

Kang, Ng, Su, and Yuan (2020) recently developed a deterministic IO-LP model to identify a cost-effective strategy for the reduction in economy-wide CO2 emissions through a shift in electricity mix. The modelling assumptions are as follows. 1) The final demand of various commodities in the future can be precisely projected; 2) The total electricity demand in the economy can be jointly meet by various types of domestic generation technologies, e.g., coal-fired, wind, and solar; 3) The electricity import from other countries is not considered[2]; 4) The technical coefficients in IO matrix keep unchanged over the modelling period. Based on the assumptions, the IO-LP model can be formulated as follows,

$$\min_{\boldsymbol{x},\boldsymbol{h}} \quad LCOE = \sum_{t}^{T}(1+\sigma)^{-t}\sum_{j\in J_e}(\alpha_j^t x_j^t + \beta_j^t h_j^t) \tag{1.1}$$

[2] This assumption holds for many countries with sufficient self-electricity supply. Taking China as an example, the shares of import and export of electricity from other countries are extremely low compared with its domestic supply CEPY 2018.

$$\text{s.t.} \quad \sum_j a_{ij} x_j^t + \sum_{j \in J_e} b_{ij} \Delta z_j^{t+\tau_j} + d_i^t \le \sum_{j \in J_i} x_j^t \qquad \forall i, t \tag{1.2}$$

$$\sum_t \sum_j f_j^t x_j^t \le \overline{CO2} \tag{1.3}$$

$$h_j^t = c_j(1 - \eta_j t) + z_j^t \qquad \forall j \in J_e, t \tag{1.4}$$

$$z_j^{t+\tau_j} = z_j^t + \Delta z_j^{t+\tau_j} - \Delta z_j^{t+\tau_j - q_j} \qquad \forall j \in J_e, t \tag{1.5}$$

$$h_j^t \le \bar{h}_j^t \qquad \forall j \in J_e, t \tag{1.6}$$

$$x_j^t \le \rho \epsilon_j p_j h_j^t \qquad \forall j \in J_e, t \tag{1.7}$$

$$\boldsymbol{x}, \boldsymbol{\Delta z}, \boldsymbol{z}, \boldsymbol{h} \ge 0 \tag{1.8}$$

Objective (1.1) is to minimize the accumulated LCOE over the entire modelling period, including the variable cost associated with generation output and the fixed cost associated with generation capacity. A discount rate σ is used to levelize annual generation cost during the modelling period. Constraint (1.2) is the Leontief production constraint, which states that the sum of intermediate demand and final demand should not exceed the total output. This constraint is based on an augmented IO matrix, which has been explicitely explained in Kang, Ng, Su, and Yuan (2020). Constraint (1.3) states that the accumulated economy-wide CO2 emissions during the entire modelling period should not exceed a certain emissions target. The CO2 emissions of various sectors/technologies are calculated based on production output and emissions intensity. Constraint (1.4) states that total generation capacity of electricity technology can be differentiated into old capacity installed before base year and new capacity installed after base year. Because the remaining life time of old capacity is unknown, the old capacity is assumed to decrease linearly during the modelling period at a fixed annual depreciation rate (η_j). On the other hand, the new capacity will not depreciate until the end of its life time, but will entirely retired when its lifetime has passed. Constraint (1.5) states that the accumulated new capacity equals to the existing new capacity plus the installed new capacity[3], and minus the decommissioned new capacity. Note that the construction periods (τ_j) and life time (q_j) of various generation capacity types are taken into consideration in this constraint. Constraint (1.6) sets an upper limit on generation capacity of each type of technology due to limited exploitable resources, areas, and investments for new capacity installation. Constraint (1.7) states that the total output of generation technology should not exceed the maximum output of capacity during each time period. The maximum output of capacity can be calculated based on the total capacity (h_j^t), the maximum annual operation hours ($\rho = 8760$), the capacity utilization rate (ϵ_j), and the electricity price (p_j). Finally, constraint (1.8) is the non-negativity constraint for decision variables in the model.

[3] Instead of using discrete variables, continuous variables are used here to represent capacity additions of generation technologies due to the following reasons. 1. Compared to bottom-up model, IO-LP model only considers a smaller number of electricity technologies at high aggregation level due to data unavailability. Those technologies generally include a variety of specific technologies with different capacity levels. Hence, it is difficult to specify a discrete capacity unit for each technology in the IO-LP model. 2. Due to the high volume of annual capacity installation in China, the capacity addition of different electricity technologies in IO-LP model could be very close to continuous variable. 3. Finally, adding binary capacity variables for future planning periods will require the restriction that the capacity addition decisions are regarded static rather than dynamic decisions. In spite of the limitations, our model still presents a feasible solution, and there should be no computational issues.

3.2. Robust IO-LP model

In order to address the data uncertainties of technology cost (i.e., α_j^t, β_j^t) and final demand (i.e., d_i^t), a robust IO-LP model is developed in this subsection. We choose to use robust optimization model instead of stochastic optimization model mainly due to the following three considerations: 1) Stochastic optimization model requires more uncertainty information, e.g. distribution information, compared to robust optimization model. In practice, those information could be difficult to collect. 2) Compared to stochastic optimization model, robust optimization model is able to generate a more reliable capacity planning solution under certain predefined target. 3) The proposed robust IO-LP model is applicable to a dynamic optimization problem in which the exact values of uncertain parameters in each period are only observed during that period but not in advance. Similar dynamic property is difficult to be proven for a stochastic IO-LP model. In the followings, the data uncertainties of the two groups of model parameters are handled step by step.

3.2.1. Handling uncertainty of technology cost

Assume that only the technology costs are uncertain parameters, yet all the other parameters in model (1) are exactly known. Plus, suppose we are only informed of the interval information of uncertain parameters, but do not have any additional distribution information. Define $\boldsymbol{\omega} = \{(1+\sigma)^{-t}\alpha_j^t, (1+\sigma)^{-t}\beta_j^t\}'$ as the vector of uncertain cost parameters, the set of $\boldsymbol{\omega}$ can be defined as Ω as follow,

$$\Omega = \left\{ \omega \left| \begin{array}{l} \underline{\alpha}_j^t \le (1+\sigma)^{-t}\alpha_j^t \le \bar{\alpha}_j^t, \\ \underline{\beta}_j^t \le (1+\sigma)^{-t}\beta_j^t \le \bar{\beta}_j^t, \\ N \le \underline{N} + \theta(\bar{N} - \underline{N}), \\ 0 \le \theta \le 1, \\ \forall j \in J_e, t = 1, \ldots, T \end{array} \right. \right\} \tag{2}$$

where $\bar{\alpha}_j^t$ and $\underline{\alpha}_j^t$ are the upper and lower bounds of variable cost of technology j in year t; $\bar{\beta}_j^t$ and $\underline{\beta}_j^t$ are the upper and lower bounds of fixed cost of technology j in year t; $N = \sum_t \sum_{j \in J_e} (1+\sigma)^{-t}(\alpha_j^t + \beta_j^t)$ is the summation of all uncertain cost parameters; $\bar{N} = \sum_t \sum_{j \in J_e} (\bar{\alpha}_j^t + \bar{\beta}_j^t)$ and $\underline{N} = \sum_t \sum_{j \in J_e} (\underline{\alpha}_j^t + \underline{\beta}_j^t)$ are the upper and lower bounds of N respectively; Ω represents a set of an infinite number of cost scenarios corresponding to certain parameter θ. Here, the parameter θ can be interpreted as the tolerance of cost uncertainty, ranging between 0 and 1. Apparently, the higher the tolerance value is, the larger number of cost scenarios can be deemed as robust scenarios in the optimization model. Assume that the exact values (i.e. lower and upper bounds) of the technology costs in each period are are only known in that period and not before that. A dynamic robust optimization problem can be formulated to minimize the worst-case LCOE by deciding technology portfolio stage-by-stage as follow.

$$\min_{y_1 \in Y} \left\{ \max_{\omega_1 \in \Omega} \omega_1' y_1 + \min_{y_2 \in Y(y_1)} \left\{ \max_{\omega_2 \in \Omega(\omega_1)} \omega_2' y_2 + \ldots + \min_{y_T \in Y(y_1, \ldots, y_{T-1})} \max_{\omega_T \in \Omega(\omega_1, \ldots, \omega_{T-1})} \omega_T' y_T \right\} \right\} \tag{3}$$

where $Y = \{\boldsymbol{y} = \{\boldsymbol{x}, \boldsymbol{h}\}' | (1.2) - (1.8)\}$ is the feasible set of technology portfolio, i.e., output and capacity; $\boldsymbol{y_t} = \{\boldsymbol{x^t}, \boldsymbol{h^t}\}'$ is the technology portfolio in period t; $Y(\boldsymbol{y}_1, \ldots, \boldsymbol{y}_{t-1}) = \{\boldsymbol{y}_t \in Y | \boldsymbol{y}_1 = \hat{\boldsymbol{y}}_1, \ldots, \boldsymbol{y}_{t-1} =$

$\hat{\boldsymbol{y}}_{t-1}\}$ is the feasible set of technology portfolio in period t conditioning on the technology portfolio from period 1 to period $t-1$; $\boldsymbol{\omega}_t$ is the technology cost in period t; $\Omega(\boldsymbol{\omega_1}, ..., \boldsymbol{\omega_{t-1}}) = \{\boldsymbol{\omega}_t \in \Omega | \boldsymbol{\omega}_1 = \hat{\boldsymbol{\omega}}_1, ..., \boldsymbol{\omega}_{t-1} = \hat{\boldsymbol{\omega}}_{t-1}\}$ is the feasible set of technology cost in period t conditioning on the observed values of technology cost from period 1 to period $t-1$. To solve the dynamic optimization problem, we can firstly transform it into a single-stage optimization model based on the following proposition.

Proposition 1. *Consider the following optimization problem,*

$$\min_{\boldsymbol{y}\in Y}\max_{\boldsymbol{\omega}\in\Omega} \boldsymbol{\omega}'\boldsymbol{y} \tag{4}$$

where $\boldsymbol{\omega} = \{\boldsymbol{\omega}_1, ..., \boldsymbol{\omega}_T\}'$ *and* $\boldsymbol{y} = \{\boldsymbol{y}_1, ..., \boldsymbol{y}_T\}'$. *Then, model (3) is equivalent to model (4).*

Proof. Y and Ω are both convex sets according to their definitions. Define the feasible solution in model (3) and model (4) as $\{\boldsymbol{y}, \boldsymbol{\omega}\}$ and $\{\bar{\boldsymbol{y}}, \bar{\boldsymbol{\omega}}\}$ respectively. Define the optimal objective values of model (3) and model (4) as s and $\bar{s}$. For any fixed $\bar{\boldsymbol{y}}$, $\{\bar{\boldsymbol{y}}, \boldsymbol{\omega}\}$ is a feasible but not necessarily optimal solution to (4). Hence, there is

$$\boldsymbol{\omega}'\bar{\boldsymbol{y}} \le \bar{s} \tag{4.1}$$

For any fixed $\boldsymbol{\omega}$, $\{\bar{\boldsymbol{y}}, \boldsymbol{\omega}\}$ is a feasible but not necessarily optimal solution to model (3). Therefore, there is

$$s \le \boldsymbol{\omega}'\bar{\boldsymbol{y}} \tag{4.2}$$

Combining (4.1) and (4.2), we have $s \le \bar{s}$.

Next, let's define

$$\hat{s} = \max_{\boldsymbol{\omega}\in\Omega}\min_{\boldsymbol{y}\in Y} \boldsymbol{\omega}'\boldsymbol{y} \tag{4.3}$$

with feasible solution $\{\hat{\boldsymbol{y}}, \hat{\boldsymbol{\omega}}\}$. For any fixed $\hat{\boldsymbol{\omega}}$, $\{\boldsymbol{y}, \hat{\boldsymbol{\omega}}\}$ is a feasible but not necessarily optimal solution to (4.3). Therefore, there is

$$\hat{s} \le \hat{\boldsymbol{\omega}}'\boldsymbol{y} \tag{4.4}$$

For any fixed $\boldsymbol{y}$, $\{\boldsymbol{y}, \hat{\boldsymbol{\omega}}\}$ is a feasible but not necessarily optimal solution to model (3). Therefore, there is

$$\hat{\boldsymbol{\omega}}'\boldsymbol{y} \le s \tag{4.5}$$

Combining (4.4) and (4.5), we have $\hat{s} \le s$. Hence, we have shown that

$$\hat{s} \le s \le \bar{s} \tag{4.6}$$

According to Sion's minimax theorem (Sion, 1958), there is

$$\bar{s} = \hat{s} \tag{4.7}$$

Combining (4.6) and (4.7), there is $s = \bar{s}$. Hence, proposition 1 holds.

Model (4) is a single-stage robust optimization problem, which can be further transformed into a deterministic linear programming problem according to the following proposition. □

Proposition 2. *Solving the robust optimization problem (4) is equivalent to solving the following deterministic linear programming problem (5).*

$$\min_{\boldsymbol{x},\boldsymbol{h}} \quad G(\boldsymbol{h};\theta) = \underline{N}\gamma_5 + \theta(\bar{N} - \underline{N})\gamma_5 + \sum_{j\in J_e}(\bar{\alpha}_j^t\gamma_{1j} - \underline{\alpha}_j^t\gamma_{2j} + \bar{\beta}_j^t\gamma_{3j} - \underline{\beta}_j^t\gamma_{4j}) \tag{5.1}$$

$$\text{s.t.} \quad \sum_j^m a_{ij}x_j^t + d_i^t + \sum_{j\in J_e} b_{ij}\Delta z_j^{t+\tau_j} \le \sum_{j\in J_i} x_j^t \quad \forall i,t \tag{5.2}$$

$$\sum_t^T\sum_j^m f_j^t x_j^t \le \overline{CO2} \tag{5.3}$$

$$h_j^t = c_j(1-\eta_j t) + z_j^t \qquad \forall j\in J_e, t \tag{5.4}$$

$$z_j^{t+\tau_j} = z_j^t + \Delta z_j^{t+\tau_j} - \Delta z_j^{t+\tau_j-q_j} \qquad \forall j\in J_e, t \tag{5.5}$$

$$h_j^t \le \bar{h}_j^t \qquad \forall j\in J_e, t \tag{5.6}$$

$$x_j^t \le \rho\epsilon_j p_j h_j^t \qquad \forall j\in J_e, t \tag{5.7}$$

$$\sum_t (1+\sigma)^{-t}x_j^t \le \gamma_{1j} - \gamma_{2j} + \gamma_5 \qquad \forall j\in J_e \tag{5.8}$$

$$\sum_t (1+\sigma)^{-t}h_j^t \le \gamma_{3j} - \gamma_{4j} + \gamma_5 \qquad \forall j\in J_e \tag{5.9}$$

$$\boldsymbol{\Delta z}, \boldsymbol{z}, \boldsymbol{h}, \boldsymbol{x}, \boldsymbol{\gamma_1}, \boldsymbol{\gamma_2}, \boldsymbol{\gamma_3}, \boldsymbol{\gamma_4}, \gamma_5 \ge 0 \tag{5.10}$$

Proof. See Appendix A where γ_1, γ_2, γ_3, γ_4, γ_5 are dual variables related to the primal problem (4). Model (5) is a linear programming problem, which can be efficiently solved with commercial software. By solving model (5), we are able to find the optimal strategy for the minimization of worst-case LCOE by determining technology portfolio stage-by-stage based on updated uncertainty information of technology cost. □

3.2.2. Handling uncertainty of final demand

Now, assume that final demand (d_i^t) is also uncertain parameter with known interval information in addition to technology cost. The set of final demand can be defined as follow,

$$D = \left\{\boldsymbol{d} \mid \underline{\boldsymbol{d}} \le \boldsymbol{d} \le \underline{\boldsymbol{d}} + \delta(\bar{\boldsymbol{d}} - \underline{\boldsymbol{d}}) \le \bar{\boldsymbol{d}}\right\} \tag{6}$$

where $\boldsymbol{d}$ is the vector of uncertain final demand; $\underline{\boldsymbol{d}}$ and $\bar{\boldsymbol{d}}$ are respectively the lower and upper bounds of final demand; $\underline{\boldsymbol{d}} + \delta(\bar{\boldsymbol{d}} - \underline{\boldsymbol{d}})$ is a newly introduced upper bound on final demand parameterized by δ. Here, the parameter δ can be interpreted as the tolerance of demand uncertainty, ranging from 0 to 1. D represents a set of infinite number of final demand scenarios with parameter δ. Apparently, the greater the tolerance is, the larger number of possible final demand scenarios can be considered as robust scenarios in the optimization model. Assume that the exact values (i.e. lower and upper bounds) of the technology costs and final demand in each period are are only known in that period and not before that. A dynamic robust optimization problem can be formulated to minimize the worst-case LCOE by deciding technology portfolio stage-by-stage as follow.

$$\min_{y_1\in Y}\left\{\max_{\omega_1\in\Omega, d_1\in D}\omega_1'y_1 + \min_{y_2\in Y(y_1)}\left\{\max_{\omega_2\in\Omega(\alpha_1), d_2\in D(d_1)}\omega_2'y_2 + \dots + \min_{y_T\in Y(y_1,\dots,y_{T-1})}\max_{\omega_T\in\Omega(\omega_1,\dots,\omega_{T-1}), d_T\in D(d_1,\dots,d_{T-1})}\omega_T'y_T\right\}\right\} \tag{7}$$

where $\boldsymbol{d}_t$ is the final demand in period t; $D(\boldsymbol{d}_1, ..., \boldsymbol{d}_{t-1}) = \{\boldsymbol{d}_t \in D | \boldsymbol{d}_1 = \hat{\boldsymbol{d}}_1, ..., \boldsymbol{d}_{t-1} = \hat{\boldsymbol{d}}_{t-1}\}$ is the feasible set of final demand in period t conditioning on the observed final demand values from period 1 to period $t-1$. The dynamic optimization problem (7) can be difficult to solve in general. However, it can be transformed into a single-stage optimization problem in our specific case based on the following proposition,

Proposition 3. *Model (7) is equivalent to the following optimization problem*

$$\min_{\boldsymbol{y}\in Y(\underline{\boldsymbol{d}}+\delta(\bar{\boldsymbol{d}}-\underline{\boldsymbol{d}}))}\max_{\boldsymbol{\omega}\in\Omega} \boldsymbol{w}'\boldsymbol{y} \tag{8}$$

Proof. See Appendix B

Model (8) is a single-stage optimization problem, which can be reformulated as a deterministic linear programming model by proposition 2 as follow,

$$\min_{\boldsymbol{x},\boldsymbol{h}} \quad G(\boldsymbol{h};\theta,\delta) = \underline{N}\gamma_5 + \theta(\bar{N}-\underline{N})\gamma_5 + \sum_{j\in J_e}(\bar{\alpha}_j^t\gamma_{1j} - \underline{\alpha}_j^t\gamma_{2j} + \bar{\beta}_j^t\gamma_{3j} - \underline{\beta}_j^t\gamma_{4j}) \tag{9.1}$$

$$\text{s.t.} \quad \sum_j^m a_{ij}x_j^t + \underline{d}_i^t + \delta(\bar{d}_i^t - \underline{d}_i^t) + \sum_{j\in J_e} b_{ij}\Delta z_j^{t+\tau_j} \le \sum_{j\in J_i} x_j^t \qquad \forall i,t$$
$$(5.3)-(5.10) \tag{9.2}$$

Now, the dynamic optimization problem (7) has been transformed into a linear programming problem (9), which is computationally tractable and easier to implement. Solving Eq. (9), we are able to find the optimal strategy for the minimization of worst-case LCOE by deciding technology portfolio stage-by-stage based on the updated uncertainty information of both technology cost and final demand. □

3.2.3. Maximizing tolerance of data uncertainty

In reality, decision-makers may not be confident to specify how large an uncertainty assumption should be made for long-term uncertainties. Hence, we maximize instead the largest amount of uncertainty that a capacity plan can tolerate under certain budget constraint. Tolerance optimization methods have been widely applied in the mechanical engineering where designers may prefer designs that can tolerate noise as much as possible. However, this concept has rarely been used in an IO-LP framework for electricity planning. Suppose there is a predefined budget (Γ) set on the accumulated LCOE over the entire period, another optimization model can be formulated to explore the optimal capacity planning solution for the maximization of tolerance of cost uncertainty and tolerance of demand uncertainty. The two-objective optimization model can be rewritten into a series of single-objective LP models with adjustable tolerance of demand uncertainty as follow,

$$\max_{\boldsymbol{h},\theta} \quad \theta \tag{10.1}$$

$$\text{s.t.} \quad \sum_{j\in J_i} x_j^t - \sum_j^m a_{ij}x_j^t - \sum_{j\in J_e} b_{ij}\Delta z_j^{t+\tau_j} \ge \underline{d}_i^t + \delta(\bar{d}_i^t - \underline{d}_i^t) \qquad \forall i,t \tag{10.2}$$

$$\sum_t^T\sum_j^m f_j^t x_j^t \le \overline{CO2} \tag{10.3}$$

$$h_j^t = c_j(1-\eta_j t) + z_j^t \qquad \forall j\in J_e, t \tag{10.4}$$

$$z_j^{t+\tau_j} = z_j^t + \Delta z_j^{t+\tau_j} - \Delta z_j^{t+\tau_j-q_j} \qquad \forall j\in J_e, t \tag{10.5}$$

$$h_j^t \le \bar{h}_j^t \qquad \forall j\in J_e, t \tag{10.6}$$

$$x_j^t \le \rho\epsilon_j p_j h_j^t \qquad \forall j\in J_e, t \tag{10.7}$$

$$\sum_t (1+\sigma)^{-t}x_j^t \le \gamma_{1j} - \gamma_{2j} + \gamma_5 \qquad \forall j\in J_e \tag{10.8}$$

$$\sum_t (1+\sigma)^{-t}h_j^t \le \gamma_{3j} - \gamma_{4j} + \gamma_5 \qquad \forall j\in J_e \tag{10.9}$$

$$G(\boldsymbol{h},\theta;\delta) \le \Gamma \tag{10.10}$$

$$0 \le \theta \le 1 \tag{10.11}$$

$$\boldsymbol{\Delta z}, \boldsymbol{z}, \boldsymbol{h}, \boldsymbol{x}, \boldsymbol{\gamma_1}, \boldsymbol{\gamma_2}, \boldsymbol{\gamma_3}, \boldsymbol{\gamma_4}, \gamma_5 \ge 0 \tag{10.12}$$

Eq. (10) is a non-linear optimization model, which cannot be solved directly. However, since $G(\boldsymbol{h},\theta)$ is non-decreasing in θ, Eq. (10) can be solved using bisection search algorithm on θ. In each iteration of the algorithm, the following query is made for a given value of $\theta = \hat{\theta}$: "*Does there exist some* $\boldsymbol{h}\in\Phi$ *such that* $G(\boldsymbol{h};\hat{\theta}) \le \Gamma$?". Denote $G^*(\hat{\theta}) = \min_{\boldsymbol{h}}\left\{ G(\boldsymbol{h};\hat{\theta}) \mid s.t.\ (10.2)-(10.12)\right\}$, the above query is equivalent to "*Dose there exist some* $\boldsymbol{h}\in\Phi$ *such that* $G^*(\hat{\theta}) \le \Gamma$?". If the answer to the above question is yes, then $\theta^* \ge \hat{\theta}$, otherwise, $\theta^* \le \hat{\theta}$. The procedure of bisection search algorithm can be described as follows.

Algorithm 1. Binary search algorithm for computing θ^*.

Step 1: Initialization.

Set $k:=1$, $L:=0$, $U:=1$, $\varepsilon:=0.0001$.

Step 2: Check $U-L$.

If $U-L <= \varepsilon$, update $\theta^*:=L$, terminate the algorithm.

Else Go to Step 3.

End If

Step 3: Set $\hat{\theta} = (U+L)/2$ and compute $G^*(\hat{\theta})$.

If $G^*(\hat{\theta}) \le \Gamma$, update $L := \hat{\theta}$.

Else, update $U := \hat{\theta}$, $k := k+1$, and go to Step 2.

End If

By implementing algorithm 1 on θ, the solutions of Eq. (10) can be approximated with a number of iterations with which we are able to find the capacity planning solution for the maximization of tolerance of cost uncertainty under predefined budget and fixed tolerance of demand uncertainty.

3.3. Stochastic IO-LP model

In addition to robust optimization approach, stochastic optimization approach has been widely used to handle data uncertainty in the electricity capacity planning problem Panos 2014,(Boffino et al., 2019; Domnguez et al., 2015). Here, we also develop a stochastic IO-LP model to handle the data uncertainties of technology costs and final demand, as an alternative option to the robust IO-LP model. Suppose the technology costs and final demand follow uniform distributions between their upper and lower bounds. Define $\boldsymbol{\pi} = \{\alpha_j^t, \beta_j^t, d_i^t\}'$ as the vector of all uncertain parameters, the set of $\boldsymbol{\pi}$ can be written into the following form,

$$\Pi = \left\{ \pi \;\middle|\; \begin{array}{l} \alpha_j^t \sim U(\underline{\alpha}_j^t \bar{\alpha}_j^t) \\ \beta_j^t \sim U(\underline{\beta}_j^t, \bar{\beta}_j^t) \\ d_i^t \sim U(\underline{d}_i^t, \bar{d}_i^t) \\ \forall j\in J_e, i=1,\dots,N, t=1,\dots,T \end{array} \right\} \tag{11}$$

Then, the following stochastic optimization model can be formulated to address the data uncertainties of technology cost and final demand,

$$\min_{\boldsymbol{h}} \mathbb{E}_{\boldsymbol{\pi}\in\Pi}(\min_{\boldsymbol{x}}\{LCOE(\boldsymbol{x};\boldsymbol{h},\boldsymbol{\pi})|s.t.\ LCOE(\boldsymbol{x};\boldsymbol{h},\boldsymbol{\pi})$$

$$\leq \Gamma, (1.2) - (1.8)\}) \tag{12}$$

Eq. (12) aims to identify the capacity planning solution for the minimization of expected LCOE under data uncertainty. Though Eq. (12) is computationally intractable in its original form, it can be reformulated into the following deterministic LP problem using sampling average approximation (SAA) approach according to Shapiro and Philpott (2007),

$$\min_{\boldsymbol{x_k},\boldsymbol{h}} \quad \frac{1}{K}\sum_{k=1}^{K}\left(\sum_{t}^{T}(1+\sigma)^{-t}\sum_{j\in J_e}(\alpha_{j,k}^{t}x_{j,k}^{t}+\beta_{j,k}^{t}h_{j}^{t})\right) \tag{13.1}$$

$$\text{s.t.} \quad \sum_{j}a_{ij}x_{j,k}^{t}+\sum_{j\in J_e}b_{ij}\Delta z_{j}^{t+\tau_j}+d_{i,k}^{t}\leq\sum_{j\in J_i}x_{j,k}^{t} \qquad \forall i,t,k \tag{13.2}$$

$$\sum_{t}\sum_{j}f_{j}^{t}x_{j,k}^{t}\leq\overline{CO2} \qquad \forall k \tag{13.3}$$

$$\sum_{t}^{T}(1+\sigma)^{-t}\sum_{j\in J_e}(\alpha_{j,k}^{t}x_{j,k}^{t}+\beta_{j,k}^{t}h_{j}^{t})\leq\Gamma \qquad \forall k \tag{13.4}$$

$$h_{j}^{t}=c_{j}(1-\eta_{j}t)+z_{j}^{t} \qquad \forall j\in J_e,t \tag{13.5}$$

$$z_{j}^{t+\tau_j}=z_{j}^{t}+\Delta z_{j}^{t+\tau_j}-\Delta z_{j}^{t+\tau_j-q_j} \qquad \forall j\in J_e,t \tag{13.6}$$

$$h_{j}^{t}\leq\bar{h}_{j}^{t} \qquad \forall j\in J_e,t \tag{13.7}$$

$$x_{j,k}^{t}\leq\rho\epsilon_{j}p_{j}h_{j}^{t} \qquad \forall j\in J_e,t,k \tag{13.8}$$

$$\boldsymbol{x_k},\boldsymbol{\Delta z},\boldsymbol{z},\boldsymbol{h}\geq 0 \qquad \forall k \tag{13.9}$$

where generation capacity ($\boldsymbol{h}$) is the first-stage decision variable, and output ($\boldsymbol{x_k}$) is the second-stage decision variable which depends on generation capacity and sampling values of uncertain parameters; $\boldsymbol{\pi}_k$ is the kth sample of uncertain parameter generated from Π; K is the sample size in SAA approach.

4. Case study of China

China has actively promoted the development of non-fossil electricity over the past years. Its cumulative installed capacity of non-fossil electricity in 2015 was almost four times of that in 2002 CEPY 2018. On the 30th of June 2015, China submitted an INDC, including an intention to lower its CO2 emissions per unit of gross domestic product (GDP) by 60-65% from the 2005 level, and to raise its share of non-fossil fuels in primary energy consumption to around 20% in 2030. Under this circumstance, the robust IO-LP model is applied to identify the cost-effective options of electricity generation technologies for reduction in economy-wide CO2 emissions in China from 2020 to 2050 under data uncertainty. In the followings, the data used is firstly introduced. Then, the main results of robust IO-LP model are reported.

4.1. Data

4.1.1. Data source

The Chinese IO table in 2017 with 44 sectors was utilized to derive the input-output structure of China's economy. The table was obtained from the National Statistical Bureau of China (NBSC, 2019). The *Production and Supply of Electric Power* sector in IO table was disaggregated into seven generation technologies, including coal-fired, gas-fired, nuclear, hydro, wind, solar photovoltaic (PV), and biomass[4]. Detailed disaggregation process of the electricity sector in IO table can be found in Kang, Ng, Su, and Yuan (2020). After the disaggregation, there are in total 44 non-electricity sectors, 7 electricity generation technologies, and 45 commodities in the augmented IO matrix. The capital coefficients of generation technologies were estimated based on the investment cost and the investment structure of generation technologies. Detailed estimation process of the capital coefficient has also been provided in Kang, Ng, Su, and Yuan (2020). The existing capacities of various generation technologies in 2020 were obtained from the China Electric Power Yearbook CEPY 2018. The lower and upper bounds of technology costs in China in 2020 were obtained from the Projected Costs of Generating Electricity (IEA, 2015). The cost lower and upper bounds are assumed to change by certain learning rates from 2020 to 2050 referring to Li, Lukszo, and Weijnen (2015). The lower and upper bounds of final demand in IO table from 2020 to 2050 were projected using linear regression analysis based on the historical demand data. The other parameters in case study of China can be referred in Kang, Ng, Su, and Yuan (2020). The optimization model contains 13246 variables and 3683 constraints, and was performed using *DOCPLEX* package in Python environment.

4.1.2. Overview of data uncertainty

Fig. 1 depicts the cost intervals of seven generation technologies in China in the base year 2020. As can be seen, great uncertainties can be observed in both variable and fixed costs of generation technologies. The non-fossil generation technologies, e.g. nuclear, biomass, hydro, and wind, have the greatest uncertainty in fixed cost. The uncertainty can be mainly explained by the variety in technology designs. For instance, various types of nuclear reactors are currently used in China, including general light water reactor, advanced light water reactor, and generic generation III reactor. Due to different reactor designs, the fixed cost of nuclear generation technology in China varies from 28,821 yuan/kW to 86,464 yuan/kW. On the other hand, the thermal generation technologies, i.e., coal-fired and gas-fired, have the greatest uncertainty in variable cost. As shown in Fig. 1, the variable cost of coal-fired technology ranges from 65 yuan/MVh to 195 yuan/MVh, and the variable cost of gas-fired technology ranges from 81 yuan/MVh to 243 yuan/MVh. The uncertainty can be due to the difference in fuel combustion efficiency of different technology designs. For instance, the fuel combustion efficiency of pulverized coal-fired power (PCFP) stations with sub critical boiler type (sub) is much lower than the efficiency of PCFP with ultra-super critical boiler type (USC). As a consequence, the fuel cost of PCFP-USC can be significantly lower than the fuel cost of PCFP-sub (Linder, Legault, & Guan, 2013).

4.2. Results

The results of robust IO-LP model are presented in this subsection. Four scenarios are designed, including one Business-As-Usual (BAU) scenario and three mitigation scenarios, i.e., BAU-10, BAU-20, and BAU-30. The BAU scenario is the scenario with no CO2 emissions target constraint. The three mitigation scenarios are designed by setting a series of cumulative emissions targets in optimization model which are lower than the BAU emissions target by certain levels. For instance, the cumulative emissions target in BAU-10 sce-

[4] The seven electricity generation technologies are currently in use in China. The oil-fired generation technology is not considered due to the small share of oil-fired electricity in total electricity generation in China. The Carbon Capture Storage (SSC) technology is not included given the uncertainties and challenges in large-scale deployment of the technology in the future.

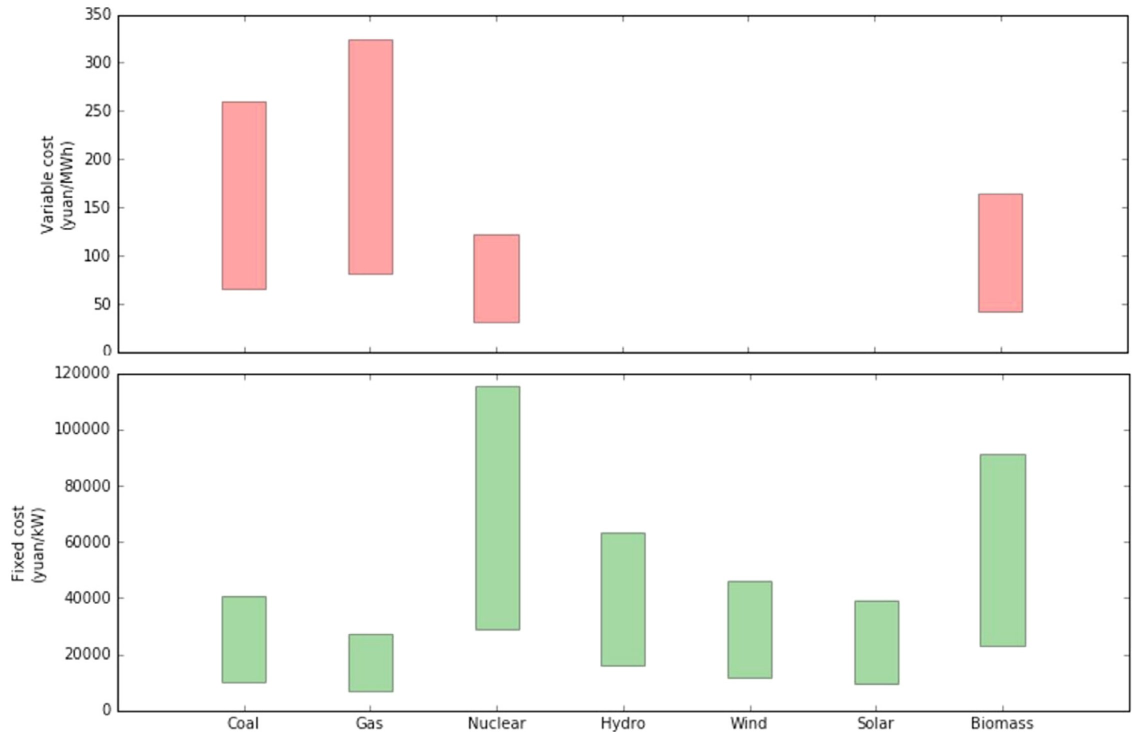

Fig. 1. Cost intervals of generation technologies in China in 2020 (IEA, 2015).

nario is 10% lower than the accumulated CO2 emissions in BAU scenario. The budget of LCOE is set as 171,502 Billion RMB[5].

4.2.1. Tradeoff between tolerance of cost uncertainty and tolerance of demand uncertainty

Fig. 2 depicts tradeoffs between the tolerance of cost uncertainty and the tolerance of demand uncertainty under different emissions scenarios. A higher value in tolerance of cost uncertainty indicates that a greater number of possible cost scenarios can be covered in the robust optimization model. A higher tolerance of demand uncertainty means that a greater number of possible final demand scenarios are deemed as robust scenarios in the optimization model. It can be seen from Fig. 2 that the tolerance of cost uncertainty declines along with the rise in tolerance of demand uncertainty under constant emission target. The result indicates that a certain sacrifice in one tolerance indicator is needed in order to improve the other tolerance indicator. Regarding to the relationship between emissions target and tolerance of cost uncertainty, Fig. 2 shows that the tolerance of cost uncertainty decreases when moving from BAU scenario to BAU-30 scenario under a fixed tolerance of demand uncertainty. The result reveals that the a more stringent emissions target is always accompanied with a smaller tolerance of data uncertainty. The finding is consistent with our intuition that the ambitious emissions target is less likely to be achieved compared to the relaxed emissions target. Besides, another interesting finding is that the sensitivity of tolerance of cost uncertainty to change in emissions target becomes smaller when raising up the tolerance of demand uncertainty. The result can be explained by the fact that the number of feasible cost scenarios is smaller with a higher tolerance of demand uncertainty under constant budget constraint. As a result, there is not enough space for a further improvement in tolerance of cost uncertainty through changing emissions target.

4.2.2. Identification of optimal technological options

By setting the tolerance of demand uncertainty as 0.5[6], the capacity planning solutions of generation technologies from 2020 to 2050 in BAU and BAU-30 scenarios were obtained as shown in Fig. 3. As can be seen in Fig. 3(a), only two generation technologies will be greatly developed in the BAU scenario, including coal-fired and hydro generation technologies. The results can be explained by the fact that both generation technologies have relatively lower cost compared to the other generation technologies (See Fig. 1). Hence, without setting any CO2 emissions target, the optimization model will always choose the cheapest technologies in order to maximize the tolerance of cost uncertainty under constant budget. In order to reduce the accumulated CO2 emissions by 30% compared to the BAU emissions level, the proportion of coal-fired electricity in total electricity generation will decrease gradually. As a replacement, various types of low-carbon electricity, including gas-fired, hydro, nuclear, wind, solar, and biomass, will be introduced into the electricity mix as shown in Fig. 3(b). The technology portfolio in BAU-30 scenario is quite similar to the technology portfolio in INDC scenario generated from bottom-up ESOMs (He, 2016; Wang, Chen, Zhang, & Li, 2019).

The time-series economy-wide CO2 emissions and aggregate carbon intensity[7] in China from 2020 to 2050 in BAU and BAU-30 scenarios are drawn in Fig. 4. As can be seen, the introduction of low-carbon electricity is able to significantly reduce CO2 emissions

[5] The budget is calibrated using a deterministic IO-LP model. First, we solved a deterministic IO-LP model with pessimistic technology cost setting, i.e., upper bound of cost interval. The optimal LCOE value obtained can be considered as the most conservative LCOE under data uncertainty. Then, the budget target was determined by lowering the LCOE value down by 5%.

[6] The tolerance of demand uncertainty can be set as any value between 0 and 1. The value 0.5 is just an illustrative case. The optimization results corresponding to tolerance of demand uncertainty of 0.25 and 0.75 are provided in Appendix C.

[7] The aggregate carbon intensity is the ratio between aggregate CO2 emissions and GDP. The GDP in China from 2020 to 2050 is collected from the GDP Long-term Forecast by OECD (2018).

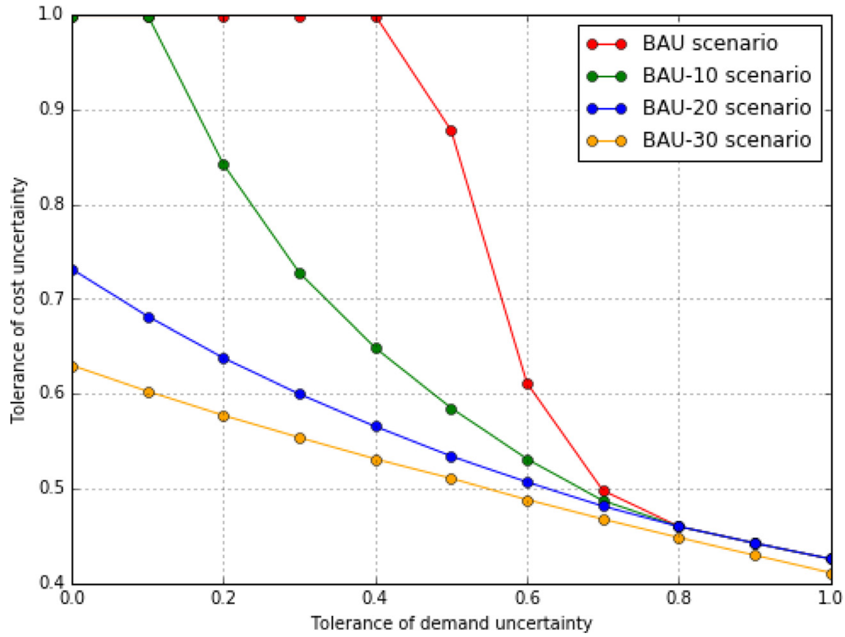

Fig. 2. Tradeoff between tolerance of cost uncertainty and tolerance of demand uncertainty.

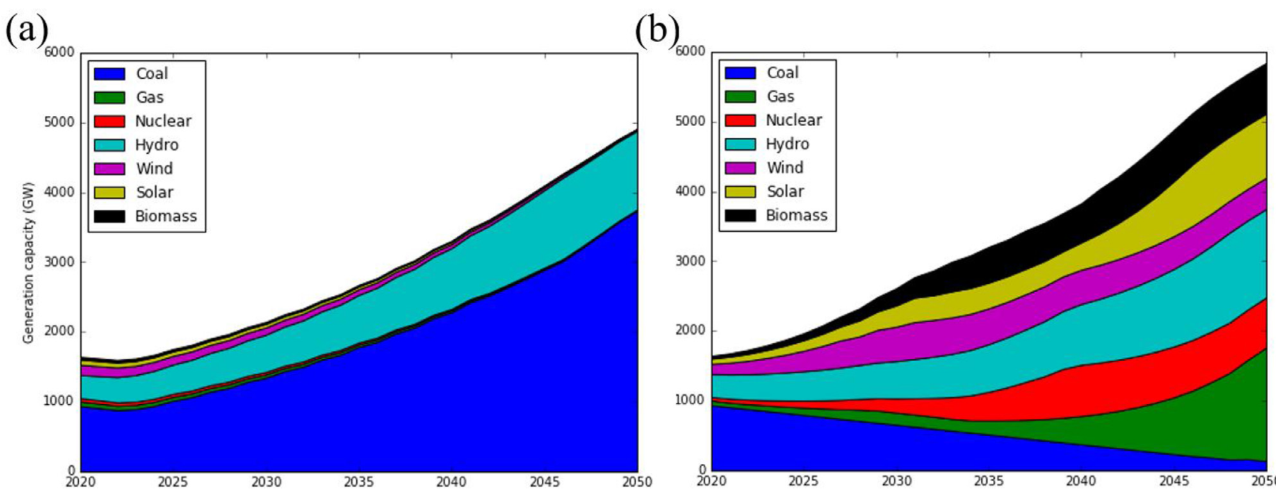

Fig. 3. Capacity of generation technologies from 2020 to 2050 in BAU (a) and BAU-30 (b).

in China during the entire modelling period. The CO2 emissions in 2050 in BAU-30 scenario is 43% lower than the BAU emissions in 2050. The result is quite consistent with the projection from IEA that the introduction of non-fossil electricity is able to decrease CO2 emissions in China by around 40% in 2050 compared to the BAU emissions level (IEA, 2018). Besides, the aggregate carbon intensity in China can be lowered down remarkably through the shift in electricity generation mix. As depicted in Fig. 4, the aggregate carbon intensity will drop by 69% in 2030 compared to the carbon intensity level in 2005 in the BAU-30 scenario. The result implies that the 2030 carbon intensity target in China (60-65% reduction in carbon intensity in 2030 compared to the 2005 level) can be possibly achieved though the penetration of low-carbon electricity.

4.2.3. Comparison of deterministic, robust, and stochastic IO-LP models

Finally, we compared the performance of deterministic, robust, and stochastic IO-LP models for data uncertainty handling in the following way. First, we solved different models respectively to generate various sets of capacity planning solutions[8]. Two different cost settings are considered in the deterministic model, including optimistic cost (i.e. lower bounds of cost interval) and pessimistic cost (i.e. upper bounds of cost interval). As a result, four different optimization models, including one robust model, one stochastic model, and two deterministic models are compared in this subsection. Next, we input the four sets of capacity planning solutions back into the robust IO-LP model as exogenous parameters. By solving the robust IO-LP model under different sets of capacities, a series of tolerance values of cost uncertainty can be calculated, which are deemed as the performances of different optimization models for data uncertainty handling.

Fig. 5 depicts the performances of four optimization models in BAU, BAU-10, BAU-20, and BAU-30 scenarios. As can be seen, the robust IO-LP model is able to improve the performance for data

[8] In this step, the predefined cost budget is still set as 171,502 Billion RMB. The tolerance of demand uncertainty for robust model is set as 0.5. The final demand in deterministic models is replaced by the upper bound of demand interval under same tolerance value.

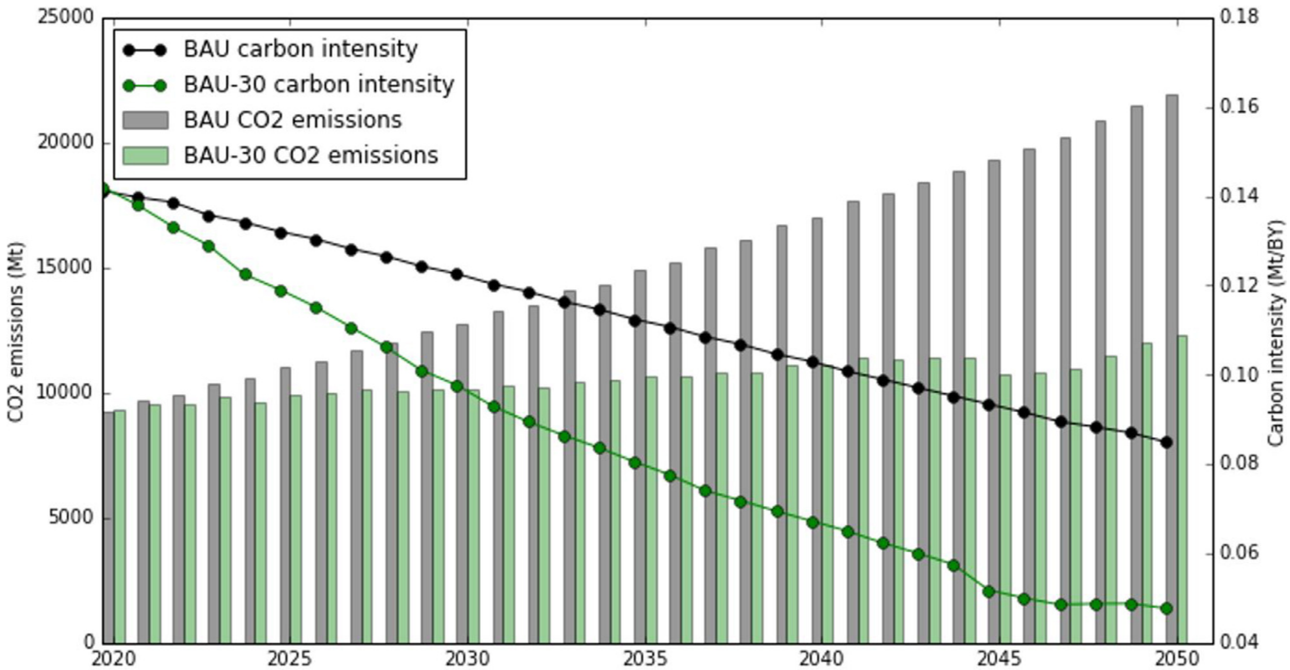

Fig. 4. CO2 emissions and carbon intensity in China from 2020 to 2050 in BAU and BAU-30.

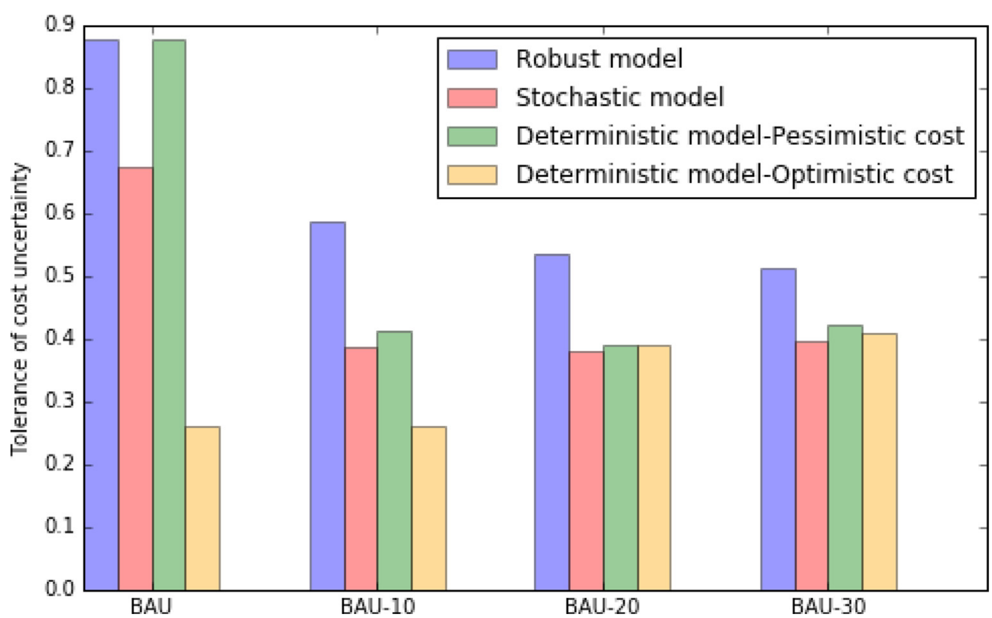

Fig. 5. Tolerance of cost uncertainty of capacity planning solutions of four alternative models.

uncertainty handling compared to the other models. Nevertheless, the performance difference between robust model and the other models in the BAU scenario is quite small. The small difference can be explained by the fact that the predefined cost budget can be easily meet with no emissions target constraint. Hence, even the capacity solutions generated from deterministic and stochastic models are able to achieve a relatively high tolerance of data uncertainty. When lowering down the emissions target, the gaps in performance between robust model and the other models become noticeable. As can be seen in Fig. 5, the performance of robust model is significantly higher than the performance of other models in the BAU-10, BAU-20, and BAU-30 scenarios. The comparison results indicate that the capacity planning solutions calculated by robust model can be more reliable than those calculated by deterministic and stochastic models under data uncertainty, and the superiority is particularly significant under ambitious emissions targets. It is worth mentioning that the performance of robust model is even better than the performance of deterministic model with pessimistic cost setting. This finding contradicts to the intuition that the solution of deterministic model with pessimistic cost set-

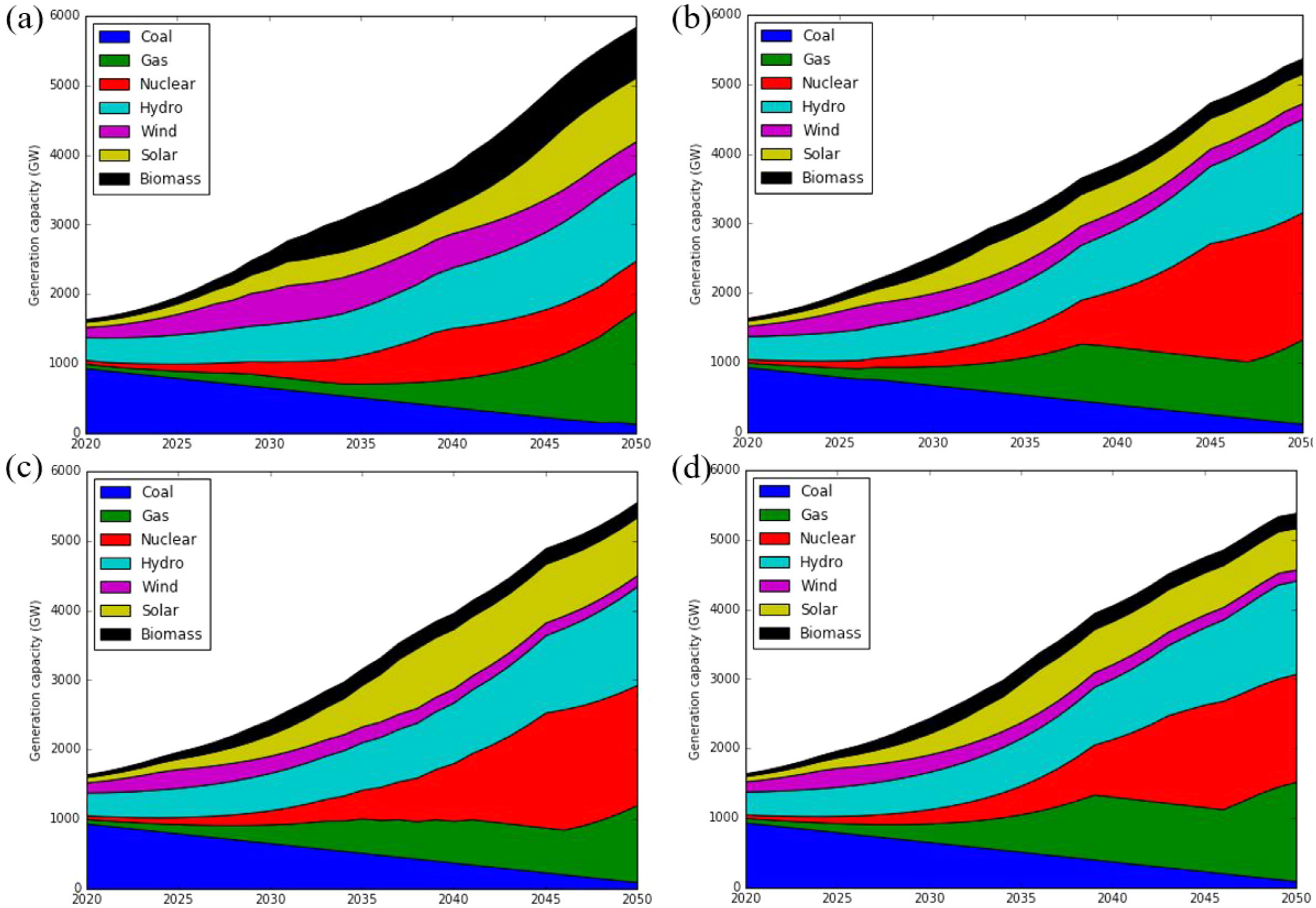

Fig. 6. Capacity planning solutions of robust model (a), stochastic model (b), deterministic model with pessimistic cost (c), and deterministic model with optimistic cost (d) under BAU-30 scenario.

ting should always be the most robust solution under data uncertainty. The finding demonstrates the effectiveness of the robust IO-LP model.

Fig. 6 draws the capacity planning solutions calculated by different models in the BAU-30 scenario. As can be seen, the total generation capacities generated by four different models are close with each other (i.e., nearly 6000 GW in 2050). However, the generation mix generated by the robust model and the other models varies notably. Compared to the deterministic and stochastic models, the robust model tends to select the technologies with small uncertainty in LCOE, yet avoids the technologies with large uncertainty in LCOE. As can be seen in Fig. 6, the proportion of nuclear generation capacity generated by robust model (Fig. 6a) is much smaller than the proportion generated by the other three models (Fig. 6b-6 d). The results can be due to the high uncertainty in fixed cost of nuclear generation technology (See Fig. 1). On the contrary, the proportions of wind and biomass generation technologies generated by robust model (Fig. 6a) are higher than those generated by the other three models (Fig. 6b-6 d). The results can be explained by the small uncertainty in LCOE of both technologies[9] as seen in Fig. 1. By avoiding the generation technologies with large uncertainty in LCOE, the robust optimization model ensures the satisfaction of a predefined cost budget with high tolerance of data uncertainty.

5. Conclusion and discussions

This study adopts an IO-LP model to identify a cost-effective strategy for reduction in economy-wide CO2 emissions through a shift in the electricity generation mix. To address the data uncertainties of technology cost and final demand, a robust IO-LP model is further developed to maximize the tolerance of data uncertainty under a dynamic uncertainty setting. The modelling results in case of China show that coal-fired and hydro generation technologies should be greatly developed from 2020 to 2050 in the BAU scenario with no emissions target constraint. In order to reduce accumulated CO2 emissions in China by 30% compared to the BAU emissions level, various types of low-carbon generation technologies, including gas-fired, hydro, nuclear, wind, solar, and biomass should be introduced into the electricity mix. However, the decrease in emissions target could compromise the tolerance of data uncertainty by a certain level. Finally, we compared performance of the robust IO-LP model with those of the deterministic and stochastic IO-LP models for data uncertainty handling. The comparative analysis shows that the robust IO-LP model tends to select technologies with small uncertainty in LCOE, and is able to improve the robustness of capacity planning solution under data uncertainty compared to the alternative models.

Compared to the existing optimization models for electricity system planning, the pros and cons of the robust IO-LP model

[9] Though the uncertainty in cost of biomass technology is significant as shown in Fig. 1, the data uncertainty in LCOE of biomass technology is actually not large due to its high capacity utilization rate (See Table E1). Hence, the biomass generation technology will be encouraged by robust optimization model

are discussed as follows. It must be admitted that bottom-up optimization models are able to generate more reliable solutions for the decarbonization of electricity system due to their technology-richness and the more accurate description of the interactions between the different elements in electricity system (e.g. transmission network, ramp up and down constraints). From this perspective, IO-LP model is limited by its high aggregation level of economic sectors, which leads to a certain loss in technological and operational details. Nevertheless, IO-LP model still has its great value, especially when it comes to adding information on the indirect impacts in the entire economic system, e.g. employment, value added creation, and capital-related CO2 emissions. The information generally cannot be obtained from bottom-up optimization models. Besides, IO-LP model is able to easily link the optimization of electricity system to the economy-wide emissions targets (e.g. INDC targets), which are generally of more concerns compared to the sectoral emissions targets. For example, we demonstrated that the aggregate carbon intensity target in China can be possibly achieved through a shift of electricity generation mix. However, in the bottom-up models for electricity planning, much more data are required in order to gain those insights. Regarding to the handling of data uncertainty, compared to the deterministic and stochastic optimization models which mostly seek the least-cost strategy, the robust IO-LP model seeks the strategy for the maximization of tolerance of data uncertainty under predefined budget. As a result, the robust IO-LP model is able to generate more reliable capacity planning solutions under data uncertainty compared to the other alternative models. Plus, the robust IO-LP model is applicable to a dynamic optimization problem in which the exact values of uncertain parameters in each period are only known in that period but not in advance. Compared to the one-stage optimization problem, the dynamic optimization problem can be more consistent to the real decision process.

Some possible extensions of the current study are provided as follows. First, in addition to technology costs and final demand, technical coefficients in IO-LP model can be also with great data uncertainty, which should be further taken into consideration in the future. Second, the proposed model is a single-region IO-LP model, which fails to take into account the cross-regional electricity transmission (Wang et al., 2019, 2020). To address the issue, a multi-region robust IO-LP model can be further developed by combining a multi-regional input-output model with an electricity optimization model. Third, the robust IO-LP model only relies on the interval information of uncertain parameters. Consequently, the obtained optimization results can be too conservative. To address the issue, the stochastic and robust optimization techniques can be combined by taking more uncertainty information, e.g. distribution information, into consideration. Finally, while the dynamic tolerance optimization approach for data uncertainty handling is applied to an IO-LP model in this study, it can be further adopted in bottom-up energy planning models in the future, e.g. MARKAL family models.

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Supplementary material

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References

Ang, B. W., & Su, B. (2016). Carbon emission intensity in electricity production: A global analysis. *Energy Policy, 94*, 56–63.

Antunes, C. H., Oliveira, C., & Clmaco, J. (2002). A study of the interactions between the energy system and the economy using TRIMAP. *In D.*. Bouyssou, E., Jacquet-Lagrze, P., Perny, R., Slowinski, D., Vanderpooten, P., Vincke (Eds.), Aiding decisions with multiple criteria (pp. 407-427). New York: Springer

Aviso, K. B., Tan, R. R., Culaba, A. B., & Cruz, J. (2011). Fuzzy input-output model for optimizing eco-industrial supply chains under water footprint constraints. *Journal of Cleaner Production, 19*(2-3), 187–196.

Boffino, L., Conejo, A., Sioshansi, R., & Oggioni, G. (2019). A two-stage stochastic optimization planning framework to decarbonize deeply electric power systems. *Energy Economics, 84*, 104457.

Borges, A. R., & Antunes, C. H. (2003). A fuzzy multiple objective decision support model for energy-economy planning. *European Journal of Operational Research, 145*(2), 304–316.

Carvalho, A., Antunes, C. H., & Freire, F. (2016). Economic-energy-environment analysis of prospective sugarcane bioethanol production in brazil. *Applied Energy, 181*, 514–526.

Chang, S. L., & Juang, M. C. (1998). Decision analysis on CO2 reduction for industrial and energy sectors an FMOLP approach. in proceedings of the conference on east asian environmental and resource economics and policy. Institute of Economics, March 2 3. Taipei, Taiwan. http://www.seeds.usp.br/pir/arquivos/congressos/IAEE2005/program/pdf/CS17-3%20Ssu-li%20Chang.pdf.

Cho, S. G. (2014). Reliability-based optimum tolerance design for industrial electromagnetic devices. *IEEE Trans. Magn., 50*(2), 713–716.

Dilekli, N., & Duchin, F. (2015). Prospects for cellulosic biofuel production in the northeastern united states: A scenario analysis. *Journal of Industrial Ecology, 20*, 120–131.

Domnguez, R., Conejo, A. J., & Carrin, M. (2015). Toward fully renewable electric energy systems. *IEEE Transactions on Power Systems, 30*, 1.

He, G. (2016). SWITCH-china: A systems approach to decarbonizing chinas power system. *Environ. Sci. Technol., 50*, 5467–5473.

He, P., Ng, T. S., & Su, B. (2015). Energy import resilience with input-output linear programming models. *Energy Economics, 50*, 215–226.

He, P., Ng, T. S., & Su, B. (2017). Energy-economic recovery resilience with input-output linear programming models. *Energy Economics, 68*, 177–191.

He, P., Ng, T. S., & Su, B. (2019). Energy resilience with multi-region input-output linear programming models. *Energy Economics, 84*, 104569.

Henriques, C. O., Coelho, D. H., & Antunes, C. H. (2015). A multi-objective input-output model to assess e4 impacts of building retrofitting measures to improve energy efficiency. *Technological and Economic Development of Economy, 21*(3), 483–494.

Honda, H., Moriizumi, Y., & Sakao, T. (2006). A method for technology selection considering environmental and socio-economic impacts: Input-output optimization model and its application to housing policy. *Int. J. Life Cycle Assess, 11*(6), 383–393.

IEA (2015). *Projected Costs of Generating Electricity*. Paris: International Energy Agency.

IEA (2018). *World Energy Outlook*. Paris: International Energy Agency. 2018

Kang, J., Ng, S., Su, B., & Yuan, R. (2020). Optimizing the chinese electricity mix for CO2 emissions reduction: An input-output linear programming model with endogenous capital. *Environ. Sci. Technol., 54*, 697–706.

Lara, C., Mallapragada, D., Papageorgiou, D., Venkatesh, A., & Grossmann, I. (2018). Deterministic electric power infrastructure planning: Mixed-integer programming model and nested decomposition algorithm. *European Journal of Operational Research, 271*, 1037–1054.

Lee, J. G., Hwang, N. W., Ryu, H. R., Jung, H. K., & Woo, D. K. (2017). Robust optimization approach applied to permanent magnet synchronous motor. *IEEE Trans. Magn., 53*(6). Art. no. 8001804

Lei, G., Wang, T., Zhu, J., Guo, Y., & Wang, S. (2015). System-level design optimization method for electrical drive systems-robust approach. *IEEE Trans. Ind. Electron., 62*(8), 4702–4713.

Li, Y., Lukszo, Z., & Weijnen, M. (2015). The implications of CO2 price for china's power sector decarbonization. *Applied Energy, 146*, 53–64.

Linder, S., Legault, J., & Guan, D. (2013). 25,3,300–320Disaggregating the electricity sector of China's input-output table for improved environmental life-cycle assessment. Economic Systems Research

Ma, B., Lei, G., Liu, C., Zhu, J., & Guo, Y. (2018). Art. no. 8102404. 54, 3Robust Tolerance Design Optimization of a PM Claw Pole Motor With Soft Magnetic Composite Cores. IEEE Trans. Magn.

Mc Kenzie, E., & Durango-Cohen, P. (2010). An input-output approach for the efficient design of sustainable goods and services. *Int J Life Cycle Assess, 15*(9), 383–393.

Moret, S., Babonneau, F., Bierlaire, M., & Mar chal, F. (2019). Decision support for strategic energy planning: A robust optimization framework. *European Journal of Operational Research (in press)*.

Munoz, F. D., Hobbs, B. F., & Watson, J. P. (2016). New bounding and decomposition approaches for MILP investment problems: Multi-area transmission and generation planning under policy constraints. *European Journal of Operational Research, 248*, 888–898.

National Bureau of statistics of china (NBSC) (2019). Input-output Table of China in 2017. China Statistics Press.

Oliveira, C., & Antunes, C. H. (2002). An input-output model for decision support in energy-economy planning-a multi-objective interactive approach. *Journal of Systems Analysis Modelling Simulation, 42*(5), 769–790.

Oliveira, C., & Antunes, C. H. (2004). A multiple objective model to deal with economy-energy-environment interactions. *European Journal of Operational Research, 153*(2), 370–385.

Oliveira, C., & Antunes, C. H. (2011). A multi-objective multi-sectoral economy-energy-environment model: Application to portugal. *Energy, 36*(5), 2856–2866.

Oliveira, C., & Antunes, C. H. (2012). Interactions of economic growth, energy consumption and the environment in the context of the crisis-a study with uncertain data. *Energy, 48*, 415–422.

Pan, L., Liu, P., Li, Z., & Wang, Y. (2018). A dynamic input-output method for energy system modeling and analysis. *Chem. Eng. Res. Des., 131*, 183–192.

Parpas, P., & Webster, M. (2014). A stochastic multiscale model for electricity generation capacity expansion. *European Journal of Operational Research, 232*, 359–374.

Pehl, M., Arvesen, A., Humpenoder, F., Popp, A., Hertwich, E. G., & Luderer, G. (2017). Understanding future emissions from low-carbon power systems by integration of life-cycle assessment and integrated energy modelling. *Nature energy*, (2), 939–945.

Ruiz, C., & Conejo, A. J. (2015). Robust transmission expansion planning. *European Journal of Operational Research, 242*, 390–401.

Shapiro, A., & Philpott, A. (2007). A tutorial on stochastic programming. manuscript (2007). 1–35. https://www2.isye.gatech.edu/people/faculty/Alex_Shapiro/TutorialSP.pdf.

Song, J., Yang, W., Higano, Y., & Wang, X. (2015a). Dynamic integrated assessment of bioenergy technologies for energy production utilizing agricultural residues: an input-output approach. *Applied Energy, 158*, 178–189.

Song, J., Yang, W., Higano, Y., & Wang, X. (2015b). Introducing renewable energy and industrial restructuring to reduce GHG emission: Application of a dynamic simulation model. *Energy Conversion and Management, 96*, 625–636.

Tan, R. R., Aviso, K. B., Barilea, I. U., Culaba, A. B., & Cruz, J. (2012). A fuzzy multi-regional input-output optimization model for biomass production and trade under resource and footprint constraints. *Applied Energy, 90*(1), 154–160.

Tan, R. R., Ballacillo, J. B., Aviso, K. B., & Culaba, A. B. (2009). A fuzzy multiple-objective approach to the optimization of bioenergy system footprints. *Chem. Eng. Res. Des., 87*, 1162–1170.

UNFCCC (2015). Intended nationally determined contributions (INDC) submissions. United Nations Framework Convention on Climate Change (UNFCCC), individual countrys INDC can be found at the website: https://www.unfccc.int/Submissions/INDC.

Wang, H., Chen, W. Y., Zhang, H. J., & Li, N. (2019). Modeling of power sector decarbonization in china: comparisons of early and delayed mitigation towards 2-degree target. Climate Change. https://doi-org.libproxy1.nus.edu.sg/10.1007/s10584-019-02485-8.

Wang, H. Y., Su, B., Mu, H. L., Li, N., Jiang, B., & Kong, X. (2019). Optimization of electricity generation and interprovincial trading strategies in Southern China. *Energy, 174*, 696–707.

Wang, H. Y., Su, B., Mu, H. L., Li , N., Gui, S., Duan, Y., & Jiang, B. (2020). Optimal way to achieve RPS policy goals from electricity generation, transmission and trading perspectives in Southern China. *Energy Policy, 139*, 111319.

Wen, S., Xu, F., Wen, Z., & Lin, C. (2014). Robust linear optimization under matrix completion. *Science China Mathematics, 57*(4), 699–710.

Xiao, S., Li, Y., Rotaru, M., & Sykulski, J. K. (2015). Six sigma quality approach to robust optimization. *IEEE Trans. Magn., 51*(3). Art. no. 7201304.