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Innovative Applications of O.R.

A stochastic-robust optimization model for inter-regional power system planning

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ABSTRACT

This study develops a stochastic-robust optimization model for inter-regional power system planning. The model is formulated as Mathematical Programs with Equilibrium Constraints (MPEC) with two levels of decision makers. In the bottom-level, various individual regions separately make generator investment, operating, and trading plans for the minimization of their own costs in a perfectly competitive market. In the top-level, a central system operator makes the investment plan of cross-border transmission lines for the minimization of total system cost, anticipating how generators in various regions respond to those investments. Two different levels of data uncertainties are considered in the problem, namely scenario and local uncertainties. The uncertainties are handled by combining the advantages of stochastic programming and robust optimization methods. The proposed model is applied for power system planning in the Association of Southeast Asian Nations (ASEAN) between 2020 and 2040. The modelling results show that the integration of a cross-border power grid results in a substantial shift in the generation portfolio, and can potentially reduce total costs by up to 6.0%. The cost savings primarily result from the increased utilization of renewable energy resources, facilitated by cross-border electricity transmission. We assessed the performance of our proposed approach in handling data uncertainties by comparing it with existing practices. The comparison results demonstrate that our stochastic-robust approach not only enhances the capacity expansion plan's robustness to meet power demand and CO_2 emissions targets, but also significantly reduces investment and operational costs.

1. Introduction

The accumulation of greenhouse gases (GHGs) emissions in the atmosphere continues to threaten natural and socio-economic systems through global warming. To mitigate GHG emissions, 195 countries submitted their Intended Nationally Determined Contribution (INDC) during the 2015 Paris climate conference under the United Nations Framework Convention on Climate Change (UNFCCC, 2015). Recently, many countries have announced ambitious targets to achieve carbon neutrality (NPUC, 2021). The emissions mitigation targets cannot be achieved without deep decarbonization in the power sector, which accounted for roughly a quarter of global carbon dioxide (CO_2) emissions in 2019 (IEA, 2020a). Replacing fossil fuel-based generation, including coal, oil, and gas-fired power plants, with renewable generation, including hydro, wind, and solar, is a crucial strategy for decarbonizing the power sector. Yet, the unbalanced distribution of renewable resources and demand cross various regions greatly increases the challenge towards a clean electricity transition. Expansion of cross-border power grids is an important solution to addressing such problem. To achieve this, a co-optimization of transmission and generation investments in inter-regional power systems is necessary.

Data uncertainty is a critical issue for power system optimization problems. The exact values of many parameters, such as technology costs, power demand, and resource availability, may not be precisely known in advance, especially when planning spans several years or even decades. Various levels of data uncertainty can be associated with parameters, including scenario uncertainty and local uncertainty. *Scenario uncertainty* refers to uncertainty on future projections and outlooks, usually resulting from different policy and technological assumptions. In the literature, scenario uncertainty is usually expressed as a discrete number of scenarios

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Nomenclature

Indices

r, r'	index of region
j	index of generation technology
t	index of time period
k	index of parameter scenario

Sets

R	set of regions
J	set of generation technologies
T	set of time periods
K	set of parameter scenarios
$\mathscr{H}$	set of generation capacity
$\mathscr{Z}$	set of electricity generation and trading
$\mathscr{F}$	probability distribution set of parameter scenarios
Ω_k	set of cost parameters in scenario k
Φ_k	set of demand and resource availability in scenario k
Z^+	set of non-negative integers

Parameters

$C^{gen}_{j,t,r}$	variable cost for electricity generation of technology j in region r in period t (\$/kWh)
$C^{geninv}_{j,t,r}$	investment cost of generation capacity of technology j in region r in period t (\$/kWh)
C^{tran}	service fee for transmitting one unit of electricity from one region to another region (\$/kWh)
$C^{traninv}_{r,r',t}$	investment cost of transmission capacity between region r and region r' (\$/kWh)
$\bar{y}_{r,t}$	maximum electricity demand in region r in period t (kWh)
$f_{j,r,t}$	emission intensity of technology j in region r in period t (kg CO_2/kWh)
$CO2_{r,t}$	CO_2 emissions target in region r in period t (kg CO_2)
a	annual depreciation rate of transmission capacity
e_j	annual depreciation rate of generation capacity of technology j
$\underline{\alpha}_{j,r,t}$	minimum resource availability of generation technology j in region r in period t
$\bar{h}_{j,r,t}$	upper bound of generation capacity of technology j in region r in period t (kWh per period)
$\hat{h}_{j,r}$	generation capacity of technology j in region r in the initial modelling period (kWh per period)
$\hat{u}_{r,r'}$	transmission capacity between region r and region r' in the initial period (kWh per period)
N	minimum addition in generation capacity (kWh)
M	minimum addition in transmission capacity (kWh)
$P_{r,k}$	probability of parameter scenario k in assumed by region r
Γ^C_r	budget of cost uncertainty in region r
Γ^y_r	budget of demand uncertainty in region r
Γ^α_r	budget of availability uncertainty in region r
$\mathbb{P}_r$	probability distribution of parameter scenarios in region r

Variables

$\Delta h_{j,r,t}$	new generation units of technology j built in region r in period t
$h_{j,r,t}$	total generation capacity of technology j in region r in period t (kWh per period)
$\Delta u_{r,r',t}$	new transmission units from region r to region r' built in period t
$u_{r,r',t}$	total transmission capacity from region r to region r' in period t (kWh per period)
$x_{j,r,t}$	generation output of technology j in region r in period t (kWh)
$b_{r,r',t}$	electricity bought from region r by region r' in period t (kWh)
$s_{r,r',t}$	electricity sold from region r to region r' in period t (kWh)
p^{buy}, p^{sell}	electricity buying and selling prices (\$/kWh)
$z_{r,k}$	vector of decision variables on electricity generation and trading in region r
ω_k	vector of cost parameters in scenario k
ϕ_k	vector of demand and resource availability in scenario k

with known or ambiguous probability distributions. *Local uncertainty*, on the other hand, refers to variability caused by aggregation and estimation errors, which typically cannot be explained. Local uncertainty is generally expressed in the literature as box or other assumed uncertainty sets. In actual practice, each parameter in the optimization model could be associated with both scenario and local uncertainties. For example, the investment cost of solar photovoltaic (PV) may be subject to scenario uncertainty due to different learning rate projections in the future (See Fig. 1). Additionally, within each scenario, the cost value may also contain local uncertainty due to aggregation and estimation error (e.g., the investment cost of commercial PV in 2020 ranged from 1030 USD/kW to 1968 USD/kW (IEA, 2020b)). Other parameters, such as fuel cost, power demand, and renewable resource availability, may also simultaneously suffer from scenario and local uncertainties. Both levels of data uncertainties can substantially impact the optimal solutions generated by power system optimization models and should, therefore, be appropriately considered.

In this paper, we present a stochastic-robust optimization model for exploring the transmission and generation expansion plan in an inter-regional power system under both scenario and local uncertainties. The model is formulated as a Mathematical Program with Equilibrium Constraints (MPEC), with decision-making at two levels. At the top-level, a system operator decides the cross-border transmission expansion plan to minimize system costs, anticipating the equilibrium of the bottom-level problem. At the bottom-level, different regions independently decide their investment, generation, and trading plans to minimize their own worst-case expected costs in a perfectly competitive market. The uncertain parameters in the optimization model include the investment and fuel costs of generation technologies, power demand, and resource availability. To illustrate the approach, we apply the model to power system planning in the Association of Southeast Asian Nations (ASEAN) from 2020 to 2040.

An important assumption in this study is that the electricity market is a perfectly competitive market, with firms acting as “price takers”. The prices for cross-border trading are determined by perfect competition, which can be modelled through a centralized optimization problem. Perfect competition is an efficient way to allocate resources and can be achieved through the establishment of a single-price auction system and improved supervision and regulation. Currently, many real-world electricity markets are undergoing reforms to become perfectly competitive. For example, the European Union (EU) has implemented numerous policies and directives over the past few decades to transform its cross-border electricity market into a perfectly competitive one. These policies include subjecting all cross-border trades to at least one negotiated third party, allowing individual EU member states to select the most competitive contract plans, and granting all generators

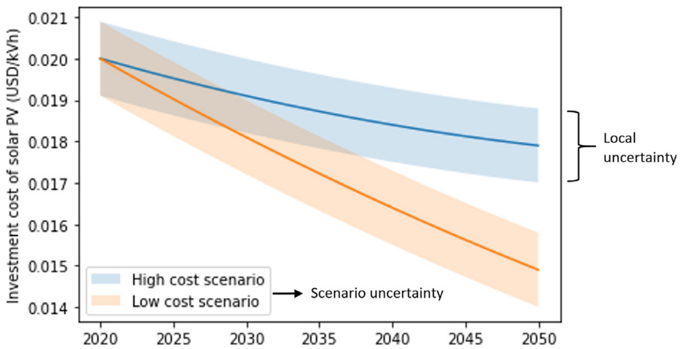

Fig. 1. Scenario and local uncertainties of investment cost of solar PV.

free entry into a wholesale market arrangement. Market reforms in the United States and Europe indicate that measures to mitigate market power, designed to create competitive markets, are effective in improving market efficiency (CASIO, 2012; DG ENERGY, 2012; PJM, 2012).

Our study contributes to the literature in the following four aspects. Firstly, the proposed stochastic-robust optimization approach can address both scenario and local uncertainties simultaneously in power system planning, even when there are ambiguous probability distributions. Secondly, we prove that the Mathematical Program with Equilibrium Constraints (MPEC) problem under the stochastic-robust setting is equivalent to a centralized optimization problem. Thirdly, we reformulate the stochastic-robust optimization model into a mixed-integer linear programming (MILP) model, which can be solved efficiently using commercially-available platforms. Lastly, we apply the proposed model to identify the long-term transmission and generation expansion plan in the ASEAN power system.

The remainder of this paper is organized as follows. Section 2 provides a literature review of optimization models for inter-regional capacity expansion planning. Section 3 presents the problem statement and underlying assumptions. Section 4 introduces the model formulation, while Section 5 illustrates the model solving approach. In Section 6, the model is applied to a case study of the ASEAN power system. Finally, Section 7 concludes the work and proposes some future extensions.

2. Literature review

Capacity expansion optimization model is a commonly-used tool for medium- to long-term power system planning. Recently, the model has been increasingly applied to the inter-regional power system to identify the cost-optimal transmission and generation capacity expansion plan (Guerra et al., 2016; He et al., 2016; Li et al., 2020; Maeder et al., 2021; Spyrou et al., 2017; Wang et al., 2020; Zappa et al., 2019). However, the majority of the existing optimization models for power system planning are deterministic models that assume all parameters to be precisely known. However, in real-world power system planning, many parameters, such as natural, social, economic, technical, and political factors, cannot be known with certainty. Thus, these assumptions may not be applicable in real-world scenarios.

To address uncertainties in power system planning, various data uncertainty handling approaches have been developed, with stochastic programming and robust optimization being the most commonly used ones. Stochastic programming is a method that considers multiple possible parameter scenarios and identifies the optimal capacity expansion plan for minimizing expected cost. It has been applied in power system planning in recent years, with examples including Boffino et al. (2019); Dominguez et al. (2020); Ioannou et al. (2019); Li et al. (2016); Munoz et al. (2013); Scott et al. (2020); Seddighi & Ahmadi-Javid (2015); Van Der Weijde & Hobbs (2012), and Domínguez et al. (2021). Stochastic programming has the advantage of considering multiple scenarios and finding optimal plans that strike a compromise between the consequences of various scenarios. However, one shortcoming of this method is the requirement of accurate probability information for parameters, which can be difficult to collect in practice. Distributionally-robust optimization (DRO) approach, an extension of stochastic programming, has been increasingly used to tackle uncertainty with ambiguous probability distributions. The approach involves designing an ambiguity set of distributions and aims to protect the model against the worst distribution within that set. Recent applications of DRO in power system planning include Pozo et al. (2018); Velloso et al. (2020), and Guevara et al. (2020).

Robust optimization is another popular approach for data uncertainty handling, and has been increasingly applied for power system planning (Ahmadi et al., 2020; Fanzeres et al., 2019; Kang et al., 2020; Mínguez & García-Bertrand, 2016; Moreira et al., 2021; Ramirez et al., 2020; Roldán et al., 2018; Street et al., 2011; Zugno & Conejo, 2015). This approach needs less uncertainty information than stochastic programming and is applicable when the probability information of uncertain parameters is unknown. However, the solutions yielded by robust optimization can be too conservative as the approach only looks at the worst-case parameter scenario. Given the advantages of stochastic programming and robust optimization, the two approaches have been combined to address scenario and local uncertainties in energy system planning (Abedinia et al., 2019; Brigatto & Fanzeres, 2022; El-Meligy & El-Sherbeeny, 2022; Fanzeres et al., 2014; Zhong et al., 2021). The combined approach can be termed as “stochastic-robust” optimization approach. This approach allows for more comprehensive data uncertainty information to be considered compared to using either stochastic programming or robust optimization alone, leading to a more reliable solution. Although the stochastic-robust optimization approach has been applied to energy system planning, it has rarely been used to address the uncertainties of cost, demand, and resource availability in power system planning under ambiguous probability distributions.

In addition to the above, it is worth noting that inter-regional power system planning models are typically performed in a centralized manner where a central planner makes all decisions. However, in today’s restructured power markets, generation capacity expansion, operation, and trading decisions are mostly decentralized. To address this situation, equilibrium expansion models have been extensively used for decentralized capacity expansion planning, assuming that every region is a selfish stakeholder seeking only its own benefit. Equilibrium expansion models can be performed under either imperfect competition or perfect competition assumptions. Recent equilibrium expansion studies under imperfect competition include Ambrosius et al. (2020); Kasina & Hobbs (2020); Pozo et al. (2012), and Egerer et al. (2021), in which the expansion problems are formulated as multilevel imperfectly competitive Stackelberg models. In this paper, we focus on equilibrium expansion problems under perfect competition. The problem can be generally transformed into a single-objective centralized optimization problem, which can be easily solved using state-of-the-art solvers. However, previous studies have only proven that the equivalence condition holds in the context of deterministic optimization (Boucher & Smeers, 2001; Gurkan et al., 2013; Özdemir et al., 2015), stochastic programming (Ozdemir, 2013), and robust optimization (Biefel et al., 2022; Çelebi et al., 2021; Krebs et al., 2022; Krebs & Schmidt, 2020). Our paper contributes to this area by proving the equivalence between the market equilibrium problem and centralized optimization problem under the stochastic-robust setting.

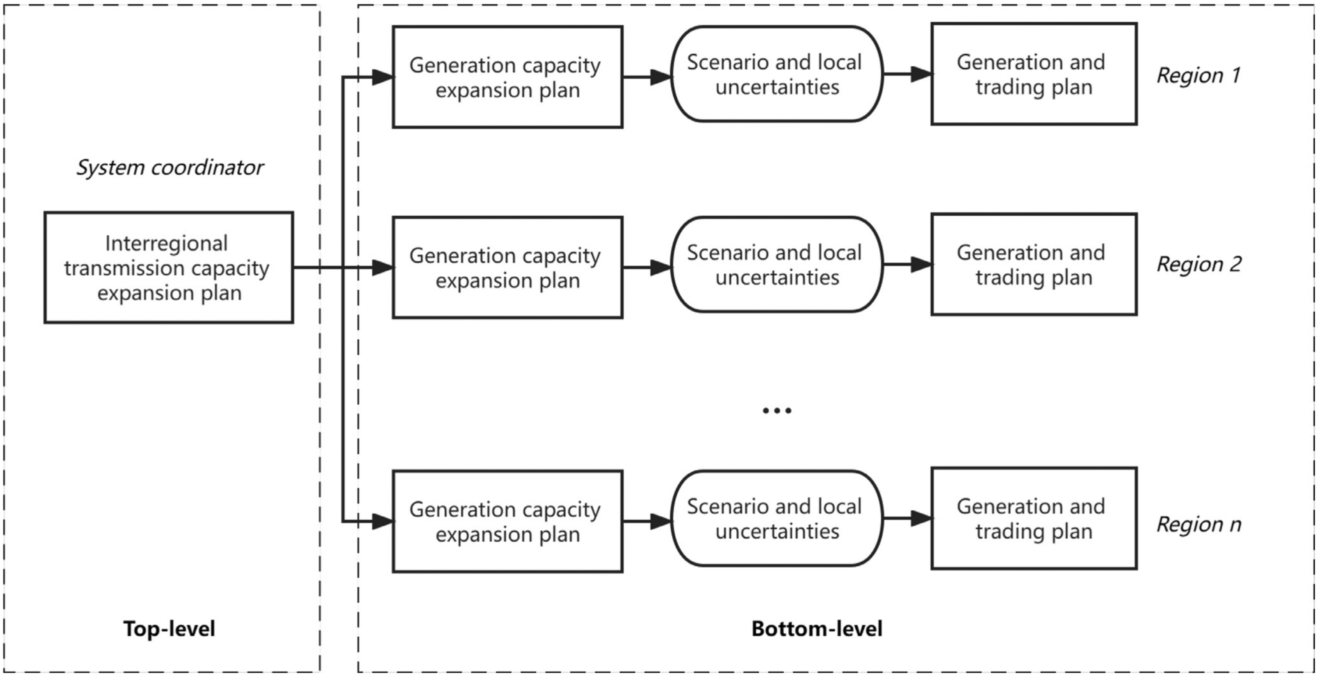

Fig. 2. Decision making process in interregional power system expansion problem.

3. Problem statement and assumptions

We consider an inter-regional transmission and generation expansion problem, where the overall decision process flow is illustrated in Fig. 2. At the top-level, the system operator determines the cross-border transmission capacity expansion plan and trading prices for the minimization of total system cost, by anticipating the response of the generators in the various regions. For a given cross-border transmission capacity plan, generators at the bottom-level first determine their respective generation capacity plans before the observation of data uncertainties, and then make the operation and trading decisions after the observation of data uncertainties, to minimise their own respective costs.

In practice, trading is usually performed in an electricity market, facilitated by a market operator. Examples of large scale electricity spots markets covering several zones include the European power exchange (Biskas et al., 2014) and Nord pool (Jani et al., 2022). In such markets, participants submit their bids on the trading platform, and typically, a centralized optimization-based market clearing model is solved by the market operator, who then announces the market clearing prices and the generation dispatch. The centralized optimization problem depicts a perfectly competitive environment, and incentivizes efficient participants. The market trading prices in turn guide capacity investments for each region, who behaves in a self-interested manner and optimises it's capacity investment decisions to minimise his own costs. We remark that our work focuses on the optimal cross-border transmission capacity expansion under uncertainty, and hence does not address the determination of the actual trading prices in detail (which require consideration of many technical requirements such as ramping constraints, etc.). In reality, the actual trading prices in each round should be solved by a final market clearing model separately. Nevertheless, our model does embed some features of the optimization-based market clearing models as mentioned above, particularly in the bottom-level problem in Fig. 2, where the generation trading plans for each region are determined under uncertainty. Specifically, we show that solving a centralized optimization problem modelling the overall decision process in Fig. 2 yields trading prices that result in a market equilibrium for all the regions jointly. Finally, although we represent each region by a single node, each node can be further disaggregated into sub-regions or even at the generation company level, and the same modelling structure still applies. Scenario and local uncertainties are considered for various parameters, including variable cost of electricity generation, fixed cost of generating capacity, power demand, and resource availability.

4. Model formulation

Based on the above context, in this section, an MPEC with stochastic-robust approach is developed for the problem. In the following, the data uncertainty sets are first defined. Next, the model formulations are presented, followed by an introduction of the model solution approach. The notations used throughout the entire paper are summarized in Nomenclatures. A variable missing a certain index denotes the vector or matrix containing all the items corresponding to the index, e.g., $y_r = (y_{r,t,k})_{t\in T, k\in K}$.

4.1. Modelling the data uncertainties

We state the following key assumptions on the uncertainty models that are used in the rest of the paper. These assumptions enable some technical results and tractable optimization problems to be derived subsequently.

Assumption 4.1. We assume that there is a common reference set of K scenarios considered in the problem by all regions.

Assumption 4.2. We assume that all data uncertainty sets are independently defined by each region, and are uncorrelated across regions. The data uncertainty sets are also assumed to be known (or made known) to the system operator.

The Assumption 4.1 above can be reasonable in practice, for instance, in the case where different regions take reference to a standard and reputable publication on future energy outlook scenarios. The set K can also be simulated by the system operator by combining projections from the different regions of interest. For

Assumption 4.2, a practical example is when each region considers uncertainty sets based on marginal distributions of uncertain parameters for its own region, and hence the choice of uncertain parameters in one region does not influence the choice of uncertain parameters in the other regions.

We denote the variable cost of electricity generation, fixed cost of generating capacity, power demand, and resource availability as C^{gen}, C^{geninv}, y, and α respectively. Suppose K parameter scenarios are made for those uncertain parameters, of which the probability distribution is defined as $\mathbb{P}_r = \{P_{r,k}, \forall k \in K\}, \ \forall r, \in R$. $\mathbb{P}_r$ itself is with uncertainty, which lies in an arbitrary polyhedral uncertainty set $\mathscr{F}_r$ as follow:

$$\mathscr{F}_r = \left\{ \mathbb{P}_r = \{P_{r,k} \geq 0\} \middle| \sum_k A_{r,k} P_{r,k} \leq B_r, \sum_{k \in K} P_{r,k} = 1 \right\}, \forall r \in R \quad (1)$$

where $A_{r,k}$ and B_r are suitably defined vectors of appropriate dimension to support ambiguity set $\mathscr{F}_r$. The supporting information in $\mathscr{F}_r$ could include, for example, the lower and upper bounds of scenario weights, expected technology costs, expected power demand, and expected resource availability. Suppose the uncertain parameter in each given parameter scenario is further associated with local uncertainty. Denote $\omega_{r,k} = \{C^{gen}_{r,k}, C^{geninv}_{r,k}\}$ as the vector of uncertain cost parameters. The local uncertainty set of $\omega_{r,k}$ is expressed as:

$$\Omega_{r,k} = \left\{ \omega_{r,k} \middle| \begin{array}{ll} \underline{C}^{gen}_{j,r,t,k} \leq C^{gen}_{j,r,t,k} \leq \bar{C}^{gen}_{j,r,t,k}, \ \forall j \in J, t \in T & (a) \\ \underline{C}^{geninv}_{j,r,t,k} \leq C^{geninv}_{j,r,t,k} \leq \bar{C}^{geninv}_{j,r,t,k}, \ \forall j \in J, t \in T & (b) \\ \sum_{t \in T} \sum_{j \in J} \left(C^{gen}_{j,r,t,k} + C^{geninv}_{j,r,t,k} \right) \leq \Gamma^C_{r,k} & (c) \end{array} \right\}, \forall r \in R, k \in K \quad (2)$$

where $\Omega_{r,k}$ represents the set of an infinite number of cost parameter realizations in region r in scenario k. Constraints (2a) and (2b) set upper and lower bounds of cost parameters of generation technologies. Constraint (2c) states that the summation of variable and fixed cost parameters of various technologies over the entire modelling period should be bounded by a certain uncertainty budget $\Gamma^C_{r,k}$. The uncertainty budget reflects the decision-makers' tolerance of cost uncertainty while making strategic plans. Similarly, denote $\phi_{r,k} = \{y_{r,k}, \alpha_{r,k}\}$ as the vector of uncertain demand and resource availability. We consider both scenario and local uncertainties for the demand and availability. However, we assume that the operational decisions adapt to the scenarios, but need to be robust against local uncertainties. For each scenario k, the uncertainty set of $\phi_{r,k}$ is generalised as:

$$\Phi_{r,k} = \left\{ \phi_{r,k} \middle| \begin{array}{l} \sum_{t \in T} y_{r,t,k} \leq \Gamma^y_{r,k} \\ \sum_{t \in T} \alpha_{j,r,t,k} \geq \Gamma^\alpha_{j,r,k}, \ \forall j \in J \\ \underline{y}_{r,t,k} \leq y_{r,t,k} \leq \bar{y}_{r,t,k}, \ \forall t \in T \\ \underline{\alpha}_{j,r,t,k} \leq \alpha_{j,r,t,k} \leq \bar{\alpha}_{j,r,t,k}, \ \forall j \in J, t \in T \\ y_{r,k}, \alpha_{r,k} \geq 0 \end{array} \right\}, \forall r \in R, k \in K \quad (3)$$

where $\Phi_{r,k}$ represents the set of an infinite number of demand and resource availability realizations in region r in scenario k; $\underline{y}$ and $\bar{y}$ are the lower and upper bounds of power demand; $\underline{\alpha}$ and $\bar{\alpha}$ are the lower and upper bounds of resource availability; $\Gamma^y_{r,k}$ and $\Gamma^\alpha_{j,r,k}$ are the uncertainty budgets of demand and availability variations.

4.2. Bottom-level problem

The bottom-level problem is a generation expansion equilibrium problem under data uncertainty. In the problem, the cross-border transmission capacity (u) and trading prices (p^{buy}, p^{sell}) are considered as exogenous parameters as they have already been determined in the top-level problem.

In this work, the decision-maker for each region is assumed to be uncertainty-averse, so that they tend to make their generation capacity investment plan for the minimization of worst-case costs under uncertainty. The problem for each individual region can then be formulated as a multi-stage optimization problem as follows:

$$\begin{aligned} & Cost_r\left(u, p^{buy}, p^{sell}\right) \\ & = \min_{h_r \in \mathscr{H}_r} \max_{\mathbb{P}_r \in \mathscr{F}_r} \mathbb{E}_{\mathbb{P}_r}\Bigg[\max_{\omega_{r,k} \in \Omega_{r,k}} \min_{z_{r,k} \in \mathscr{Z}_{r,k}} \Bigg(\sum_{t \in T} \sum_{j \in J} C^{geninv}_{j,r,t,k} h_{j,r,t} \\ & + \sum_{t \in T} \sum_{j \in J} C^{gen}_{j,r,t,k} x_{j,r,t,k} \\ & + \sum_{t \in T} \sum_{r' \in R} \left(p^{buy}_{r,r',t,k} b_{r,r',t,k} - p^{sell}_{r,r',t,k} s_{r,r',t,k} \right) \Bigg) \Bigg], \forall r \in R \end{aligned} \quad (4)$$

In the first stage, the investment decision of electricity generator (h_r) is made before the realization of data uncertainty. In the second stage, the probability weights of parameter scenarios ($\mathbb{P}_r$) are realized. In the third stage, the worst-case cost parameter ($\omega_{r,k}$) in each scenario is realized. In the fourth stage, the generation and trading decision ($z_{r,k}$) in each region is made under the worst-case demand and resource availability. In the last stage, the demand and resource availability ($\phi_{r,k}$) are realized. We assume here that the operational decisions $z_{r,k}$ can adapt to the local uncertainties in costs $\omega_{r,k}$, but not adapt to the local uncertainties in demand and availability $\phi_{r,k}$. We make this assumption because the update cycle of technology cost (e.g., months or years) is usually much longer than the update cycle of demand and availability (e.g., hours or days). Therefore, it is reasonable to assume that the operation decision $z_{r,k}$ is made after the observation of cost uncertainty, but before the observation of demand and availability uncertainty (e.g., day-ahead market). Objective function (4) aims to minimize the worst-case expected cost in region r. The cost components include the fixed cost of generating capacity[1], the variable cost of electricity generation, and the electricity trading cost. Here our assumption is that each region is a fairly simple decision agent optimising based on a static expansion plan. This means that the investment decisions are made once at the very beginning of the time horizon. Admittedly, dynamic programming could better reflect the real decision process under multi-period uncertainty (Kang et al., 2020; Marañón-Ledesma & Tomasgard, 2019). However, two stage adjustable robust optimization is in general difficult to solve (Yanıkoğlu et al., 2019). For the dynamic case, the nonlinear (discrete) nature of the expansion variables poses further computational challenges for such approaches (Iancu et al., 2013). Based on this practical consideration, we choose to use static expansion model instead of dynamic expansion model to keep the model tractable, following many other practices (Dominguez et al., 2020; Moreira et al., 2021; Scott et al., 2021; Yin et al., 2021).

h_r is the vector of generating capacity in region r, of which the set can be expressed as:

$$\mathscr{H}_r = \left\{ h_r \geq 0 \middle| \begin{array}{ll} \exists \Delta h_r : h_{j,r,0} = \hat{h}_{j,r}, \ \forall j \in J, & (a) \\ h_{j,r,t} = h_{j,r,t-1}(1 - e_j) + \Delta h_{j,r,t} N, \ \forall j \in J, t \in T, & (b) \\ h_{j,r,t} \leq \bar{h}_{j,r,t}, \ \forall j \in J, t \in T, & (c) \\ \Delta h_r \in Z^+, & (d) \end{array} \right\}, \forall r \in R \quad (5)$$

Constraint (5a) sets a fixed value on the generating capacity of technology j in region r in the initial modelling period. Constraint (5b) claims that the generating capacity in period t should equal to

[1] The fixed cost of generation and transmission capacity is not counted at once, but is annualized over the entire life time of capacity to make the fixed and variable costs comparable with each other.

the capacity in period $t-1$ minus capacity depreciation and plus capacity addition (ΔhN) in period t. N denotes the minimum addition in generation capacity. Constraint (5c) claims that the generating capacity of technology in each modelling period should be constrained by certain upper bound $\bar{h}_{j,r,t}$ because of the limitation in exploitable resources, land spaces and investment budget. Constraint (5d) states that the number of capacities to build is a non-negative integer.

The generation and trading decisions in region r are denoted by vector $z_r = \{x_r, b_{r,r'}, s_{r,r'}\}_{\forall r' \in R}$. $\mathscr{Z}_{r,k}$ is the set of $z_{r,k}$, which can be expressed as:

$$\mathscr{Z}_{r,k} = \left\{ z_{r,k} \geq 0 \left| \begin{array}{ll} y_{r,t,k} \leq \sum_{j\in J} x_{j,r,t,k} + \sum_{r'\in R} b_{r,r',t,k} - \sum_{r'\in R} s_{r,r',t,k}, & \\ \forall y_{r,t,k} \in \Phi_{r,k}, \forall t \in T & (a) \\ \sum_{j\in J} f_{j,r,t} x_{j,r,t,k} \leq CO_{2\ r,t}, \ \ \forall t \in T & (b) \\ x_{j,r,t,k} \leq \alpha_{j,r,t,k} h_{j,r,t}, \ \ \forall \alpha_{j,r,t,k} \in \Phi_{r,k}, \forall j \in J, t \in T & (c) \\ s_{r,r',t,k} \leq u_{r,r',t}, \ \ \forall r' \in R, t \in T & (d) \\ b_{r,r',t,k} \leq s_{r',r,t,k}, \ \ \forall r' \in R, t \in T & (e) \\ s_{r,r',t,k} \geq b_{r',r,t,k}, \ \ \forall r' \in R, t \in T & (f) \end{array} \right. \right\}, \forall r \in R, k \in K \tag{6}$$

We assume that the feasible set of operational decisions $\mathscr{Z}_{r,k}$ must be feasible to all local uncertainties of demands and availability $\phi_{r,k} \in \Phi_{r,k}$. Constraint (6a) is the supply-demand balance constraint, claiming that electricity demand should never exceed domestic electricity output plus electricity import and minus electricity export under all the possible realizations of demand $y_{r,t,k} \in \Phi_{r,k}$. Constraint (6b) states that the annual CO_2 emissions in the region should not exceed certain predefined emissions targets ($CO_{2\ r,t}$). The CO_2 emissions are calculated based on the emissions intensity and production output of various generation technologies. Constraint (6c) states that the generation output of each generation technology is limited by the maximum output of capacity under all the possible realizations of resource availability $\alpha_{j,r,t,k} \in \Phi_{r,k}$. The maximum output of capacity can be calculated as a multiplication of total generating capacity (in unit of kWh per year) and resource availability (α). Constraint (6d) states that the electricity trading amount in each region should be constrained by the available transmission capacity (u). Constraints (6e) and (6f) state that the electricity amount region r is willing to buy from region r' should never exceed the electricity amount region r' is willing to sell to region r. Note that variables $b_{r',r}, s_{r',r}, \forall r' \in R$ are the decision variables in region r', and constraints (6e) and (6f) are coupling constraints among the optimization problems in various regions. The simultaneous optimization for all regions lead to an market equilibrium problem in the bottom-level.

$$\mathscr{U} = \left\{ u \geq 0 \left| \begin{array}{ll} \exists \Delta u : u_{r,r',0} = \hat{u}_{r,r'}, \ \ \forall r \in R, r' \in R, & (a) \\ u_{r,r',t} = u_{r,r',t-1}(1-a) + \Delta u_{r,r',t} M, \ \ \forall r \in R, r' \in R, t \in T, & (b) \\ \Delta u_{r,r',t} = \Delta u_{r',r,t}, \ \ \forall r \in R, r' \in R, t \in T, & (c) \\ u_{r,r',t} \leq \bar{u}_{r,r',t}, \ \ \forall r \in R, r' \in R, t \in T, & (d) \\ \Delta u \in Z^+ & (e) \end{array} \right. \right\} \tag{8}$$

4.3. Top-level problem

In the top-level problem, a system operator chooses cross-border transmission capacity (u) and electricity trading prices (p^{buy}, p^{sell}) that minimize the total cost of the entire system by anticipating how the regional planners will react by expanding the generation capacities and making operating and trading decisions. The trading prices are modelled by solving a centralized optimization model that will be introduced later. The top-level problem can be formulated as:

$$\min_{u\in\mathscr{U}, p^{buy}, p^{sell}} \quad \sum_{r\in R} Cost_r\left(u, p^{buy}, p^{sell}\right) \tag{7a}$$

$$\text{s.t.} \qquad \text{The optimal conditions of problem (4)}, \ \forall r \in R \tag{7b}$$

Objective function (7a) aims to minimize the total system costs[2]. The system operator is assumed to be a benevolent planner, which invests and manages the cross-border transmission lines in the best interest of the entire system (Ambrosius et al., 2020; Kasina & Hobbs, 2020; Sauma & Oren, 2006). Constraint (7b) states that the generating investment and trading variables in various regions should satisfy the optimal condition of bottom-level problem (4) for all regions. The decision variables in the top-level problem are cross-border transmission investment u and trading prices p^{buy}, p^{sell}. The feasible set of u can be expressed as:

Constraint (8a) sets the inter-regional transmission capacity in the initial modelling period as $\hat{u}$. Constraint (8b) states that the transmission capacity in period t should equal to the transmission capacity in period $t-1$ minus capacity depreciation and plus transmission capacity addition in period t (ΔuM). M denotes the minimum addition in transmission capacity. Constraint (8c) states that the transmission capacity from region r to region r' should equal to the transmission capacity from region r' to region r. Constraint (8d) sets an upper bound on the transmission capacity in each modelling period. Constraint (8e) states that the number of transmission capacities to build is a non-negative integer.

5. Model solution approach

The MPEC problem (7) is solved in the following way. We first propose a centralized optimization problem in which a central planner decides everything for the minimization of total system cost. Then, we prove that the MPEC problem under perfect competition is equivalent to the centralized problem. Finally, the equivalent centralized problem is transformed into a single-level MILP problem, which can be efficiently solved with the state-of-the-art solver.

5.1. Centralized optimization problem

The centralized optimization problem can be formulated as:

$$\min_{u\in\mathscr{U}, h\in\mathscr{H}} \max_{\mathbb{P}\in\mathscr{F}} \mathbb{E}_{\mathbb{P}}\left[\max_{\omega_k\in\Omega_k} \min_{z_k\in\mathscr{Z}_k} \left(\sum_{t\in T}\sum_{r\in R}\sum_{j\in J} C^{geninv}_{j,r,t,k} h_{j,r,t} + \sum_{t\in T}\sum_{r\in R}\sum_{j\in J} C^{gen}_{j,r,t,k} x_{j,r,t,k} + \sum_{t\in T}\sum_{r\in R}\sum_{r'\in R} C^{tran} b_{r,r',t,k} \right)\right] \tag{9}$$

[2] The central system operator pays for the investment cost of cross-border transmission lines by collecting transmission service fee from the various agents. The collected transmission service fee is included in the trading costs as the congestion rents resulting from the cross-border trade are non-zero.

The objective function aims to minimize the total costs in the system, including the investment cost, generation cost, and transmission service fee. The transmission service fee ($C^{tran} b_{r,r',t,k}$) is collected from various regions to cover the investment cost of cross-border transmission lines. C^{tran} is the unit transmission service fee, denoting the fee to be paid for transmitting one unit of electricity. $\mathscr{H} = \{h \ |h_r \in \mathscr{H}_r, \forall r \in R\}$, $\mathscr{F} = \{\mathbb{P} \ |\mathbb{P}_r \in \mathscr{F}_r, \forall r \in R\}$, $\Omega_k = \{\omega_k \ |\omega_{r,k} \in \Omega_{r,k}, \forall r \in R\}$, and $\Phi_k = \{\phi_k \ |\phi_{r,k} \in \Phi_{r,k}, \forall r \in R\}$. Define $z_k = \{x_k, b_k, s_k\}$. $\mathscr{Z}_k$ is the set of z_k in the centralized optimization problem, which can be expressed as:

$$\mathscr{Z}_k = \left\{ z_k \geq 0 \left| \begin{array}{ll} y_{r,t,k} \leq \sum_{j\in J} x_{j,r,t,k} + \sum_{r'\in R} b_{r,r',t,k} - \sum_{r'\in R} s_{r,r',t,k}, & \\ \forall y_{r,t,k} \in \Phi_k, \forall t \in T, r \in R & (\epsilon'_{r,t,k})(a) \\ \sum_{j\in J} f_{j,r,t} x_{j,r,t,k} \leq CO2_{r,t}, \ \ \forall t \in T, r \in R, & (b) \\ x_{j,r,t,k} \leq \alpha_{j,r,t,k} h_{j,r,t}, \ \ \forall \alpha_{j,r,t,k} \in \Phi_k, \forall j \in J, t \in T, r \in R, & (c) \\ s_{r,r',t,k} \leq u_{r,r',t}, \ \ \forall r' \in R, r \in R, t \in T, & (\eta'_{r,r',t,k})(d) \\ b_{r,r',t,k} = s_{r',r,t,k}, \ \ \forall r' \in R, r \in R, t \in T, & (e) \end{array} \right. \right\} \forall k \in K \tag{10}$$

The feasible set of operational decisions $\mathscr{Z}_k$ must be feasible to all local uncertainties of demands and availability $\phi_k \in \Phi_k$. $\epsilon'_{r,t,k}$ and $\eta'_{r,r',t,k}$ are the dual variables corresponding to constraints (10a) and (10d). Both dual variables have classical interpretations in the energy economics literature. $\epsilon'_{r,t,k}$ can be interpreted as nodal price, while $\eta'_{r,r',t,k}$ can be interpreted as congestion price. In the following subsection, we will illustrate how to use the optimal values of nodal and congestion prices obtained by solving the centralized problem (9) to construct a set of feasible equilibrium prices in MPEC problem (7).

5.2. Equivalence between MPEC and centralized problem

In the following, we show that the MPEC problem (7) is equivalent to the centralized optimization problem (9) under perfect competition.

Proposition 5.1. *The solution of MPEC problem (7) coincides with the solution of centralized optimization problem (9) in a perfectly competition market, i.e., the trading prices in (7) are set as* $(p^{buy}, p^{sell}) := (p^{buy'}, p^{sell'})$*, where* $p^{buy'}_{r,r',t,k} = \hat{\epsilon}'_{r,t,k}$ *and* $p^{sell'}_{r,r',t,k} = \hat{\epsilon}'_{r,t,k} + \hat{\eta}'_{r,r',t,k}, \forall r, r' \in R, t \in T, k \in K$*, and* $\hat{\epsilon}'$ *and* $\hat{\eta}'$ *are the optimal solutions of dual variables* ϵ' *and* η' *by solving the centralized problem (9).*

Proof. In order to prove the equivalence between (7) and (9), we starts by showing the equivalence between their inner-most problems. Since we assume that the region operational decisions do not adapt to the local uncertainties of demand and availability, the worst-case value of y and α in each time period will always be the upper or lower bounds, i.e., $\bar{y}$ and $\underline{\alpha}$. Hence, the inner-most minimization problem on $z_{r,k} \in \mathscr{Z}_{r,k}$ in (7) can be equivalently transformed into the minimization problem on $z_{r,k} \in \mathscr{Z}_{r,k}(\bar{y}_{r,k}, \underline{\alpha}_{r,k})$, and the inner-most minimization problem on $z_k \in \mathscr{Z}_k$ in (9) can be equivalently transformed into the minimization problem on $z_k \in \mathscr{Z}_k(\bar{y}_k, \underline{\alpha}_k)$. Thus, the inner-most minimization problem in MPEC problem (7) can be rewritten as:

$\forall r \in R, k \in K,$

$$F_r(u, h_r, \omega_{r,k}) = \min_{x_{r,k}, b_{r,k}, s_{r,k}} \left(\sum_{t\in T}\sum_{j\in J} C^{gen}_{j,r,t,k} x_{j,r,t,k} + \sum_{t\in T}\sum_{r'\in R}\left(p^{buy}_{r,r',t,k} b_{r,r',t,k} - p^{sell}_{r,r',t,k} s_{r,r',t,k}\right)\right) \tag{11a}$$

$$\text{s.t.} \ \ \bar{y}_{r,t,k} \leq \sum_{j\in J} x_{j,r,t,k} + \sum_{r'\in R} b_{r,r',t,k} - \sum_{r'\in R} s_{r,r',t,k}, \ \ \forall t \in T \ \ (\epsilon_{r,t,k}) \tag{11b}$$

$$\sum_{j\in J} f_{j,r,t} x_{j,r,t,k} \leq CO2_{r,t}, \ \ \forall t \in T \ \ (\gamma_{r,t,k}) \tag{11c}$$

$$x_{j,r,t,k} \leq \underline{\alpha}_{j,r,t,k} h_{j,r,t}, \ \ \forall j \in J, t \in T \ \ (\zeta_{j,r,t,k}) \tag{11d}$$

$$s_{r,r',t,k} \leq u_{r,r',t}, \ \ \forall r' \in R, t \in T \ \ (\eta_{r,r',t,k}) \tag{11e}$$

$$b_{r,r',t,k} \leq s_{r',r,t,k}, \ \ \forall r' \in R, t \in T \ \ (\sigma_{r,r',t,k}) \tag{11f}$$

$$s_{r,r',t,k} \geq b_{r',r,t,k}, \ \ \forall r' \in R, t \in T \ \ (\hat{\sigma}_{r,r',t,k}) \tag{11g}$$

$$x_{r,k}, b_{r,k}, s_{r,k} \geq 0 \tag{11h}$$

The inner-most minimization problem in (9) can be rewritten as:

$\forall k \in K,$

$$F(u, h, \omega_k) = \min_{x_k, b_k, s_k} \left(\sum_{r\in R}\sum_{t\in T}\sum_{j\in J} C^{gen}_{j,r,t,k} x_{j,r,t,k} + \sum_{t\in T}\sum_{r\in R}\sum_{r'\in R} C^{tran} b_{r,r',t,k} \right) \tag{12a}$$

$$\text{s.t.} \ \ \bar{y}_{r,t,k} \leq \sum_{j\in J} x_{j,r,t,k} + \sum_{r'\in R} b_{r,r',t,k} - \sum_{r'\in R} s_{r,r',t,k}, \ \ \forall r \in R, t \in T \ \ (\epsilon'_{r,t,k}) \tag{12b}$$

$$\sum_{j\in J} f_{j,r,t} x_{j,r,t,k} \leq CO2_{r,t}, \ \ \forall r \in R, t \in T \ \ (\gamma'_{r,t,k}) \tag{12c}$$

$$x_{j,r,t,k} \leq \underline{\alpha}_{j,r,t,k} h_{j,r,t}, \ \ \forall r \in R, j \in J, t \in T \ \ (\zeta'_{j,r,t,k}) \tag{12d}$$

$$s_{r,r',t,k} \leq u_{r,r',t}, \ \ \forall r \in R, r' \in R, t \in T \ \ (\eta'_{r,r',t,k}) \tag{12e}$$

$$b_{r,r',t,k} \leq s_{r',r,t,k}, \ \ \forall r \in R, r' \in R, t \in T \ \ (\sigma'_{r,r',t,k}) \tag{12f}$$

$$s_{r,r',t,k} \geq b_{r',r,t,k}, \ \ \forall r \in R, r' \in R, t \in T \ \ (\hat{\sigma}'_{r,r',t,k}) \tag{12g}$$

$$x_k, b_k, s_k \geq 0 \tag{12h}$$

where $\epsilon_r, \gamma_r, \zeta_r, \eta_r, \sigma_r, \hat{\sigma}_r$ are the dual variables of (11), and $\epsilon', \gamma', \zeta', \eta', \sigma', \hat{\sigma}'$ are the dual variables of (12). To show the equivalence between (11) and (12), the following claim is given.

Claim 1. *At the optimum of centralized optimization problem (9), the following equality must holds.*

$$\sum_{r\in R}\sum_{r'\in R} C^{tran} b_{r,r',t,k} = \sum_{r\in R}\sum_{r'\in R}\left(p^{buy'}_{r,r',t,k} b_{r,r',t,k} - p^{sell'}_{r,r',t,k} s_{r,r',t,k}\right), \quad \forall t\in T, k\in K \tag{13}$$

Proof. See Appendix A □

According to Claim 1, problem (12) can be rewritten into the following form.

$$F(u,h,\omega_k) = \min_{z_k\in\mathscr{Z}_k(\omega_k,\phi_k)}\left(\sum_{r\in R}\sum_{t\in T}\sum_{j\in J} C^{gen}_{j,r,t,k} x_{j,r,t,k} + \sum_{t\in T}\sum_{r\in R}\sum_{r'\in R}\left(p^{buy'}_{r,r',t,k} b_{r,r',t,k} - p^{sell'}_{r,r',t,k} s_{r,r',t,k}\right)\right), \forall k\in K \tag{14}$$

The Lagrangian function of (14) can be written as:
$\forall k\in K$,

$$\begin{aligned}
&\mathscr{L}_k\left(z_k,\epsilon'_k,\gamma'_k,\zeta'_k,\eta'_k,\sigma'_k,\hat{\sigma}'_k\right)\\
&= \sum_{r\in R}\sum_{t\in T}\sum_{j\in J} C^{gen}_{j,r,t,k} x_{j,r,t,k}\\
&+ \sum_{t\in T}\sum_{r\in R}\sum_{r'\in R}\left(p^{buy'}_{r,r',t,k} b_{r,r',t,k} - p^{sell'}_{r,r',t,k} s_{r,r',t,k}\right)\\
&+ \sum_{r\in R}\sum_{t\in T}\sum_{j\in J}\epsilon'_{r,t,k}\Bigg(\sum_{j\in J} x_{j,r,t,k} + \sum_{r\in R}\sum_{t\in T}\sum_{j\in J}\sum_{r'\in R} b_{r,r',t,k}\\
&- \sum_{r'\in R} s_{r,r',t,k} - \bar{y}_{r,t,k}\Bigg)\\
&+ \sum_{r\in R}\sum_{t\in T}\sum_{j\in J}\gamma'_{r,t,k}\left(CO2_{r,t} - \sum_{j\in J} f_{j,r,t} x_{j,r,t,k}\right)\\
&+ \sum_{r\in R}\sum_{t\in T}\sum_{j\in J}\zeta'_{j,r,t,k}\left(\underline{\alpha}_{j,r,t,k} h_{j,r,t} - x_{j,r,t,k}\right)\\
&+ \sum_{r\in R}\sum_{r'\in R}\sum_{t\in T}\eta'_{r,r',t,k}\left(u_{r,r',t} - s_{r,r',t,k}\right)\\
&+ \sum_{r\in R}\sum_{r'\in R}\sum_{t\in T}\sum_{j\in J}\sigma'_{r,r',t,k}\left(s_{r',r,t,k} - b_{r,r',t,k}\right)\\
&+ \sum_{r\in R}\sum_{r'\in R}\sum_{t\in T}\sum_{j\in J}\hat{\sigma}'_{r,r',t,k}\left(s_{r,r',t,k} - b_{r',r,t,k}\right)
\end{aligned} \tag{15}$$

On the other side, the Lagrangian function of (11) can be written as:
$\forall r\in R, k\in K$,

$$\begin{aligned}
&\mathscr{L}_{r,k}\left(z_{r,k},\epsilon_{r,k},\gamma_{r,k},\zeta_{r,k},\eta_{r,k},\sigma_{r,k},\hat{\sigma}_{r,k}\right)\\
&= \sum_{t\in T}\sum_{j\in J} C^{gen}_{j,r,t,k} x_{j,r,t,k}\\
&+ \sum_{t\in T}\sum_{r\in R}\sum_{r'\in R}\left(p^{buy}_{r,r',t,k} b_{r,r',t,k} - p^{sell}_{r,r',t,k} s_{r,r',t,k}\right)\\
&+ \sum_{t\in T}\sum_{j\in J}\epsilon_{r,t,k}\Bigg(\sum_{j\in J} x_{j,r,t,k} + \sum_{t\in T}\sum_{j\in J}\sum_{r'\in R} b_{r,r',t,k}\\
&- \sum_{r'\in R} s_{r,r',t,k} - \bar{y}_{r,t,k}\Bigg)\\
&+ \sum_{t\in T}\sum_{j\in J}\gamma_{r,t,k}\left(CO2_{r,t} - \sum_{j\in J} f_{j,r,t} x_{j,r,t,k}\right)\\
&+ \sum_{t\in T}\sum_{j\in J}\zeta_{j,r,t,k}\left(\underline{\alpha}_{j,r,t,k} h_{j,r,t} - x_{j,r,t,k}\right)\\
&+ \sum_{r'\in R}\sum_{t\in T}\eta_{r,r',t,k}\left(u_{r,r',t} - s_{r,r',t,k}\right)\\
&+ \sum_{r'\in R}\sum_{t\in T}\sum_{j\in J}\sigma_{r,r',t,k}\left(s_{r',r,t,k} - b_{r,r',t,k}\right)\\
&+ \sum_{r'\in R}\sum_{t\in T}\sum_{j\in J}\hat{\sigma}_{r,r',t,k}\left(s_{r,r',t,k} - b_{r',r,t,k}\right)
\end{aligned} \tag{16}$$

Through deriving the first-order optimality conditions of $\mathscr{L}_k$ and $\sum_{r\in R}\mathscr{L}_{r,k}$ respectively, it can be clearly seen that (11) and (12) share the same form of KKT conditions. Therefore, the equilibrium solution of problem (11) coincides with the optimal solution of the centralized problem (12) under the condition that $(p^{buy}, p^{sell}) = (p^{buy'}, p^{sell'})$. Therefore, we have

$$F(u,h,\omega_k) = \sum_{r\in R} F_r\left(u,h_r,\omega_{r,k},\phi_{r,k}\middle|\left(p^{buy},p^{sell}\right) = \left(p^{buy'},p^{sell'}\right)\right), \quad \forall k\in K \tag{17}$$

Note that problem (9) can be written into the following simplified form.

$$\min_{u\in\mathscr{U}}\min_{h\in\mathscr{H}}\max_{\mathbb{P}\in\mathscr{F}}\mathbb{E}_{\mathbb{P}}\left[\max_{\omega_k\in\Omega_k}\left(\sum_{r\in R}\sum_{t\in T}\sum_{j\in J} C^{geninv}_{j,r,t,k} h_{j,r,t} + F(u,h,\omega_k)\right)\right]\Bigg) \tag{18}$$

Because of the equality condition we have obtained in (17), (18) can be equivalently transformed into the following problem.

$$\min_{u\in\mathscr{U}}\min_{h\in\mathscr{H}}\max_{\mathbb{P}\in\mathscr{F}}\mathbb{E}_{\mathbb{P}}\Bigg[\max_{\omega_k\in\Omega_k,\phi_k\in\Phi_k}\Bigg(\sum_{r\in R}\sum_{t\in T}\sum_{j\in J} C^{geninv}_{j,r,t,k} h_{j,r,t} + \sum_{r\in R} F_r\left(u,h_r,\omega_{r,k}|(p^{buy},p^{sell}) = (p^{buy'},p^{sell'})\right)\Bigg)\Bigg] \tag{19}$$

Observe that $\mathscr{H} = \{h \ |h_r\in\mathscr{H}_r, \forall r\in R\}$, $\mathscr{F} = \{\mathbb{P} \ |\mathbb{P}_r\in\mathscr{F}_r, \forall r\in R\}$, $\Omega_k = \{\omega_k \ |\omega_{r,k}\in\Omega_{r,k}, \forall r\in R\}$, and $\Phi_k = \{\phi_k \ |\phi_{r,k}\in\Phi_{r,k}, \forall r\in R\}$. It means that the cost of one regions only depends on the variables and uncertainty parameters chosen in this region only, and not on the variables and uncertainty parameters chosen in the other regions. A consequence is that the inner min-max-max problems in (19) is decomposable on $r\in R$. Therefore, (19) can be rewritten into the following problem.

$$\min_{u\in\mathscr{U}}\sum_{r\in R}\min_{h_r\in\mathscr{H}_r}\max_{\mathbb{P}_r\in\mathscr{F}_r}\mathbb{E}_{\mathbb{P}_r}\Bigg[\max_{\omega_{r,k}\in\Omega_{r,k}}\Bigg(\sum_{t\in T}\sum_{j\in J} C^{geninv}_{j,r,t,k} h_{j,r,t} + F_r\left(u,h_r,\omega_{r,k}|(p^{buy},p^{sell}) = (p^{buy'},p^{sell'})\right)\Bigg)\Bigg] \tag{20}$$

which becomes exactly the same form of MPEC problem (7) under the condition that $(p^{buy}, p^{sell}) := (p^{buy'}, p^{sell'})$. Therefore, proposition 1 holds. □

We remark that the result in Proposition 1 holds as a consequence of Assumption 4.2. That is, the data uncertainty sets in different regions are uncorrelated with each other. This is termed here as *uncorrelated uncertainty case*. On the other hand, in the case of *correlated uncertainty sets*, the outcome of uncertain parameters in a region may influence the outcomes of the parameters in another. An example of correlated uncertainty sets is given and discussed in Appendix B. We demonstrate that the solution of MPEC problem may not coincide with the solution of centralized optimization problem in the correlated uncertainty case. In other words, the market equilibrium prices computed by solving a centralized optimization problem may not be market clearance prices for a decentralized market under the correlated uncertainty case.

5.3. Solving the centralized optimization problem

The centralized optimization problem (9) can be equivalently transformed into a single-stage MILP problem based on the following proposition. The MILP problem can be efficiently solved using the commercial solver, e.g., *GUROBI* and *CPLEX*.

Proposition 5.2. *Problem (9) can be equivalently transformed into the following single-stage MILP problem (21).*

$$\min_{u,h,x,b,s,\bar{\lambda},\underline{\lambda},\bar{\pi},\underline{\pi},\delta,\mu,\bar{\tau},\underline{\tau}} \quad Cost_{tot} = \sum_{r\in R}(\bar{\tau}_r - \underline{\tau}_r + B_r\mu_r) \tag{21a}$$

$$\text{s.t.} \quad \bar{y}_{r,t,k} \le \sum_{j\in J} x_{j,r,t,k} + \sum_{r'\in R} b_{r,r',t,k} - \sum_{r'\in R} s_{r,r',t,k}, \quad \forall r\in R, t\in T, k\in K \tag{21b}$$

$$\sum_{j\in J} f_{j,r,t} x_{j,r,t,k} \le CO2_{r,t}, \quad \forall r\in R, t\in T, k\in K \tag{21c}$$

$$\begin{aligned}\bar{\tau}_r - \underline{\tau}_r + A_{r,k}\mu_r \ge{}& \Gamma^C_{r,k}\delta_{r,k} + \sum_{t\in T}\sum_{r'\in R} C^{tran} b_{r,r',t,k} \\ &+ \sum_{t\in T}\sum_{j\in J}\Big(\bar{C}^{gen}_{j,r,t,k}\bar{\lambda}_{j,r,t,k} - \underline{C}^{gen}_{j,r,t,k}\underline{\lambda}_{j,r,t,k} \\ &+ \bar{C}^{geninv}_{j,r,t,k}\bar{\pi}_{j,r,t,k} - \underline{C}^{geninv}_{j,r,t,k}\underline{\pi}_{j,r,t,k}\Big), \quad \forall r\in R, k\in K\end{aligned} \tag{21d}$$

$$x_{j,r,t,k} \le \underline{\alpha}_{j,r,t,k} h_{j,r,t}, \quad \forall j\in J, r\in R, t\in T, k\in K \tag{21e}$$

$$b_{r,r',t,k} \le u_{r,r',t}, \quad \forall r\in R, r'\in R, t\in T, k\in K \tag{21f}$$

$$s_{r,r',t,k} \le u_{r,r',t}, \quad \forall r\in R, r'\in R, t\in T, k\in K \tag{21g}$$

$$b_{r,r',t,k} = s_{r',r,t,k}, \quad \forall r\in R, r'\in R, t\in T, k\in K \tag{21h}$$

$$\bar{\lambda}_{j,r,t,k} - \underline{\lambda}_{j,r,t,k} + \delta_{r,k} \ge x_{j,r,t,k}, \quad \forall j\in J, r\in R, t\in T, k\in K \tag{21i}$$

$$\bar{\pi}_{j,r,t,k} - \underline{\pi}_{j,r,t,k} + \delta_{r,k} \ge h_{j,r,t}, \quad \forall j\in J, r\in R, t\in T, k\in K \tag{21j}$$

$$h_{j,r,0} = \hat{h}_{j,r}, \quad \forall j\in J, r\in R \tag{21k}$$

$$h_{j,r,t} = h_{j,r,t-1}(1-e_j) + \Delta h_{j,r,t}N, \quad \forall j\in J, r\in R, t\in T \tag{21l}$$

$$h_{j,r,t} \le \bar{h}_{j,r,t}, \quad \forall j\in J, r\in R, t\in T \tag{21m}$$

$$u_{r,r',0} = \hat{u}_{r,r'}, \quad \forall r\in R, r'\in R \tag{21n}$$

$$u_{r,r',t} = u_{r,r',t-1}(1-a) + \Delta u_{r,r',t}M, \quad \forall r\in R, r'\in R, t\in T \tag{21o}$$

$$\Delta u_{r,r',t} = \Delta u_{r',r,t}, \quad \forall r\in R, r'\in R, t\in T \tag{21p}$$

$$u_{r,r',t} \le \bar{u}_{r,r',t}, \quad \forall r\in R, r'\in R, t\in T \tag{21q}$$

$$\Delta h, \Delta u \in Z^+ \tag{21r}$$

$$u, h, x, b, s, \bar{\lambda}, \underline{\lambda}, \bar{\pi}, \underline{\pi}, \delta, \mu, \bar{\tau}, \underline{\tau} \ge 0 \tag{21s}$$

Proof. See Appendix C □

To guarantee the revenue adequacy of system operator, the following optimization routine is further developed, on top of the capacity investment model (7), to search for the transmission fee parameter. The optimal value of unit transmission cost C^{tran} can be obtained by considering the following problem.

$$\min_{C^{tran}} \quad Cost^*_{tot}(C^{tran}) \tag{22a}$$

$$s.t. \quad (u^*, b^*) \in \operatorname{argmin}\{Cost_{tot} | (21b)\text{–}(21s)\} \tag{22b}$$

$$\sum_{r\in R}\sum_{r'\in R}\sum_{t\in T} C^{traninv}_{r,r',t} u^*_{r,r',t} \le \sum_{t\in T}\sum_{r\in R}\sum_{r'\in R} C^{tran} b^*_{r,r',t,k}, \quad \forall k\in K \tag{22c}$$

$$C^{tran} \ge 0 \tag{22d}$$

where $Cost^*_{tot}(C^{tran})$ is the optimal value of objective function $\sum_{r\in R}(\bar{\tau}_r - \underline{\tau}_r + B_r\mu_r)$ under the choice of unit transmission service fee C^{tran} in (21); u^* and b^* are the optimal values of variables u and b computed by solving (21). Constraint (22c) states that the total transmission service fee collected from various regions should be no less than the total investment cost for cross-border transmission lines. The above problem can be solved through a line search algorithm as described in Appendix D.

6. Case study for ASEAN power system planning

The Association of Southeast Asian Nations (ASEAN) comprises of ten member countries, namely Brunei Darussalam, Cambodia, Indonesia, Laos, Malaysia, Myanmar, the Philippines, Singapore, Thailand, and Viet Nam. The over-reliance on fossil fuel generation has resulted in significant CO_2 emissions in the region (IEA, 2019). As a result, the development of renewable generation has been identified as a crucial strategy to reduce CO_2 emissions (AEDS, 2021). However, the uneven geographical distribution of renewable resources presents a major challenge for renewable energy development in the region. One possible solution is the integration of ASEAN power grids (IEA, 2019). Against this backdrop, we apply the proposed model to identify the optimal transmission and generation capacity expansion plan for the ASEAN power system from 2020 to 2040. We describe the data used in Appendix E and define the set of ambiguous probability in Appendix F. The optimization model comprises 40,352 constraints and 46,940 variables, which we solve using the *GUROBI* solver in a Python environment with four 3.0 gigahertz processors and 16 gigabyte of RAM. The computational time for the line search algorithm with 100 iterations is less than 5 minutes.

6.1. Results and discussion

The optimization model is evaluated under three distinct scenarios that assume the same values of data uncertainties. These scenarios are as follows:

- *Isolated scenario*: This scenario assumes that the different countries are not interconnected with each other via transmission lines. The aim of this scenario is to understand how individual countries can be self-sufficient without relying on other countries for power supply.
- *Planned lines scenario*: This scenario assumes that the different countries are interconnected based on the existing transmission expansion plan, which is the transmission capacity plan from 2020 to 2040 projected by IEA (2019).

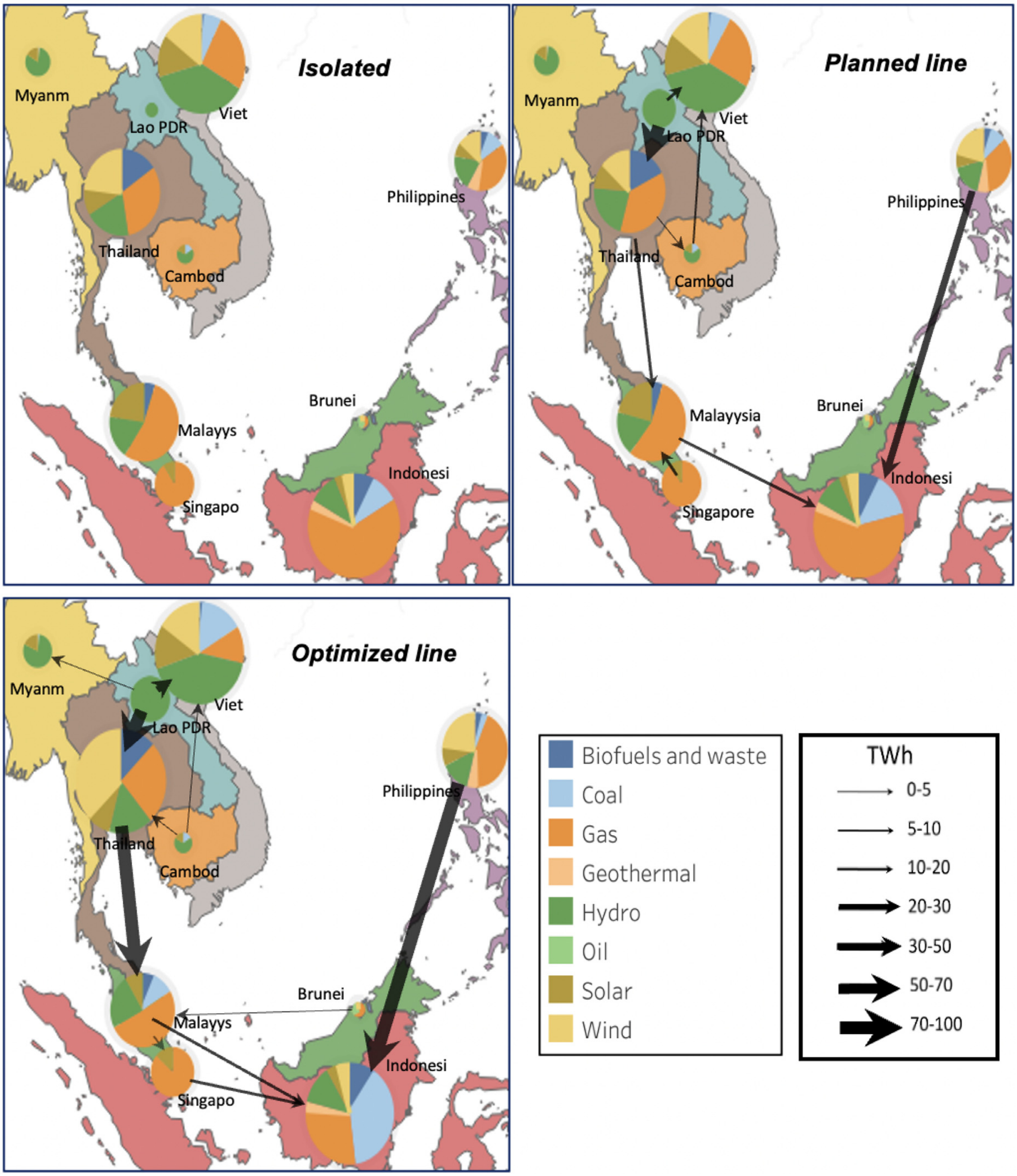

Fig. 3. Generation and transmission in 2040 under different cross-border connection scenarios.

- *Optimized lines scenario*: This scenario assumes that the different countries are interconnected based on the transmission expansion plan obtained from the optimization model itself.

6.1.1. Impacts of regional cross-border connection

Fig. 3 displays the optimal generation and transmission in different countries in 2040 under different scenarios. Table 1 reports the cumulative generation during the entire modeling period. As shown in Fig. 3, gas-fired and renewable generation contribute to the majority of total electricity generation under all three scenarios due to CO_2 emissions targets. The generation portfolios among different countries vary significantly. Gas-fired generation is primarily promoted in more economically developed regions such as Brunei, Indonesia, Malaysia, and Singapore. Hydro power mainly locates in Cambodia, Laos, and Myanmar due to their abundant hydro resources. Solar power is concentrated in Cambodia, Malaysia, Vietnam, and Singapore, while wind power is primarily developed in the Philippines and Thailand (see Fig. 3). Moving from the *isolated* scenario to the *optimized line* scenario increases the total amount of renewable electricity generation in 2040 from 1515.6 TWh to 1655.3 TWh (9.2%) (see Table 1). Meanwhile, the total amount of fossil fuel generation, including coal-fired, oil-fired, and gas-fired generation, decreases from 1387.9 TWh to 1248.2 TWh with a de-

Table 1
Cumulative generation by country from 2020 to 2040 (TWh).

		Wind	Solar	Hydro	Coal	Gas	Oil	Geothermal	Biofuels and waste	Total
Isolated	BRN	0.35	0.35	0.02	0.53	6.29	3.46	0.02	0.06	11.08
	KHM	0.00	4.53	16.50	3.17	0.00	0.00	0.00	0.97	25.17
	IDN	26.71	26.71	75.95	67.56	488.87	0.00	16.60	59.96	762.37
	LAO	0.00	0.00	14.72	0.00	0.00	0.00	0.00	0.00	14.72
	MYS	0.00	98.89	76.93	0.00	235.65	0.00	0.00	22.39	433.87
	MMR	0.00	12.39	42.83	1.05	0.53	0.00	0.00	0.00	56.80
	PHL	44.10	31.48	46.89	33.25	61.22	0.00	15.02	15.08	247.03
	SGP	0.00	16.78	0.00	0.00	120.77	0.00	0.00	3.00	140.55
	THA	91.42	84.47	99.88	0.00	167.23	0.00	0.00	80.89	523.89
	VNM	100.96	119.62	257.76	57.84	140.49	0.00	0.00	11.40	688.08
	ASEAN	263.53	395.22	631.49	163.40	1,221.05	3.46	31.63	193.76	2,903.56
Planned lines	BRN	0.35	0.35	0.02	0.53	6.29	3.46	0.02	0.06	11.08
	KHM	0.00	5.53	16.50	3.17	0.00	0.00	0.00	0.97	26.17
	IDN	26.71	26.71	75.95	96.97	432.26	0.00	16.60	59.96	735.18
	LAO	0.00	0.00	100.95	0.00	0.00	0.00	0.00	0.00	100.95
	MYS	0.00	84.24	76.93	0.00	235.65	0.00	0.00	22.39	419.21
	MMR	0.00	12.39	42.83	1.05	0.53	0.00	0.00	0.00	56.80
	PHL	47.50	37.07	46.89	24.50	88.16	0.00	15.02	15.08	274.22
	SGP	0.00	19.62	0.00	0.00	127.63	0.00	0.00	0.00	147.25
	THA	66.50	66.50	99.88	16.99	128.62	0.00	0.00	80.89	459.38
	VNM	100.96	110.24	257.76	62.84	130.11	0.00	0.00	11.40	673.31
	ASEAN	242.01	362.65	717.72	206.05	1,149.26	3.46	31.63	190.76	2,903.56
Optimized lines	BRN	0.35	0.35	0.02	0.53	8.08	3.77	0.02	0.06	13.17
	KHM	0.00	5.52	16.50	3.17	0.00	0.00	0.00	0.97	26.16
	IDN	26.71	26.71	75.95	211.62	211.62	0.00	16.60	59.96	629.18
	LAO	0.00	0.00	123.73	0.00	0.00	0.00	0.00	0.00	123.73
	MYS	0.00	32.90	76.93	34.42	158.76	0.00	0.00	22.39	325.40
	MMR	0.00	15.06	52.02	1.38	0.00	0.00	0.00	0.00	68.46
	PHL	76.85	37.36	46.89	0.00	163.66	0.00	15.02	15.08	354.86
	SGP	0.00	22.95	0.00	0.00	127.63	0.00	0.00	0.00	150.58
	THA	134.66	97.90	99.88	0.00	167.23	0.00	0.00	80.89	580.56
	VNM	100.96	104.99	257.76	96.83	59.52	0.00	0.00	11.40	631.46
	ASEAN	339.53	343.74	749.68	347.95	896.48	3.77	31.63	190.76	2,903.56

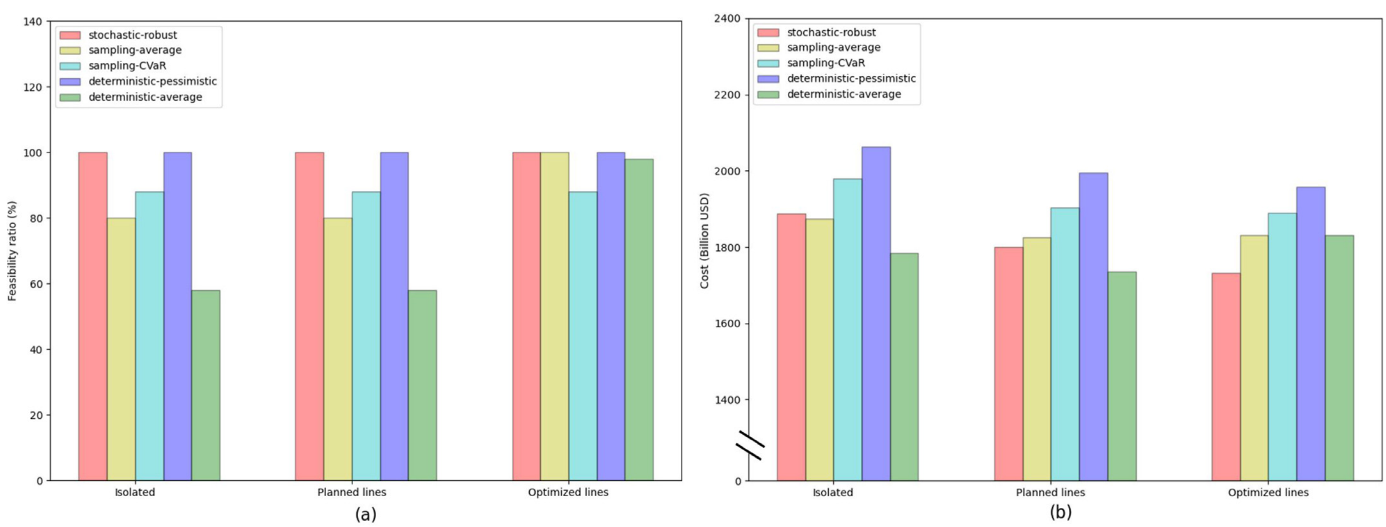

Fig. 4. Feasibility ratios and costs of different optimization models evaluated by out-of-samples approach.

creasing rate of 10.1%. The result indicates that cross-border grid integration encourages the development of renewable electricity generation. For example, Laos generates much more hydro generation output in the *planned lines* and *optimized lines* scenarios compared to the *isolated* scenario. The additional hydro power generation is exported to Thailand and Vietnam. Myanmar significantly increases its production output of hydro power in the *optimized lines* scenario and exports it to Malaysia. Thailand increases its share of wind power generation and exports electricity to Malaysia (see Fig. 3). The increase in electricity trading volumes is primarily motivated by following reasons. On the one hand, for the electricity exporting countries, installing more renewable generation capacities could lead to a reduction in the renewable power generation cost due to economies of scale. Furthermore, selling renewable energy to other countries could help generate profits without sacrificing their own CO_2 emissions targets. On the other hand, for the electricity importing countries, importing renewable electricity from other countries can help them achieve their CO_2 emissions targets in a more economic way. As such, cross-border renewable electricity trading can be considered a “Win-Win” strategy for both electricity exporters and importers.

The benefits of cross-border power grid integration are significant, as demonstrated by the cost breakdown presented in Table 2. The integration of the ASEAN power grid reduces the system cost

Table 2
Cumulative cost from 2020 to 2040 in different cross-border connection scenarios (Million USD).

		BRN	KHM	IDN	LAO	MYS	MMR	PHL	SGP	THA	VNM	ASEAN
Isolated	Gen. inv. cost	2667	9324	193,531	25,911	128,647	24,078	78,601	35,998	168,183	246,385	913,323
	Gen. cost	9626	1126	386,324	0	207,792	357	65,699	70,030	127,113	113,557	981,624
	Trad. cost	0	0	0	0	0	0	0	0	0	0	0
	Trans. cost	0	0	0	0	0	0	0	0	0	0	0
	Trans. inv. cost	–	–	–	–	–	–	–	–	–	–	0
	Total	12,293	10,450	579,855	25,911	336,438	24,435	144,299	106,029	295,296	359,942	189,4948
Planned lines	Gen. inv. cost	2667	10,419	173,385	50,113	128,275	24,078	91,429	39,174	147,385	233,581	900,505
	Gen. cost	9626	1889	357,896	0	196,640	357	75,424	75,201	79,453	109,875	906,362
	Trad. cost	0	−3966	44,248	−25,244	6591	0	−29,626	−11,133	4533	14,597	0
	Trans. cost	0	80	2662	0	2268	0	275	0	9107	1612	16,005
	Trans. inv. cost	–	–	–	–	–	–	–	–	–	–	4431
	Total	12,293	8423	578,192	24,868	333,775	24,435	137,502	103,241	240,477	359,665	1,827,302
Optimized lines	Gen. inv. cost	3958	10,308	150,912	61,238	89,804	28,573	109,580	43,115	210,590	212,704	920,783
	Gen. cost	9801	1928	318,192	0	122,388	1118	78,958	90,110	100,401	94,413	817,309
	Trad. cost	−1599	−2706	85,524	−109,886	112,308	−10,365	−45,579	−39,316	−33,120	44,738	0
	Trans. cost	100	18	6341	231	11,789	182	279	28	10,118	3315	32,400
	Trans. inv. cost	–	–	–	–	–	–	–	–	–	–	11,241
	Total	12,261	9548	560,968	−48,417	336,288	19,509	143,238	93,938	287,988	355,170	1,781,732

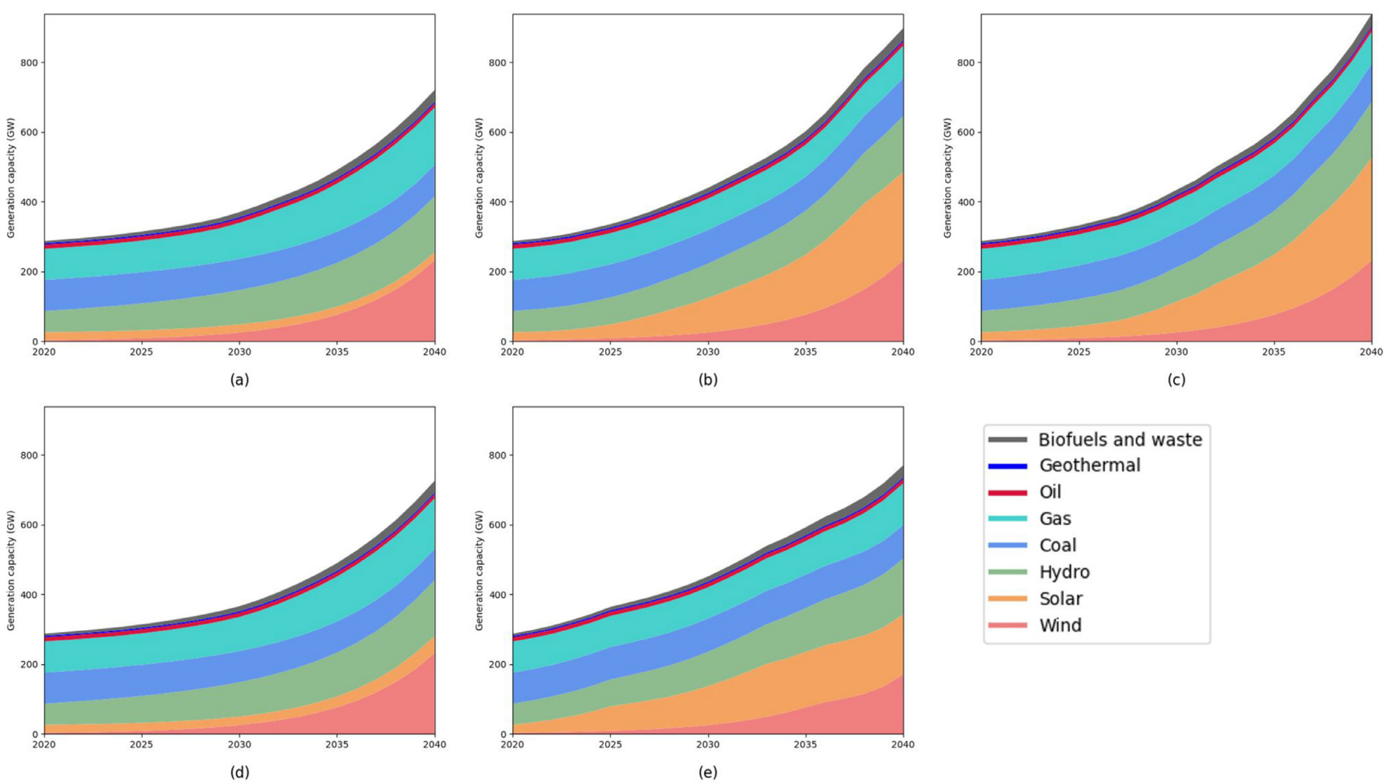

Fig. 5. Total generation capacity generated by deterministic-pessimistic (a), deterministic-average (b), sampling-average (c), sampling-CVaR (d), and stochastic-robust (e) approaches under the *optimized lines* scenario.

by 3.6% and 6.0% in the *planned lines* and *optimized lines* scenarios, respectively, compared to the *isolated* scenario. The cost breakdown shows that the *planned lines* and *optimized lines* scenarios invest an additional 4,431 and 11,241 million USD in cross-border transmission expansion, respectively, but earn 67,646 (15 times) and 113,216 (10 times) million USD in return compared to the *isolated* scenario. The cost savings earned by the investment in cross-border transmission lines are mainly from the savings in generation costs. Furthermore, Table 2 shows that all the countries benefit from the grid integration to some extent. This can be explained by the fact that the solution is one of the equilibrium solutions from a market equilibrium model, in which every country makes their investment and trading plan only for the minimization of their costs. Therefore, the cost of in the *optimized lines* scenario will never exceed the cost in the *isolated* scenario for each individual country.

6.1.2. Uncertainty handling performance evaluation

We compared the performance of the stochastic-robust optimization approach with four benchmark approaches commonly used for handling data uncertainty. These benchmark approaches include the deterministic-average optimization approach, the deterministic-pessimistic optimization approach, the sampling-average optimization approach, and the sampling-CVaR optimization approach. The formulations of these benchmark approaches are provided in Appendix G. To evaluate the performance of these approaches, we ran the above mentioned optimization models separately and obtained different sets of capacity expansion solutions.

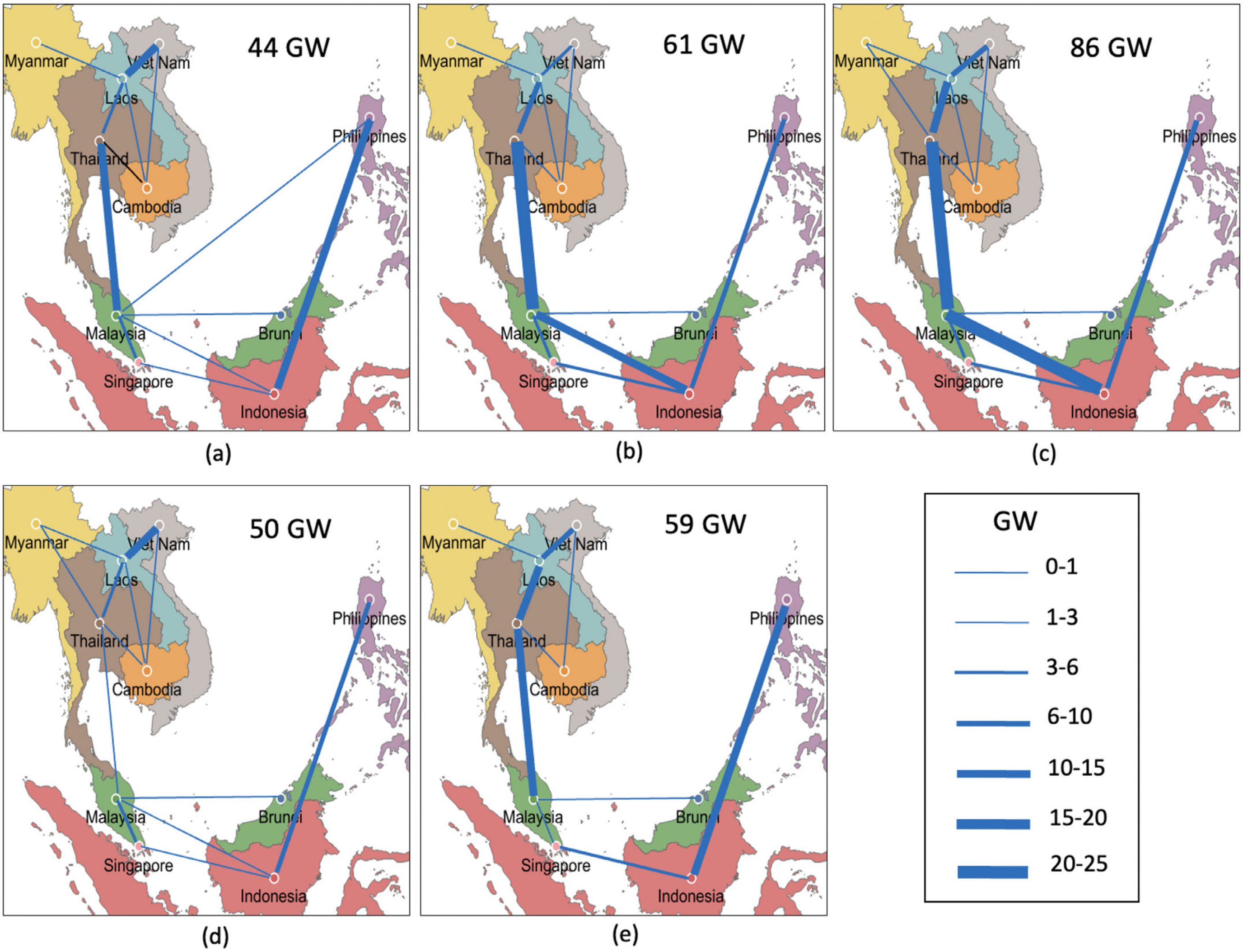

Fig. 6. Transmission capacity generated by deterministic-pessimistic (a), deterministic-average (b), sampling-average (c), sampling-CVaR (d), and stochastic-robust (e) approaches under the *optimized lines* scenario.

We then used the Monte Carlo simulation approach, as described in Appendix G, to assess the performance of these capacity solutions under data uncertainty.

Two performance indicators have been designed for model comparison: feasibility and cost. Feasibility performance measures the likelihood of the capacity solution to meet power demand and CO_2 emissions targets, while cost performance measures the expected system cost associated with the capacity solution under uncertainty (See details of the two indicators in Appendix G). Figure 4(a) and (b) illustrate the feasibility and cost performance of the capacity solutions generated by different optimization approaches, respectively. From Fig. 4(a), it can be observed that the feasibility ratios of stochastic-robust and deterministic-pessimistic approaches are 100% under all three cross-border connection scenarios, while the feasibility ratios of the other approaches fall short of 100% under some scenarios. This result indicates that the capacity expansion plans generated by stochastic-robust and deterministic-pessimistic approaches are the most reliable plans for meeting demand and CO2 emissions targets. Although both approaches have the same feasibility performance, the cost of the stochastic-robust approach is 4.5%–7.8% lower than the cost of the deterministic-pessimistic approach under different grid connection scenarios (Fig. 4(b)). Therefore, the capacity expansion solution generated by the stochastic-robust optimization approach is not only reliable for meeting demand and CO_2 emissions targets, but can also significantly reduce the investment and operation costs.[3]

The generation and transmission expansion solutions generated by different optimization approaches in the *optimized lines* scenario are compared in Figs. 5 and 6, respectively. As shown in Fig. 5, the pessimistic-deterministic and sampling-CVaR models promote more gas-fired generation over solar generation. This can be explained by the fact that these approaches only consider the (near) worst-case parameters. Since the solar generation technology is not cost-competitive compared to the gas-fired generation technology in the worst-case scenario, it will not be chosen by the two models. On the other hand, the deterministic-average and sampling-average approaches promote much more solar generation over gas-fired generation. This is due to the fact that these approaches consider both the optimistic and pessimistic cost scenarios, making solar generation technology more cost-competitive than the gas-fired generation technology, and therefore largely adopted[4]. Although

[3] It should be noted that the model comparison is performed under one certain value of cost uncertainty budget $\Gamma^C_{r,k}$. However, we have also conducted model comparisons under different values of the uncertainty budget in Appendix H, which yield similar results.

[4] From Table E8, we can see that the cost of solar generation technology will decrease significantly, while the cost of gas-fired generation technology will not decrease notably in the optimistic cost scenario

the stochastic-robust approach also considers the optimistic cost scenario, it installs less solar generation capacity but more gas-fired generation capacity compared to the deterministic-average and sampling-average approaches. This is because the solar generation technology has a larger local uncertainty compared to the gas-fired generation technology (See Table E7), and the stochastic-robust approach tends to avoid technologies with large cost uncertainty and choose technologies with small cost uncertainty to ensure that the cost uncertainty budget is not violated. In addition to the generation capacity solutions, the transmission capacity solutions generated by different approaches also vary significantly in both total capacity and connection topology (See Fig. 6). From the above comparison, we can see that the proposed stochastic-robust optimization approach is able to generate a more reliable and cost-effective capacity expansion solution, which cannot be inferred by existing practices.

7. Conclusion and future extensions

This study presents a novel stochastic-robust optimization model for inter-regional power system planning that addresses uncertainties in technology costs, demand, and resource availability. The model is formulated as a two-layer MPEC problem, where a central planner determines the cross-border transmission expansion plan at the top-level, and various regions independently decide their capacity investment, generation, and trading plans under perfect competition at the bottom-level. The results of the modelling exercise in the ASEAN region demonstrate that the integration of ASEAN power grids leads to increased renewable power generation and can reduce system costs by up to 6.0%. We compare the proposed stochastic-robust approach with several benchmark methods for data uncertainty handling, and demonstrate that the capacity expansion solution generated by our approach is not only reliable in meeting power demand and CO_2 emissions targets, but can also significantly reduce investment and operation costs. Overall, our study presents a promising approach to addressing the challenges of inter-regional power system planning in the presence of both scenario and local uncertainties.

Several avenues for future research can be considered based on the current work. First, while we have shown that the MPEC problem's solution is consistent with the solution of centralized optimization problem under uncorrelated uncertainty scenario, determining market equilibrium prices in the MPEC problem under correlated uncertainty scenario is still an open question that warrants further exploration. Second, the current study assumes a perfectly competitive market, with generators acting as price takers. However, the real inter-regional power market may be an imperfectly competitive one where regions can be price makers and act oligopolistically. Therefore, future research could explore the stochastic-robust optimization problem for inter-regional power system planning under an imperfectly competitive market and examine the impact of data uncertainties on market equilibria.

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Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ejor.2023.03.024.

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