

A Hybrid System Dynamics Model for Power Mix Trajectory Simulation In Liberalized Electricity Markets Considering Carbon And Capacity Policy

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Abstract

With the increase of Variable Renewable Energy (VRE), the Screening Curve (SC) method has been challenged in simulating the operation and generation of power plants accurately since it neglects the power plant's limited ability to adjust output. Nevertheless, the System Dynamics (SD), a suitable tool for policy evaluation and decision-making simulation in liberalized electricity markets, still widely combine with the SC method to estimate the generation mix, due to the SD platform limitations and the paradigms of modeling. In this paper, an optimization embedded SD hybrid model is developed as an alternative to the typical SC-SD combined method, allowing the SD model to simulate the trajectory change of power mix incorporating VRE more accurately, thereby better assessing the impact of policies in liberalized electricity markets. We choose the capacity mechanism and emission trading mechanism as examples of policy and compared the typical SC method and hybrid methods using real data from Hokkaido, Japan. We indicated that the hybrid method can deliver more accurate results since it includes the technical dispatch details, opposite of this, using the SC method may overestimate the abatement outcomes of the carbon policy, and underestimate the supports from capacity policy for the coal power plants. The simulation results demonstrate that the difference between the two methods increases along with the VRE share rising, when the VRE share exceeds about 40% the results of the hybrid method will be more reliable.

Keywords: System Dynamics; Screening curve; Variable renewable energy; Capacity expansion planning; Liberalized electricity market

Highlights:

- An optimization embedded System Dynamics model is developed
- Hybrid model can simulate investment decisions with engineering details
- Screening curve method overestimates the CO₂ reduction outcome of carbon pricing
- Higher renewable energy share brings a greater difference between the two methods

31 **Abbreviation**

Carbon policy	CBP
Capacity policy	CPP
Energy only market	EOM
Optimization method	OP
Screening curve method	SC
System dynamics	SD
Variable renewable energy	VRE

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1 Introduction

The electricity sector has important influence on the sustainable development and overall growth of any country[1]. Climate change, high and volatile fossil fuel prices, air pollution from conventional power plants and the need for higher levels of energy security are some of the driving factors moving the power system towards variable renewable energy (VRE), especially wind and solar [2]. The transition to renewable energy is not only important for addressing the increasing diversification of end-use energy needs but also is a key strategy for deep decarbonization of the power sector [3]. The renewable energy sector has boomed since 2008, with wind and solar having the highest growth rates. Global installed wind capacity grew rapidly from 6.1GW in 1996 to 837GW in 2021, with an average annual growth rate of 20% [4]. Ongoing electrification will lead to rising electricity demand while the increasing share of VRE will bring additional challenges to stable supply [5].

Meanwhile, the liberalization of electricity markets has been going on for decades [6], and the power industry in most developed countries is restructuring [7,8]. Scholars have pointed out that this low-carbon energy transition is strongly driven by policy [9], together with the liberalized electricity market, there are complex interactions between these two drivers [10,11]. Scholars also elaborated the importance and complexity of institutional and policy design for transition processes of the power systems [12]. Therefore, careful governance and incentive design are needed to avoid unintended counterproductive effects of policies that work against fundamental market drivers [13].

This energy transition process together with a liberalized electricity market, presents qualitatively different characteristics and challenges when compared with current systems. Addressing these challenges requires a dynamic adjustment approach for policy design, adapting to the local context, in addition to technical factors, in order to deal with the complex interactions and feedbacks in these interacting systems that operate on different time and geographical scale [14]. Simulation-based policy design offers the possibility to analyze real-world complexity. The main purpose of these simulations is to demonstrate the underlying mechanisms within the system [15]. This approach can be readily adapted to understand and reproduce the behaviors of the system [16,17]. In order to accurately simulate the response behaviors of the system, comprehensive consideration of the changes in the surrounding environment and the influencing factors within the system is necessary [18]. Simulations can be used in the design process to minimize overall design costs and prevent negligence, failures, and mistakes in design before actual implementations, especially for resource-intensive areas [19,20]. Considering the

real, long-lived, and capital-intensive characteristics of electricity system investments, the applications of simulation-based policy design can eliminate inappropriate designs as early as possible to save resources, capital, and time. Many tools and methods exist for performance simulations, in which various functions are used for specific simulation purposes.

System dynamics (SD) is a method of exploring changes in complex systems over time, which can be used to understand the effectiveness of policies and to avoid unintended consequences, especially when multiple policies interact and the overall system performance may not be immediately obvious [21]. In addition to this, the modeling process of SD can itself contribute to a holistic understanding of changes in a system's state and relevant causalities [22], which makes it a suitable tool for simulating and analyzing the changes in electricity capacity within liberalized markets [23,24]. SD has been widely used in the simulation of generation capacity expansion [25,26], electricity market policy assessment [27–30], electricity price simulation [31], transportation electrification [32], and demand side management [33]. SD modeling often uses proprietary software to conduct simulations, which construct different functions through stock-flow concepts with mathematics operations to achieve the simulation of a specific idea. For example, the TREND function in most of the SD software is constructed through a feedback loop with stock-flow variables to predict data trends, but the accuracy of the predicted results of this function is difficult to compare with the forecasts of the current leading time series analysis [22].

While SD can simulate system characteristics well, it is limited for simulating the specific technical details at the engineering level due to the limitations of the modeling platforms [34]. For example, SD modeling typically requires the use of all-in-one windowing modeling software, which provides fixed, non-extendable simulation functions. Subject to this, SD modelers have to follow specific modeling paradigms and workflows, resulting in analyses that are mostly policy-focused and do not address engineering details, such as start-up, shutdown, and ramping ability of power plants. These engineering details affect the ability to estimate short-term electricity prices and the choice of technology to ensure long-term system adequacy. The majority of research using SD simulations to examine investment in the liberalized electricity market relies on the use of the screening curve (SC) method. SC estimates the power mix and annual power dispatch results [35], a classic method, which can accurately simulate controllable technology [36]. It is widely used to quickly simulate the cost-optimal combination of power plant investment portfolio and its cost-optimal dispatch [37,38]. However, with the deployment of VRE, the assessment of generation volatility and grid flexibility has become an integral part of

electricity market design. As the proportion of non-dispatchable renewable energy in the grid continues to rise, SC's applicability has begun to be questioned [39]. The introduction of VRE has increased the uncertainty in the electricity market, making the decision-making in the electricity sector a challenge for investors and policymakers. Some scholars have suggested that the SC method cannot be fully applied to research on power generation investment in high renewable scenarios [40], as a result, the details of modeling need more attention in order to maintain a safe, reliable and affordable electricity supply. Although SD combined with the SC method can form a more comprehensive understanding of the system mechanism, it cannot carry out specific technical simulations, which affects the validity of the simulation results. Authors in a previous study [41] pointed out that SC would provide over-optimistic estimates of renewable energy outcomes, since it ignores short-term complexities, such as start-up cost, minimum run time, ramp rate, and minimum stable output constraints, and lacks a load-based non-chronological representation.

Therefore, some studies choose to improve the SC method [42–44], while some abandon the SC method, focusing on using optimization methods [45], or use the results of SC method as a preliminary reference value to estimate the possible optimal value of the model [46]. On the other hand, other studies mixed the two types of simulation tools or mixed methods for multi-objective simulation work [47,48]. Scholars provide deeper insights into electricity markets by mixing models in platforms such as MATLAB, Powersim, and Microsoft Excel [49]. However, these above studies all applied manual or semi-automatic data transmission in different software packages, the efficiency and repeatability of which needs to be strengthened. Platforms may be incompatible, manual or semi-automatic processes may be error-prone, and it would be difficult to conduct large-scale, long-term simulations. Developing a hybrid method on a single platform eliminates these compatibility issues, increases reliability, and reduces operation time [50]. Some scholars try to combine two methods in MATLAB to ease the constraints of the platform and enhance the consistency of the mixed method [51].

At the same time, optimization has been used broadly for modeling power system operation with rich technical details including system flexibility, providing realistic and robust simulations which can be used by regional decision-makers [52,53] such as simulation of generation expansion in a free market [54]. Nevertheless, optimization methods have limitations in the simulation of long-term investments in liberalized electricity markets [55]: (1) Since decisions are made by multiple self-interested companies as decentralized business practices rather than a centralized optimal expansion plan, the free

market is rife with decentralized decision-making, where there is insufficient information, influence of regulators, and strategic competition among private investors. This makes the result of market competition not necessarily consistent with the result of centralized optimization. (2) For capital-intensive industries, there is a delay in the entry and exit of the market, and a periodic rise and fall, which makes the system not always maintain the optimal capacity change trajectory.

To sum up, after fully considering the existing defects of the methods, we established a hybrid model that embeds optimization as a module into the feedback loop of SD. The proposed model simulates the long-term investment in a liberalized market and electricity capacity change trajectory while considering carbon and capacity related policies. The typical SC method is replaced by an optimization method, which allows SD to realize the modeling of power dispatch considering technical factors. We develop the model in a single environment in Python, thereby avoiding data cleaning and transmission between platforms, and preventing the compatibility issues. The hybrid model allows for simulations running at different time scales (both hourly and yearly), solving the hourly power grid dispatch optimization problem within the annual decision-making simulation of the SD model. This makes SD and the optimization method complement each other to a certain extent. We tested the model using the real data of Hokkaido, Japan in 2019, considering investment decisions under different policy implementations, comparing the results obtained by the typical SC method and the hybrid model. The advantages of the proposed hybrid model are mainly reflected in: (i) It allows more detailed technical modeling of system dynamics in investment feedback loops, simulating capacity changes; (ii) The two-level structure allows modeling at different time steps in the same feedback loop; (iii) The modular construction allows the establishment of more complex hybrid models by refining the interior of the module, which greatly improves the simulation capability of system dynamics; (iv) The code-based open source platform modeling is conducive to the realization of model reproduction, expansion and dissemination.

The rest of the paper is organized as follows: Section 2 introduces the framework and main assumptions of the proposed modeling, including the details of each module, the conditions settings, as well as the simulation environment. Section 3 compares and discusses the simulation results of the two methods. The final section provides summaries, limitations, and potential future works.

2 Method

2.1 Model structure

by adding up the revenue and cost from power generation sources and the policy sources, then the investment and decommissioning decisions of power plants are made by comparing the expected profits ("Participant decision-making" module). Finally, the current year's decision will directly change the installed capacity of each technology in the next year ("Capacity change" module), thus starting a new loop of simulation. In order to highlight the impact of policies on decision-making, we ignore the decommissioning and construction period of the power plants, since this delay will greatly increase the complexity of the system behavior[22].

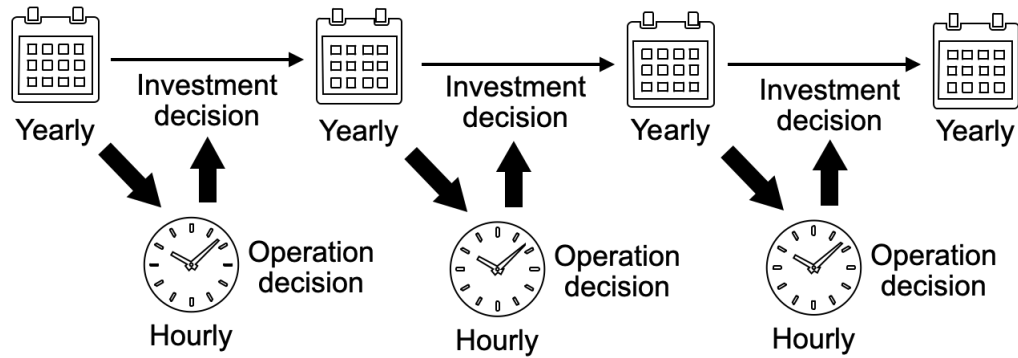


Figure 2. Two-layer time steps of the simulation model.

The power system includes a variety of characteristics of technologies – baseload power generation which has the properties of not changing the output significantly year-round; flexible power generation which has the properties of rapidly increasing and decreasing output to maintain the supply and demand balance at all times; Fluctuating and intermittent are uncontrollable outputs, fluctuating generation tends to be unstable but continuous output, and intermittent generation only outputs during a fixed period of time (such as during the day time). Therefore, there are four technologies with three different age cohorts in the model, wind and solar power as a representative of variable renewable energy, coal as a representative of base-load fossil fuel power plants, and liquid natural gas (LNG) as a representative of flexible fossil fuel power plants. The comparisons of the characteristics of these technologies are summarized in Table 1. See the appendix Table A1 for more technical details.

Table 1 comparison of the four technologies characteristics

Technologies	Power output	CO ₂ emissions	Capacity value
Thermal: Coal	Stable	High emissions	High value
Thermal: LNG	Flexible	Medium emissions	High value
VRE: Wind	Fluctuating	Zero emissions	Low value

2.2 Power dispatch module

Due to the production characteristics of the power system, the method of dispatch determines the production interests of most power plants, so the traditional investment model cannot be applied to analyze the power plant income in energy systems with high share of VREs. Therefore, the dispatch module is a very important part of simulating power investment. In this module, we compare traditional modeling with the hybrid model by performing simulations using the SC method and the optimization method, respectively. The typical way of SD modeling uses the SC to calculate the hourly and yearly power generation, which is not able to capture hourly fluctuating generation of VREs, the ramp rates and curtailment costs. The proposed hybrid model uses the optimization method to calculate the hourly and yearly power generation. In both methods, the VRE power generation is modeled as the current year's installed capacity, which is from the capacity change module, multiplied by an exogenous generation output factor, and demand is also exogenous. The model needs to calculate the power generation from the remaining technologies, the curtailment of VREs and the amount of emergency import electricity. The obtained results from this module are the basis for setting the electricity price module and capacity change module.

2.2.1 The SC method

As shown in Fig. 3, the SC is the cost curve for different technologies along with operating time, the load duration curve is the hourly demand data sorted in descending order. By combining the two, it is possible to calculate the amount of power generation from different technologies at minimum cost to meet electricity demand. The SC method is a suitable and efficient method for analyzing a power system that is dominated by conventional thermal power plants. However, with the increasing proportion of renewable energy, the accuracy of the SC may decrease, because some of the basic assumptions of the SC are against the characteristic of VREs, such as fully flexible technologies, no energy storage, and perfect information.

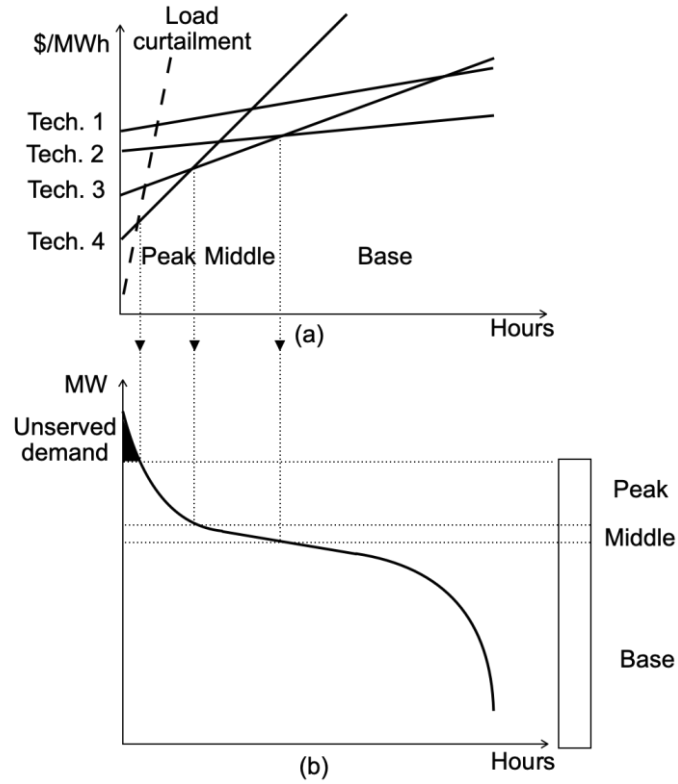


Figure 3. (a) Screening curve (b) Load duration curve [56].

2.2.2 The optimization method

For the optimization method, we define it as a self-scheduling optimization problem, to maximize power company annual profits based on historical electricity prices considering technical constraints. Eq.1 is the objective function, which contains the revenue of selling electricity at last year's price $Gen * Price$, minus the fuel cost $Gen * Fuel$, start-up cost $Start$, shutdown cost $Shut$, the curtailment penalty of VRE $Curtail * PenaltyCur$, and the imported electricity penalty $Import * PenaltyImp$. The VRE curtailment and electricity import penalty represent the preference of grid operators that integrate as much VRE as possible and import as little electricity as possible. The VRE curtailment penalty and the import penalty in the optimization model are equal to the FIP floor price and electricity price ceiling, respectively, more details can be found in section 2.5 electricity price. The technical constraints including the hourly supply-demand balance, the total generation of VRE, the minimum output, ramp rate, start-up and shutdown rate, and minimum start-up and shutdown time. The details of the optimization model can be found in the Appendix Eq. A1 to A20, with descriptions of variables and sets.

$$\begin{aligned} & \text{Maximum } (Gen * Price - Gen * Fuel - Start - Shut - Curtail * PenaltyCur \\ & \quad - Import * PenaltyImp) \end{aligned} \quad (1)$$

2.3 Capacity change module

Each technology is separated into three age cohorts, New, Mid, and Old, which are known as the aging chain model. The aging chain model contains a series of cohorts of different ages, as time goes by, the power capacity gradually ages from the new to the mid and then to the old. Along with the capacity change from one stock of the age cohort to the next stock, the overall efficiency of the technology gradually decreases as well. For instance, the fuel cost of thermal power will increase, the ramp rate will decrease, and all the other technical factors will deteriorate [57,58], as well as the power generation efficiency of VRE, which will become lower and lower [59,60], details are shown in Table 2.

Table 2 deterioration factor for efficiency of different age cohorts

Technologies \ Age cohorts			
	New	Mid	Old
VRE	100%	90%	80%
Thermal	100%	85%	70%

All capacities are firstly categorized into the three age cohorts based on their years of operation, then it is assumed that the age of capacity in the same cohorts are all set to the beginning age of the current age cohort, and the age then starts increasing when the simulation starts. For thermal power plants, this study specifies 0-20 years as the New cohort, 20-40 years as the Mid cohort, and over 40 years as the Old cohort. For VRE plants, 0-10 years is the New cohort, 10-15 years is the Mid cohort, and 15-20 years is the Old cohort. When the VREs reach 20 years, which is the end of the lifetime, they will retire due to deterioration, but when thermal power plants reach 40 years, they will not be actively decommissioned unless there are deficits (more details will be described in the section of decision-making module). The equations Eq.2 to Eq.7 of aging chain model are listed below. At the end of each year, for each of the different age cohorts *New*, *Mid* and *Old*, the capacity *Capa* of the technology *thm* and *VRE* consists of the newly invested-in capacity *NewInv* enter the market, the deteriorated capacity *Age* from the previous age cohort, minus the deteriorated capacity from the current age cohort to the next age cohort, and the deficit capacity *Decm* quits the market. There is also the life-expiring capacity *Retire* of old VRE capacity, where *y* is the number of simulation years.

$$CapaNew_{thm}(y) = Capa_{thm}(y_0) \quad (2)$$

$$+ \int_{y_0}^y NewInv_{thm}(y) - AgeNew_{thm}(y) - DecmNew_{thm}(y) \cdot dy$$

$$CapaMid_{thm}(y) = \int_{y_0}^y AgeNew_{thm}(y) - AgeMid_{thm}(y) - DecmMid_{thm}(y) \cdot dy \quad (3)$$

$$CapaOld_{thm}(y) = \int_{y_0}^y AgeMid_{thm}(y) - DecmMid_{thm}(y) \cdot dy \quad (4)$$

$$CapaNew_{VRE}(y) = Capa_{VRE}(y_0) + \int_{y_0}^y NewInv_{VRE}(y) - AgeNew_{VRE}(y) \cdot dy \quad (5)$$

$$CapaMid_{VRE}(y) = \int_{y_0}^y AgeNew_{VRE}(y) - AgeMid_{VRE}(y) \cdot dy \quad (6)$$

$$CapaOld_{VRE}(y) = \int_{y_0}^y AgeMid_{VRE}(y) - RetireOld_{VRE}(y) \cdot dy \quad (7)$$

2.4 Decision-making module

The decisions of market participants in the liberalized market are assumed as purely commercial behaviors, thereby their decisions only depend on the profits of the projects. At the end of each year, the investors of different technologies calculate the current year's cash flow as a reference to make decisions for investment, decommissioning, or no action for the next year. Although the investment decisions in the real world are decentralized, in this study, one assumption is that all investors in the same technology make a unified decision within a year, which means that all the revenue and cost of one technology are recognized as one aggregated unit instead of individual generators. The actual decision of a single company highly depends on the decision maker's own risk perception threshold, while the unified decision in a year after aggregation ignores the fluctuations of micro-individuals and reflects the overall changing of the expected returns.

The annual income streams include electricity sales and policy subsidies, and costs include fuel costs, environmental costs, and fixed maintenance costs. As summarized in Table 3 and Appendix table A2, above the regular income and cost, the adequacy policy and emission policy also affect thermal power plants' financial situation through extra charges or subsidies. As for VRE plants, they will receive the Feed-in-Premium (FIP) on the basis of electricity price, which is defined as the electricity price with a floor price (more details can be found in the section of the electricity price module). There are no variable costs of VRE and no other policies will affect their financial situation. As the decision-making module is a yearly basis dynamic simulation instead of a series of static snapshots, the initial fixed costs of each technology are calculated as a one-time expenditure when making investment decisions. This is known as the Cash Basis of Accounting, which means the annual cash flow calculation does not consider the amortization of fixed costs of power plants.

Table 3 Summary of income and cost for all technologies.

Technologies	Income	Cost	Adequacy policy	Emission policy
Coal	electricity price	Fixed and variable costs	capacity price	carbon price
LNG	electricity price	Fixed and variable costs	capacity price	carbon price
Wind	FIP	Fixed cost	-	-
PV	FIP	Fixed cost	-	-

Note: Fixed costs include the cost of building one 1 MW new unit of the technology and the fixed maintenance costs required for 1MW annual operation. Variable cost for thermal power is the fuel cost per 1MWh of power generation.

For investment decisions, this study adopts a constant status quo investment strategy that ignores fluctuation trends, assuming that the financial situation at the time of investment, including fixed cost, fuel price, current year cash flow, and the price from policies, will be constant for the entire project lifetime, without trend forecasts for the future. The overall income and average cost of technology for all age cohorts are used for calculation. The investors use the current year's earnings as a reference and calculate the internal rate of return (IRR) to evaluate the project's return, which is the project's return rate when the net present value (NPV) is equal to zero. When the IRR is greater than the expected return rate, the model chooses to make a new investment. As shown in Eq.8 and 9, the calculation of *NPV* includes the fixed cost *FixCost* in the initial year and unchanged annual cash flow *CF* throughout the lifetime. The annual cash flow is calculated as the revenue per MW *UnitRev* during the year minus the the annual per MW variable costs *UnitVar* and annual per MW maintenance costs *UnitMT*. The policy income such as emission payment *CarbonC* (annual emissions multiplied by carbon price) and capacity revenues *CapaR* (current year installed capacity multiplied by capacity price) are calculated according to the scenario setting. The invested capacity increases with the increase of the IRR until the upper limit. As shown in the Fig. 4, the start of investment threshold is set to be greater than IRR12.5% according to [55], and the upper limit is set to IRR 25% based on the authors' assumption, referring to the typical profitability of high-profit industries [61].

$$CF_{tch}(y) = UnitRev_{tch}(y) - UnitVar_{tch}(y) - UnitMT_{tch}(y) - CarbonC_{tch}(y) + CapaR_{tch}(y) \quad (8)$$

$$NPV_{tch} = -FixCost_{tch} + \sum_{y=1}^{Lifetime} \frac{CF_{tch}(y)}{(1 + IRR)^{Lifetime}} \quad (9)$$

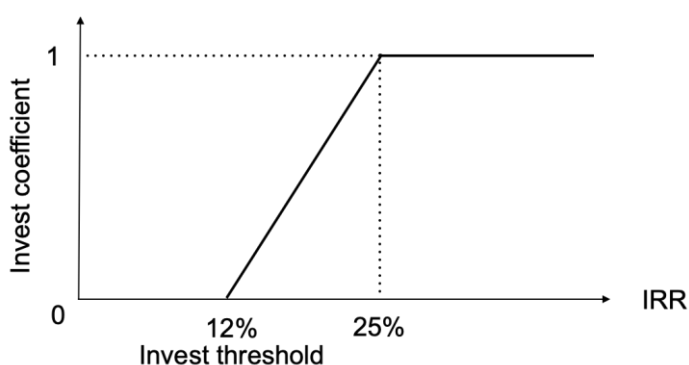


Figure 4. Threshold for investment.

For the decommissioning decision, this study assumes that thermal power plants do not retire after reaching their lifetime, but can be actively decommissioned at any age stage. On the converse, the VRE technologies can only retire when reaching their lifetime instead of being actively decommissioned at any age stage. The justification comes from the observation that many owners of older thermal power plants in the real world are willing to keep maintaining them, in order to extend the lifetime as long as they are profitable. In the meanwhile, once VRE plants are built, the owners will not actively decommission VRE until they deteriorate and reach the lifetime, since the marginal cost of VRE generation is near zero and they continuously receive the FIP subsidies. One point worth emphasizing is that the investment can only increase the capacity of the age cohort of new plants, but active decommissioning can decommission plants of any age cohort. In the model, for all the thermal power plants, once the cash flow becomes negative, which means that more operating will bring more losses, the investors will decide to temporarily take 20% of the current capacity off the market for mothballing. If the cash flow is positive in the next following year, the mothballed capacity will be released back to the market. If the cash flow of this certain type of power plant continues to be negative for two years, then the 20% mothballed capacity will be completely decommissioned.

2.5 Electricity price module

The electricity price is calculated based on the merit-order curve, shows in Fig. 5, the horizontal axis is the power generation of different technologies, and the vertical axis is the marginal generation cost of each technology. Under the assumption of perfect competition, the electricity price is equal to the highest marginal cost in the current auction hour. Therefore, the point corresponding to the sum of the total power generation of all technologies at every hour on the merit-order curve is taken as the electricity price for that hour, as shown in Fig. 6 for two methods. For thermal power plants, the

marginal cost is equal to the fuel cost, for VRE, the marginal cost is zero. When demand is higher than supply, the model assumes that the supply-demand balance will be met through temporary emergency imports of electricity, and the electricity prices will reach the highest ceiling price at the same time. The ceiling price of the electricity is taken into consideration by the regulators based on experience and the Value of Lost Load (VoLL), the current ceiling price in Japan is 200 JPY/kWh.

The Japanese electricity wholesale market adopts a single clearing price auction, all technologies that are generating electricity at the current hour will receive the same price as the settlement electricity price for that hour. The market based FIP subsidy is adopted to support VRE. The consumed electricity from VRE will be sold at market price with a fixed floor price of 20 JPY/kWh. The floor price of FIP and the fossil fuel price have a great influence on the deployment of VRE, as well as the electricity price. However, this discussion is beyond the scope of this paper, therefore the values have been set at an average subsidy level in year 2019, following the Japan Energy Regulatory Agency[62].

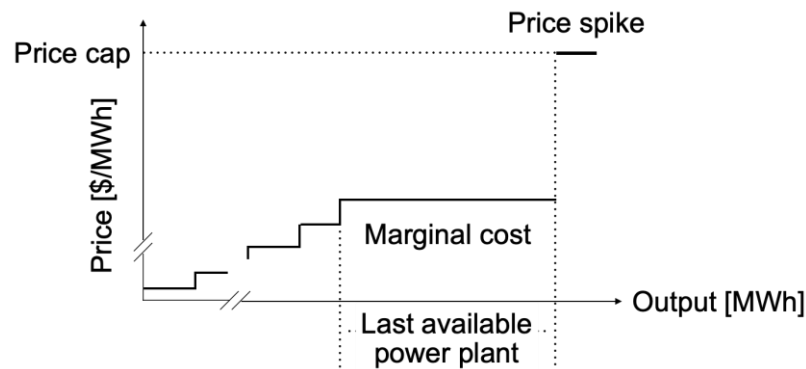


Figure 5. Merit-order curve for calculating electricity prices.

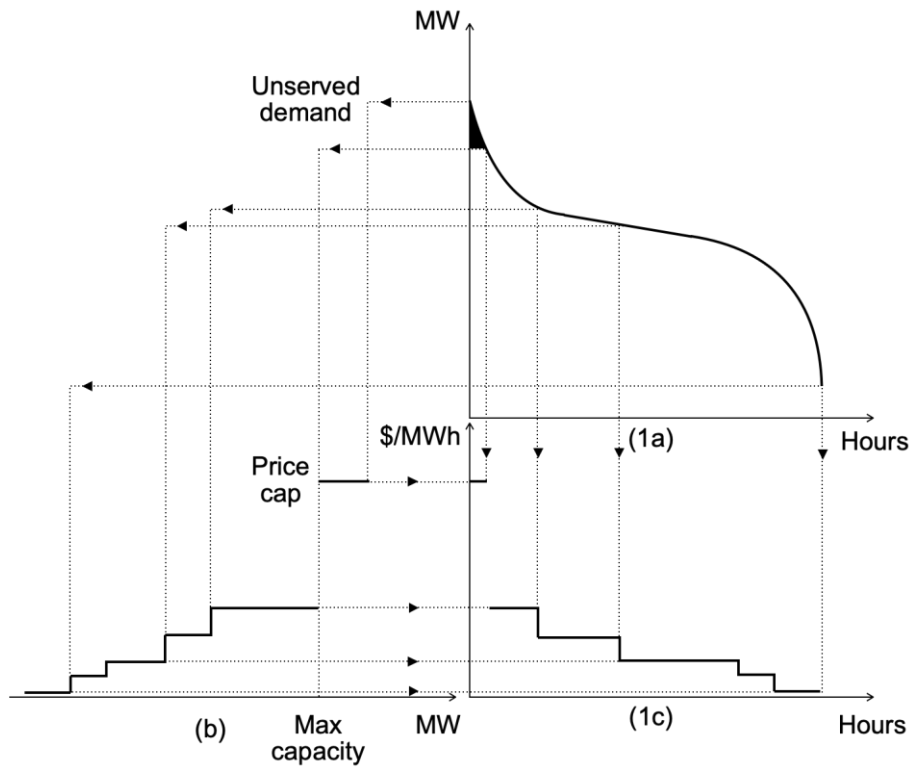


Figure 6(a). electricity price for screening curve method.

(Note: (1a) demand duration curve, (b) merit-order curve, (1c) price duration curve)

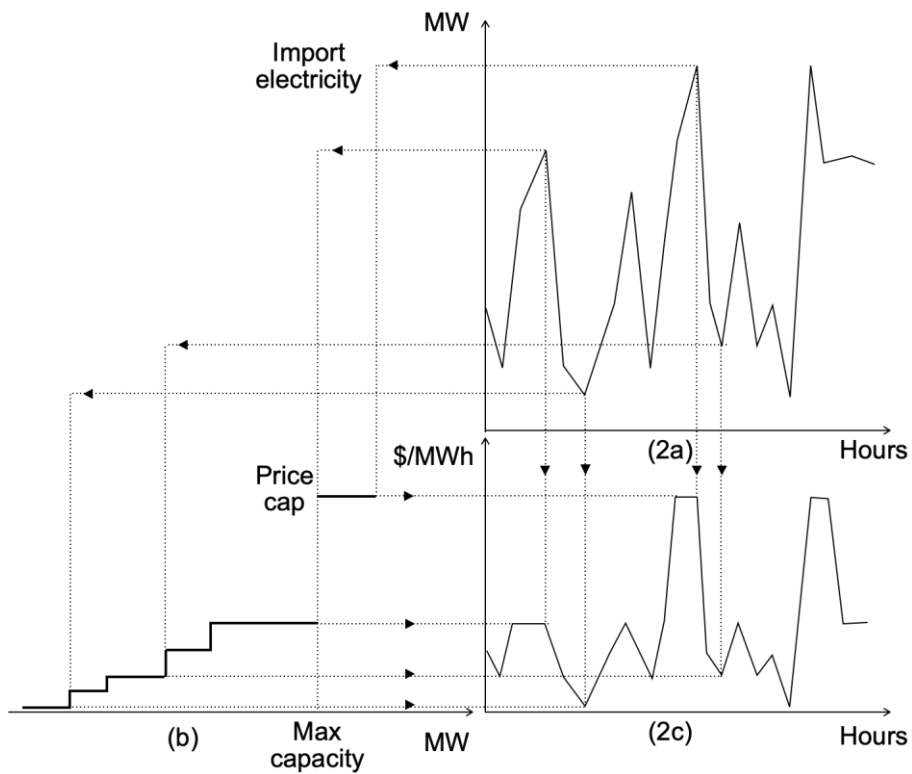


Figure 6(b). electricity price for optimization method.

(Note: (2a) demand curve, (b) merit-order curve, (2c) price curve)

2.6 Market based policy modules

2.6.1 Capacity price module

The capacity price is decided by a yearly auction, which is known as the capacity market, at which time the regulator releases the demand for capacity and organizes the auction. Fig. 7 shows the capacity demand curve used in this study, ensuring 15% higher than the maximum demand as reserve capacity. The price will change along the demand curve, if the total capacity is lower than the maximum demand, the capacity price will reach the ceiling, which is equal to 1.5 times the fixed cost of a new LNG power plant [63]. The capacity price will gradually decrease to zero along with the current capacity reaching the reserves plus the maximum yearly new investment. Compared to the vertical capacity demand curve, which is equal to the given requirement of capacity, this type of downward-sloping curve can produce a more stable price [64]. The shape of demand curves is different for each region and is usually customized to adapt to the local context. Only fully controllable thermal power plants are subsidized by the capacity policy [63]. The concept of the capacity factor (CF) is used to calculate the capacity value of different technologies. For thermal power plants, since they are recognized as fully controllable units, the capacity factor is 1; for VRE, the capacity factor is equal to the ratio of yearly generated electricity and the full nameplate load generation. This study calculated CF based on the real power generation data and VRE installed capacity of Hokkaido in 2019, which is around 0.27 for wind and 0.16 for solar.

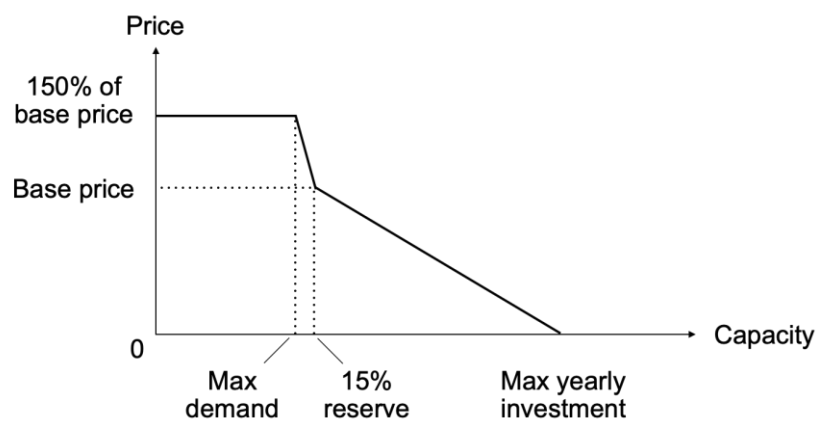


Figure 7. Demand curve of capacity.

2.6.2 Carbon price module

The carbon price is modeled as a cap-and-trade model with a ceiling and floor price, which is called the collar method, as shown in Fig. 8. The cap of the emissions allowance is set to decrease linearly to zero during the simulation time, using the emissions which are calculated based on the power generation

in the start year and the emission factors of power plants as the initial value of the allowance cap. Follows Eq.10 and 11, the carbon price **CarbonPrice** is calculated by multiplying the ratio **EmRatio** of the current year's total emissions **TotalEm** to the annual emission cap **EmCap** by the floor price **FLP**. The carbon price cannot exceed the price ceiling **PriceCap**. The floor price is set to avoid the continuous low price weakening emissions reduction when the emissions are lower than the allowance, while the ceiling price is set to protect emission-intensive companies from extreme price spikes and cost changes.

$$EmRatio(y) = \frac{TotalEm(y)}{EmCap(y)} \quad (10)$$

$$CarbonPrice(y) = \begin{cases} FLP & EmRatio(y) \leq 1 \\ FLP \times EmRatio(y) & EmRatio(y) > 1 \end{cases} \quad (11)$$

$$CarbonPrice(y) < PriceCap \quad (12)$$

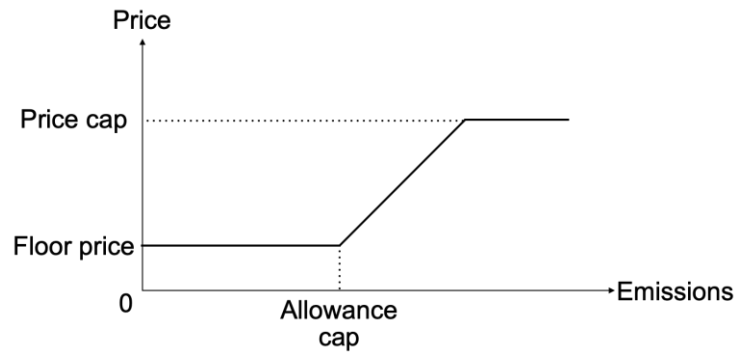


Figure 8. Collar method of carbon price calculation

In this study, the carbon price is the price for power plants to purchase the yearly emissions allowance to cover their emissions at the end of a year. It is assumed that the carbon price will not be taken into consideration in the daily operational decisions. In real-world practice, emitters need to collect enough allowances to offset their emissions at the end of the year, and emission allowances are purchased by participating in centralized intensive auctions. Therefore, in the day-ahead wholesale electricity market, the electricity price of the next day can hardly be significantly affected by the price fluctuations from centralized intensive auctions, but instead depends more on plant availability, weather, and supply-demand gap. Furthermore, usually, the marginal cost of thermal power plants is considered as primarily the fuel costs, since fuel costs are ex-ante spending, but the costs of purchasing emissions allowances are ex-post spending. Thus, the carbon price is not counted into the marginal cost of thermal

power plants in this study.

2.6 Simulation setting

Hokkaido, Japan, is chosen as a case study to simulate the capacity change. Hokkaido is isolated and only minimal interconnections with the main national grid, which means it relies more on its own generation capacity to meet local demand. The initial installed capacity of each technology at different ages is based on the real data of Hokkaido in 2019 [65]. The data of electricity demand and VRE output are the hourly supply-demand data for Hokkaido in 2019 [66]. Four sample weeks which are the highest demand week (which is also the lowest temperature week and highest electricity price week), the lowest demand week, the highest temperature week, and the cheapest electricity price week are chosen to represent one year, a total of 672 hours, see Appendix Fig A1 to A4 for more details [66,67]. These 672 hours were used to simulate the supply and demand balance during the year, then assume the rest of the year is just a multiple with the scale factor ($8760\text{h}/672\text{h}$) of the results, thereby calculating the total amount of 8760 hours a year. Changes in demand have been the most dominant and powerful factor influencing generation changes in the electricity system simulation. Nevertheless, in this study, we assume that electricity demand will not change from 2020-2050, in order to reduce the scope from the complex reality so as to focus on and enable testing of the main objective of this study. Similarly, the curve of hourly output power of wind and solar power are considered to follow the historical data, thus reducing the randomness that makes the system behavior less comprehensible, improving the interpretability of the results and thereby hopefully accessing better insights. Technical parameters are based on previous research [68] see Appendix table A1, and economic parameters are based on official statistics from Japan Ministry of Economy, Trade and Industry research reports [69,70], see Appendix table A2 and A3. All the parameters and exogenous factors are assumed remain constant over the simulation time to avoid extra complexities that could make interpretation exceedingly difficult and are likely to add to error such as interest rate, technology learning effect, and energy efficiency. The model is coded in the Python environment, using the BPTK-Py library [71] for the System Dynamics modeling, and the Pyomo library [72] for the optimization with the IBM Cplex solver.

3. Results and discussions

The proposed model simulates the long-term capacity changes, hourly electricity generation, CO₂ emissions changes, and carbon price changes. The simulation period is from 2019 to 2050, with two layers of time steps: years for investment, and hours for daily operation. There are three sets of

simulations, the energy-only market as the base case, the case with a capacity price, and the case with a carbon price, the case with both carbon and capacity policies is not examined in this paper, as the case involves complex policy interactions whose discussion is beyond the scope of this paper, but will be examined in future study. Each set of simulations was carried out with two methods in order to explore the divergence between the two methods. The model runs on a MacBook Pro with a 2 GHz Quad-Core Intel Core i5 processor, For the simulation of 672 sample hours, the running time for SC takes 1 minute and the time of the optimization-embedded hybrid model takes 14 minutes. The simulation for the hybrid method is much longer than the typical SC method, mainly because the optimization problem takes time to solve.

3.1 Installed capacity

Fig. 9 shows the simulation results of the capacity changes for three cases using the two methods. The results from the screening curve (SC) method and optimization (OP) method both show that a large amount of wind is deployed in the system due to the subsidization from the FIP, but only a very small portion of PV remains in the system and gradually retires after reaching its 20 years lifetime. The reason for PV withdrawal from the market is that Hokkaido has fewer solar resources, especially the daylight hours are short in winter. Thus, the overall power generation is not enough to bring sustainable profitability on the basis of the currently assumed level of the FIP.

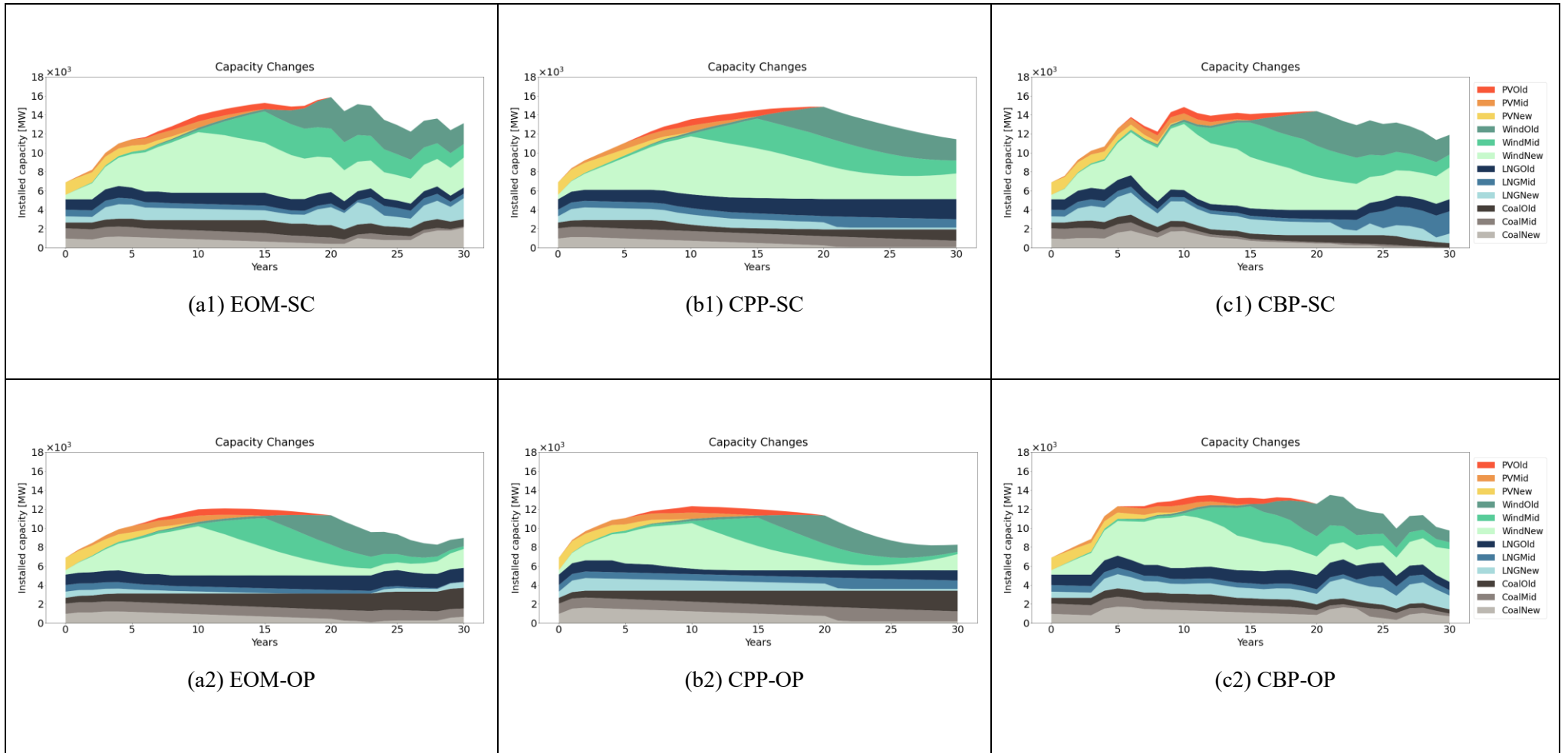


Figure 9. Installed capacity changes of all the cases.

(Note: a, b, c represent energy only market case (EOM), capacity policy case (CPP), and carbon policy case (CBP), respectively. 1 and 2 represent screening curve (SC) method and optimization (OP) method)

The wind power capacity derived by the SC is much higher than that in the OP for all cases. For the energy only market (EOM) case and the Capacity Policy (CPP) case, the maximum wind power capacity of the SC is about 4,000 MW more than the OP; while for the Carbon Policy (CBP) case, SC is about 2,000 MW more than the OP. This is due to the full flexibility assumption of the SC, which leads to more wind being deployed by the system, boosting the wind revenue and thus attracting more investment. In contrast, the OP method considers system-wide technical constraints on the ability to consume wind power, for instance, when the wind speed increases suddenly and there are not enough flexible resources in the system to reduce output to consume this wind power, the increment will be curtailed. When the amount of VRE is low, for example, the first 5 years, there is no significant difference between the two methods. Nevertheless, as the share of renewable energy continues to rise, the divergence in outcomes becomes wider. In this study, we found that for all scenarios, the results were significantly different when the VRE exceeded about 40%, which was also confirmed in the study of [73].

Throughout all three cases, the capacity of thermal power is similar in both methods, fluctuating around 5,000 to 6,000 MW. Although the overall thermal power capacity is similar, there is more coal in OP methods. This is due to the low flexibility of coal powers in the OP method, the output will not be easily changed once it is on, so there will be more power generation income than the coal power in the SC method with full flexibility assumption. Moreover, the proportion of the New age group in LNG plants of the SC method is higher than the results of the OP method. The reasons are that when the system requires thermal power to reduce output, the OP method chooses to reduce the output of the New plants group while the SC method chooses to reduce the output of the Old plants group, resulting in the New plants group having more opportunities to gain power generation profits in the SC method. Specifically, as VRE continues to increase, when VRE output increases suddenly for few hours, the thermal plants have to reduce outputs to maintain the supply-demand balance. From the economic point of view, the technology with the highest marginal cost should be reduced following the merit-order curve. From the technical point of view, only the most flexible resource have the ability to rapidly reduce output to balance the grid. Both OP and SC methods consider the economic perspective, while further technical constraints are missing in the SC method. Therefore, in the SC method, it is the group of Old LNG plants with the highest marginal cost that reduced the output, since all technologies are assumed to be equally flexible. While the OP method reduced output of the most flexible technology

which is the group of New LNG plants.

For the Capacity policy case, a smoother capacity change trajectory can be clearly observed, and the proportion of old power plants is also higher compared to the EOM. Comparing the SC and the OP, except for the difference in the wind capacity as mentioned before, the rest of the results are very similar. This is likely due to the fact that the capacity policy plays a less significant role in the daily dispatch of power plants, while the biggest difference between the SC method and OP method lies in the change of daily dispatch on the overall generation capacity at the technical level. Also, the stabilization subsidy provided by the capacity policy helps to reduce the boom-and-bust investment cycle of thermal plants, so the results of both methods are similar except for the VRE.

For the Carbon policy case, the volatility of the overall capacity change trajectory is more obvious compared to EOM, mainly due to the effect of carbon policy that exacerbates the economic exit decision of thermal power plants. At the same time, more LNG, especially new LNG, is retained in the system due to the carbon policy, as well as the capacity of older power plants significantly decreasing due to their relatively high CO₂ emissions. Comparing the SC and OP, above the difference in wind capacity, the coal capacity in the SC cases are smaller than that in the OP cases, both during the whole period and at the end of the simulation. Almost all the coal in SC exits the market near the end of the simulation, while there is still a significant amount of coal capacity remaining in the OP.

Fig. 10 shows the results for valued capacity. The valued capacity is calculated as the installed capacity of all technologies multiplied by the capacity factor. As mentioned in Section 2.5, for the thermal power technologies, the capacity factor is defined as 1 since they are considered to be completely controllable (and for the purpose of the model are assumed to have no maintenance shutdowns). For VRE, the capacity factor is 0.27 for wind power, and 0.16 for solar. Since the electricity demand is assumed not to change during the simulation period, the results of total valued capacity are stable at around 6,000MW, occasionally rising to 8,000MW due to investment fluctuations. The capacity fluctuation of EOM and CBP can be observed, and the fluctuation range of the SC results is higher than that of the OP result

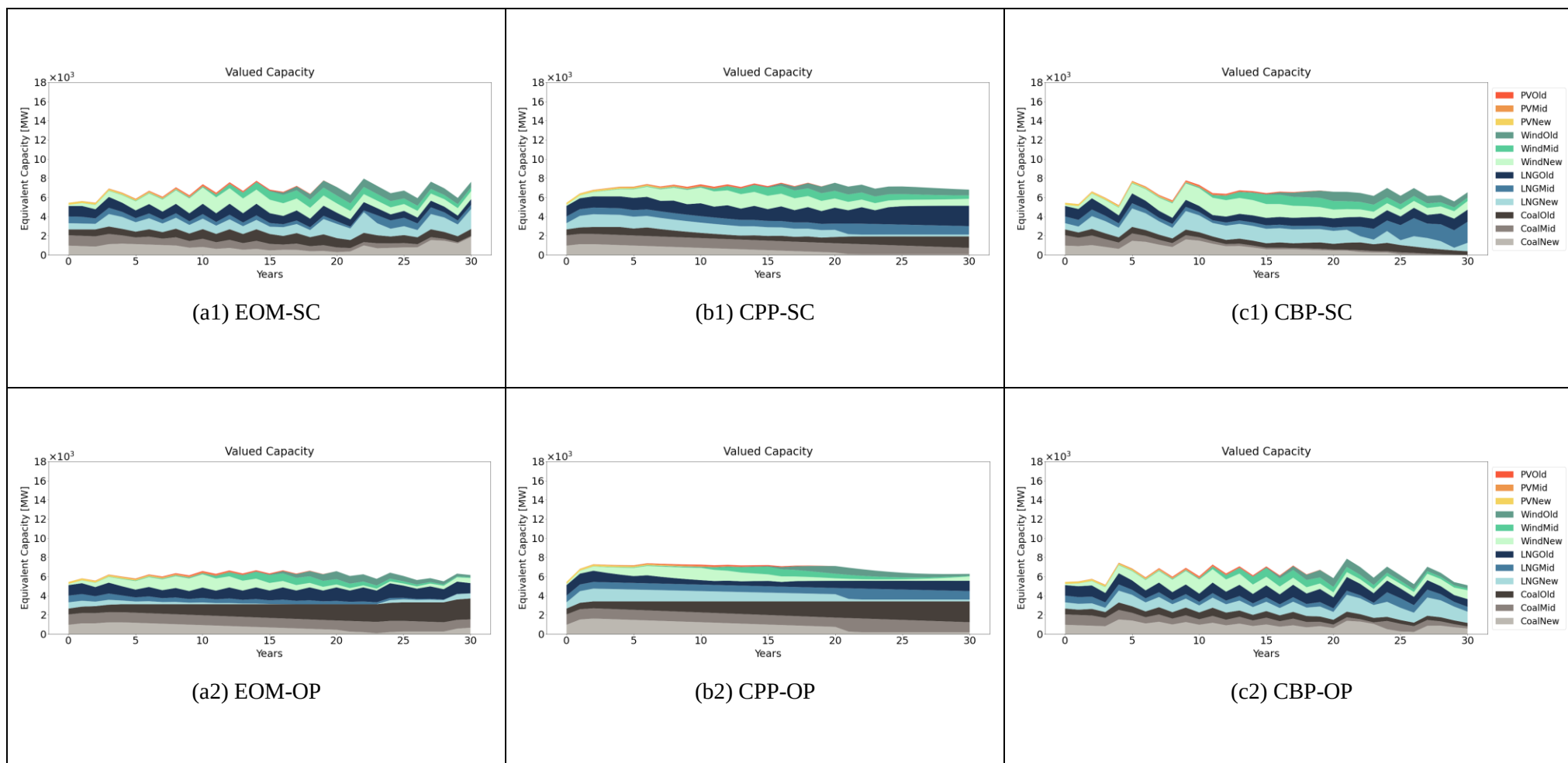


Figure 10. Valued capacity changes of all the cases

(Note: a, b, c represent energy only market case (EOM), capacity policy case (CPP), and carbon policy case (CBP), respectively. 1 and 2 represent screening curve (SC) method and optimization (OP) method)

The results of the CPP case are stabilized at around 6,300MW, which is approximately 15% above the maximum electricity demand and in line with the set target capacity of the capacity policy. Fig. 11 also shows the change in capacity prices, which corresponds to the change in valued capacity. The initial capacity in the system is close to the maximum demand, thereby the capacity price almost reaches the price cap at the beginning. Then as the installed capacity increases, it reaches the reserve of 15% above the maximum demand, and the capacity price also decreases rapidly and is stable around the base price. The timing of capacity price fluctuation is consistent with the fluctuation of valued capacity.

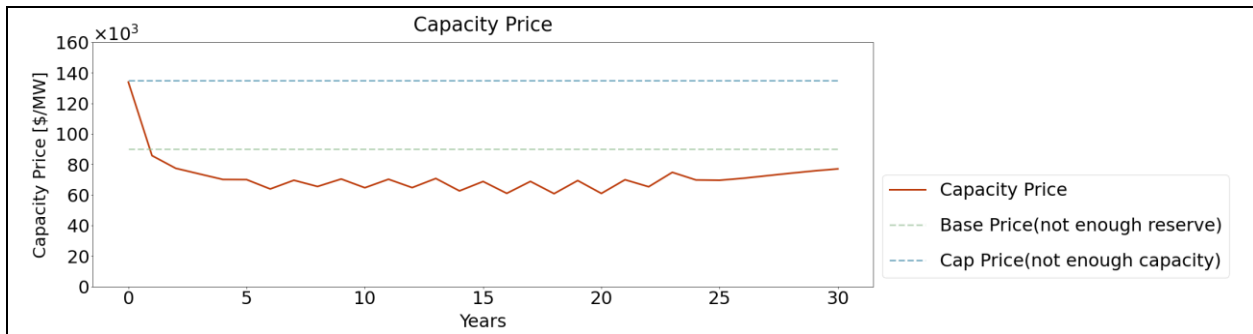


Figure 11(a). Capacity price changes of Capacity Policy Case with SC method

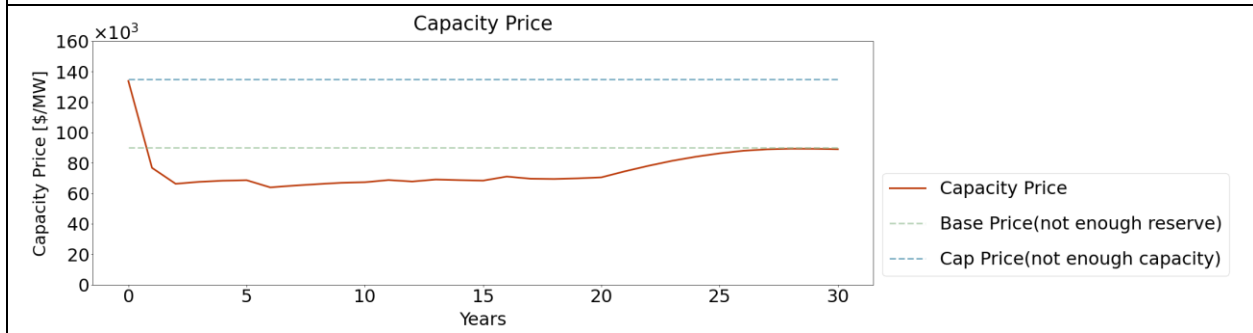


Figure 11(b). Capacity price changes of Capacity Policy Case with optimization method

3.2 Power generation and electricity prices

Fig. 12 shows more detailed yearly generation results, which are obtained by accumulating the hourly supply-demand balance results and then multiplying them with the scale factor. For all the cases, wind generation increases rapidly with the early deployment of wind power, the growth gradually slows down as the equipment ages until it stops growing at 20 years and then decreases. Among them, the proportion of wind power generation and consumption in the SC is much larger than that in the OP, and the proportion of coal power is much smaller than that in the OP. Furthermore, in the EOM and Capacity Policy Case, the proportion of generation from new power plants of each technology in the SC is larger than that in the OP. In the Carbon Policy Case, the majority of the coal power has been withdrawn from the market, leaving wind and LNG dominating all supply, while in the OP, wind, LNG, and coal power

generations are at the same level for each. This directly demonstrates that the SC optimistically estimates the low-carbon results: higher VRE generation, more retirement of coal power, and the lower age of thermal power plants.

For the Capacity Policy Case, a small amount of imported electricity occurs in the EOM case under both methods, but the imported electricity is no longer needed after the implementation of the capacity policy, which improves system adequacy. The ratio of thermal generation and VRE generation is relatively similar to the EOM under both methods, however, the share of electricity from old power plants, especially the share of old coal power increases in the SC, while the two results are almost same in the OP. This is because subsidies from capacity policy are paid on an annual basis, which affects the long-term capacity changes predominately. But the main constraint of daily operation decisions lies in technical factors in the OP, and the total capacity is a loose constraint. Moreover, the ratio of generation in the SC method is projected based on the generation cost arrangement and the ratio of capacity, so the long-term capacity changes directly affect the calculation of hourly generation.

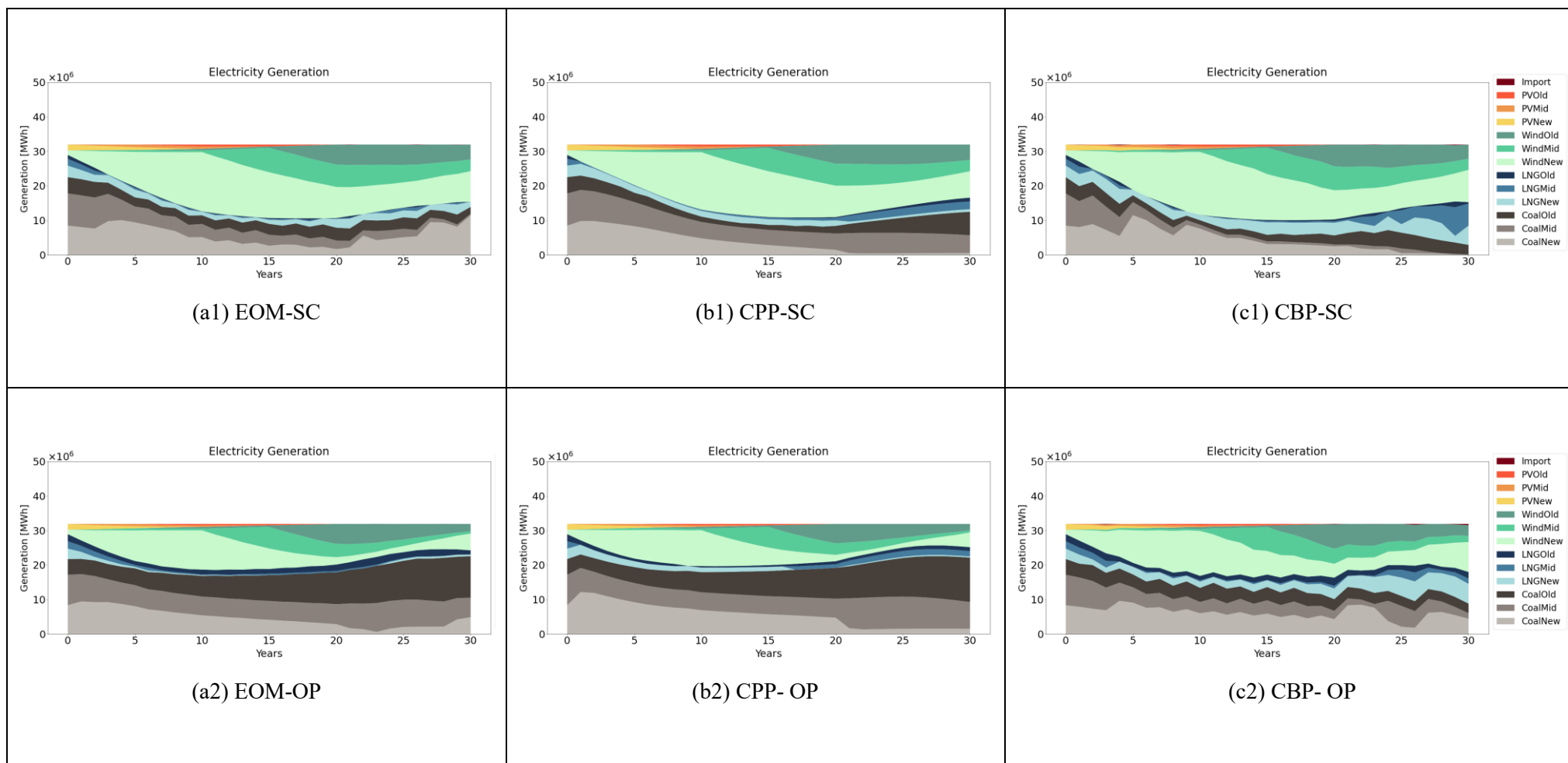


Figure 12. Power generation changes of all the cases

(Note: a, b, c represent energy only market case (EOM), capacity policy case (CPP), and carbon policy case (CBP), respectively. 1 and 2 represent screening curve (SC) method and optimization (OP) method)

For the Carbon Policy Case, the number of import events and the amount of imported electricity in the OP are much higher than the SC. Although this part of power only occupies a very small portion in the overall, but when an emergency event occurs requiring importing electricity from the mainland, the electricity price will soar to the top, as we set the price cap at \$1900/MWh, which is more than 10 times the usual price. These price spike hours have an important impact on the system-wide investment decision. Moreover, although import events occur in both the OP and the SC, the reasons are not the same. From the hourly supply and demand balance results, because of the full flexibility assumption in SC, all the imports in SC occur due to insufficient capacity, which means the current supply capacity in the system is less than the demand. Nevertheless, in the OP, except for a few insufficient capacity events, the imports occur mainly because of insufficient flexibility, which means the operating capacity cannot be changed immediately from the previous hour to meet the next hour's demand due to technical reasons, even though the supply capacity in the system is greater than the demand.

Furthermore, Fig. 13 allows a deep dive into the VRE integration and curtailment. The wind and solar generation are simulated based on the output curves from historical data. For different age groups of one technology, the same output curve was multiplied with the efficiency decline as described in Table 2 to calculate the generation. Therefore, the total VRE curtailment is determined by the supply-demand balance and then distributed among different technology age groups in proportion to the installed capacity. Corresponding to the installed capacity results, SC has higher VRE integration level than the OP, moreover, curtailment occurs from the 10th year in the SC, while it happens in the OP from the first 5 years. The ability to consume VRE is different as well, with SC stabilizing at around 20 MWh per year and the curtailment happening when the total generation is higher than 20 MWh, while the OP varies between 10 and 15 MWh per year.

The reasons for curtailment happening in the two methods are different. In the case of SC, curtailment occurs because the VRE generation in a certain hour is greater than the demand in that hour. In contrast, the curtailment in the OP occurs since the inability of thermal power plants changes the output sufficiently from hour to hour, which is decided by solving optimization problems considering technical factors. Therefore, the limit of consuming VRE generation keeps the same in SC for all three cases, the limit value is independent from the current power mix. Nevertheless, in the OP, the VRE consuming ability changes with the proportion of flexible resources in the system

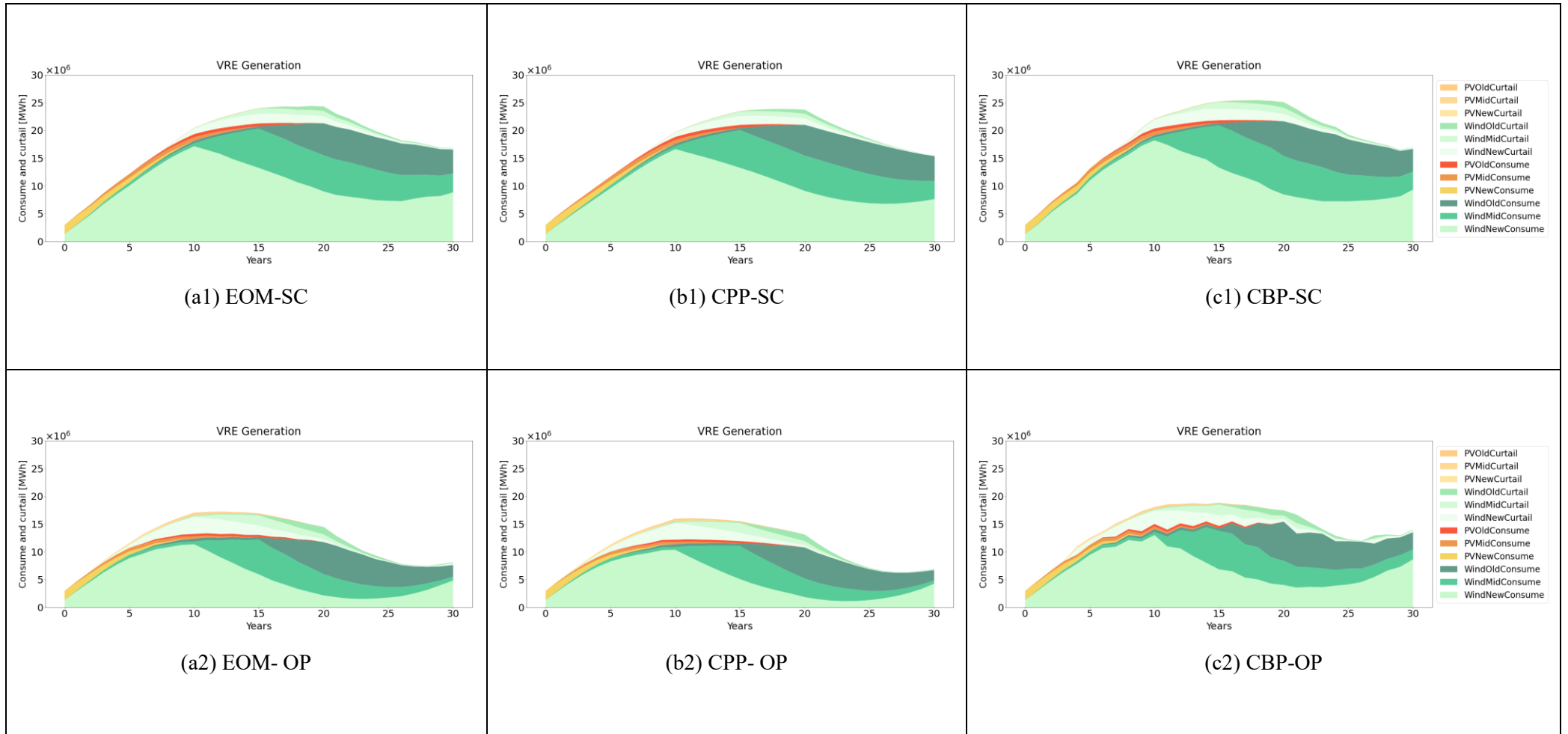


Figure 13. VRE integration and curtailment changes of all the cases.

(Note: a, b, c represent energy only market case (EOM), capacity policy case (CPP), and carbon policy case (CBP), respectively. 1 and 2 represent screening curve (SC) method and optimization (OP) method)

566

567 Fig. 14 shows the simulation results of the electricity price. It can be seen that the electricity
568 prices are at a moderate level most of the time. Prices spike when the emergency events of tight supply-
569 demand balance occur. Due to the full flexibility assumption of the SC method, the results follow the
570 merit-order curve to dispatch power sources in order from low to high marginal cost to meet the demand,
571 thereby the electricity price of the SC method presents a variety of prices. On the contrary, for the OP
572 method, although the economic dispatch planning is also carried out according to the merit-order curve,
573 due to technical constraints, it is impossible to repeatedly shut down and restart generators with different
574 fuel costs to fully reach the ideal economic state. Most of the time, the high marginal cost power plants
575 are in operation, which determined the electricity price in the one-price market. For electricity price
576 spike events, compared with EOM, the implementation of the capacity policy improves the stability of
577 the system, and the number of times the electricity price reaches the price cap is significantly reduced.
578 On the contrary, the implementation of carbon policy reduces the stability of the system, and the number
579 of electricity price spikes increases.

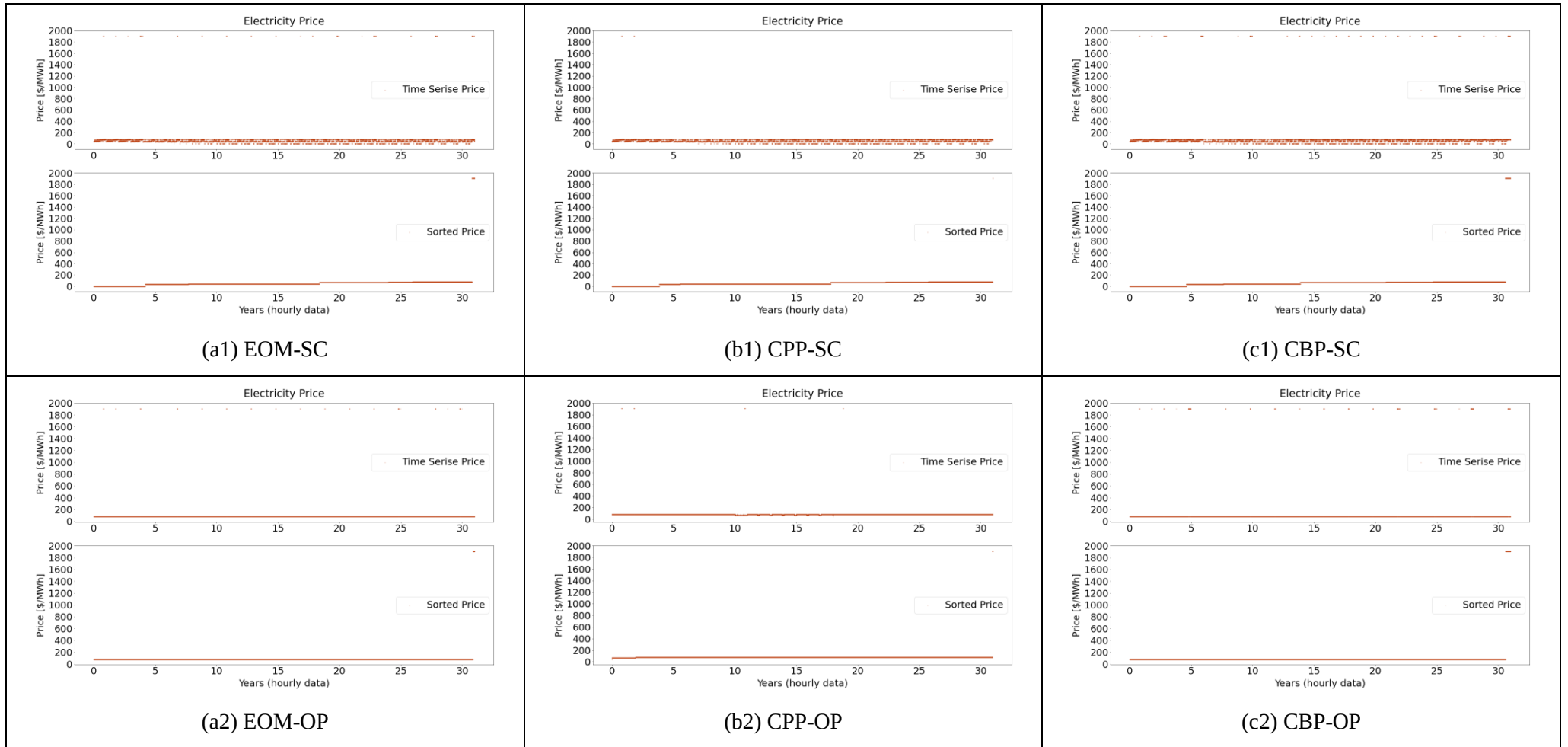


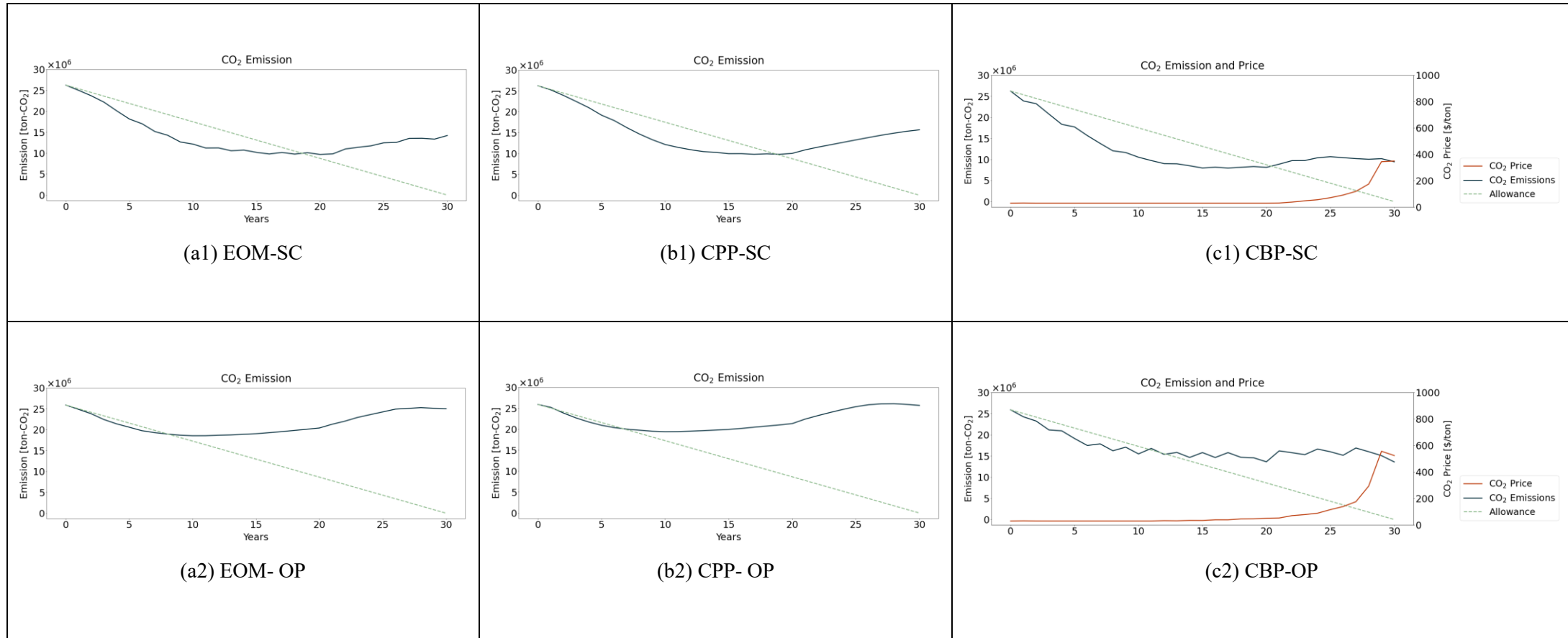
Figure 14. Electricity price changes of all the cases

(Note: a, b, c represent energy only market case (EOM), capacity policy case (CPP), and carbon policy case (CBP), respectively. 1 and 2 represent screening curve (SC) method and optimization (OP) method)

3.3 CO₂ emissions and carbon price

The changes in CO₂ emissions are directly linked to the amount of electricity generated by each technology. Fig. 15 shows the results for CO₂ emissions, calculated by multiplying the annual accumulated generation of different technologies by its emission factor. A linearly decreasing emissions cap to zero by 2050, the end year of the simulation, is developed using the first year's CO₂ emissions as the baseline. If current year emissions are below the cap, the carbon price will be the floor price, and if above the cap, the price will proportionally increase on the floor price.

Regardless of whether the carbon policy is imposed or not, the extensive deployment of VRE contributes to reducing CO₂ emissions in the early stage. CO₂ emissions fall rapidly as VRE capacity gradually approaches the system limit of VRE integration, but then the emissions gradually rise as VRE generation declines due to deterioration, while the FIP subsidy under current assumptions cannot support a higher level of VRE capacity installations. Only in the Carbon Policy Case of OP do the CO₂ emissions fluctuate in a small range after reaching the bottom without rebounding, due to the rising high carbon price from year 15. Nevertheless, under the current assumptions of this study, no case achieves zero emissions at the end of the simulation, where the lowest CO₂ emissions are achieved by the Carbon Policy Case of SC which stabilizes around 10,000,000 tons-CO₂ per year. Specifically, in all the cases of SC, significant CO₂ emission reductions can be observed in the early stage, and even in the absence of a carbon policy emissions are already below the linearly decreasing cap from the start of the simulation. It is only after the first batch of VRE reaches the end of its lifetime and starts to retire at 20 years that the CO₂ emissions slowly grow beyond the cap. In contrast to the OP, the modest VRE deployments bring emission reductions in the early stage but are not significantly lower than the emissions cap. After the implementation of the carbon policy, the early-stage emissions are only slightly below the cap, still much larger than the SC results. For the rest of the time, the emissions are much higher than the cap. The reason is that in order to reflect the characteristics of market-based policy, the carbon emission cap in the model is set as a soft constraint, rather than a mandatory requirement for the power system to achieve emission reductions, that is, to allow emissions exceeding the cap, correspondingly the carbon price will also increase as negative feedback.



610 Figure 15. CO₂ emissions and carbon price changes of all the cases

611 (Note: a, b, c represent energy only market case (EOM), capacity policy case (CPP), and carbon policy case (CBP), respectively. 1 and 2 represent screening
612 curve (SC) method and optimization (OP) method)

For both methods, the emission curves are very similar in the cases of EOM and Capacity Policy Case, while the curve under the effect of carbon policy is quite different. For SC, the trend of change in the Carbon Policy Case results is similar to the other two cases, with a rapid decrease followed by a slow increase, with the difference that the overall emissions are lower and the high carbon price at the end brings a slight decrease of emissions. For the OP, in contrast, the implantation of a carbon policy changed the way of system operation. Carbon policies lead to insufficient system flexibility after decommissioning of thermal power plants and having to import electricity for supply-demand balance at the highest price causes electricity price to spike. The high price attracts more new investment, while the emissions of new thermal power plants result in much higher carbon prices under the increasingly stringent emission cap, thereby squeezing the profit of the plants and forcing them out of the market again. This cycle places the thermal power plants in a kind of investment boom and bust cycle around the latter stage of Carbon Policy Case of OP, the capacity of thermal power plants constantly fluctuates, as well as the power generation and CO₂ emissions.

Although the carbon price is very high towards the end of the simulation, it remained stable for the first 25 years at less than \$100 per ton and most of the time only slightly above the floor price. As the cap gradually decreases to a very small value (0.01, to avoid dividing by zero) in the last 5 years, the carbon price rises rapidly to a maximum price of \$349 in SC and \$556 in the OP, the SC has a lower carbon price than the OP due to its lower CO₂ emissions. It is worth emphasizing that the carbon price in this study is determined by the set relationships of the floor price, CO₂ emissions, and the emission cap of the year. The changing trend of the carbon price is influenced by the joint interaction of current CO₂ emissions, emission cap, and the overall cost of the technology and the electricity price. In Japan, the current carbon policy is a carbon tax in a few limited areas and sectors, roughly around 3 \$/ton-CO₂, and the discussion about implementing an emission trading system in the future is ongoing [74]. Nevertheless, the main concern of this paper is the changing trend and relative relation of price changes under the potential policies and interaction with the electricity system, so the high carbon price at the end of the simulation only reflects the gap between the current year's emissions and the emission cap set by the policy, rather than strictly corresponding to the carbon price in the real world.

3.4 Mothballed and retired capacity

Thermal power plants require a high level of investment and are capital intensive, investors tend to temporarily stop losses by mothballing a portion of their capacity when their operations fall short of

expectations, rather than opting out of the market outright [75]. As discussed in Section 2.2, we assume that when a power plant has negative annual cash flows, investors will mothball 20% of their current capacity at a time and release the mothballed capacity back into the market if cash flows from the remaining capacity return to positive during the mothballed period. If its returns remain negative for 2 years, it chooses to permanently withdraw this mothballed capacity from the market. Only thermal plants will temporarily mothball capacity due to revenue changes; mothballing does not involve VRE.

Fig. 16 shows the results of mothballed capacity. LNG is the most mothballed technology, since it changes the output often due to high flexibility, especially to make more space to absorb VRE output. In the EOM case, a large amount of coal is mothballed under the SC approach, while only LNG, and especially a small number of older plants, is mothballed under the OP approach. When VRE increases, all the technologies in SC are affected, while in OP, only the more flexible technologies are affected such as LNG. For the capacity policy case, stable capacity subsidies significantly reduce the volatility of plant revenues, and only a few older plants with high marginal costs are occasionally mothballed. In the carbon policy case, the revenue of thermal power plants is affected by both the increased VRE and the carbon price. In the SC, a large amount of thermal power capacity is mothballed in the first 10 years and the carbon price spike leads to mothballing in the last 5 years. The fluctuations in mothballed capacity are more pronounced in the OP, especially in the the years 15 to 25.

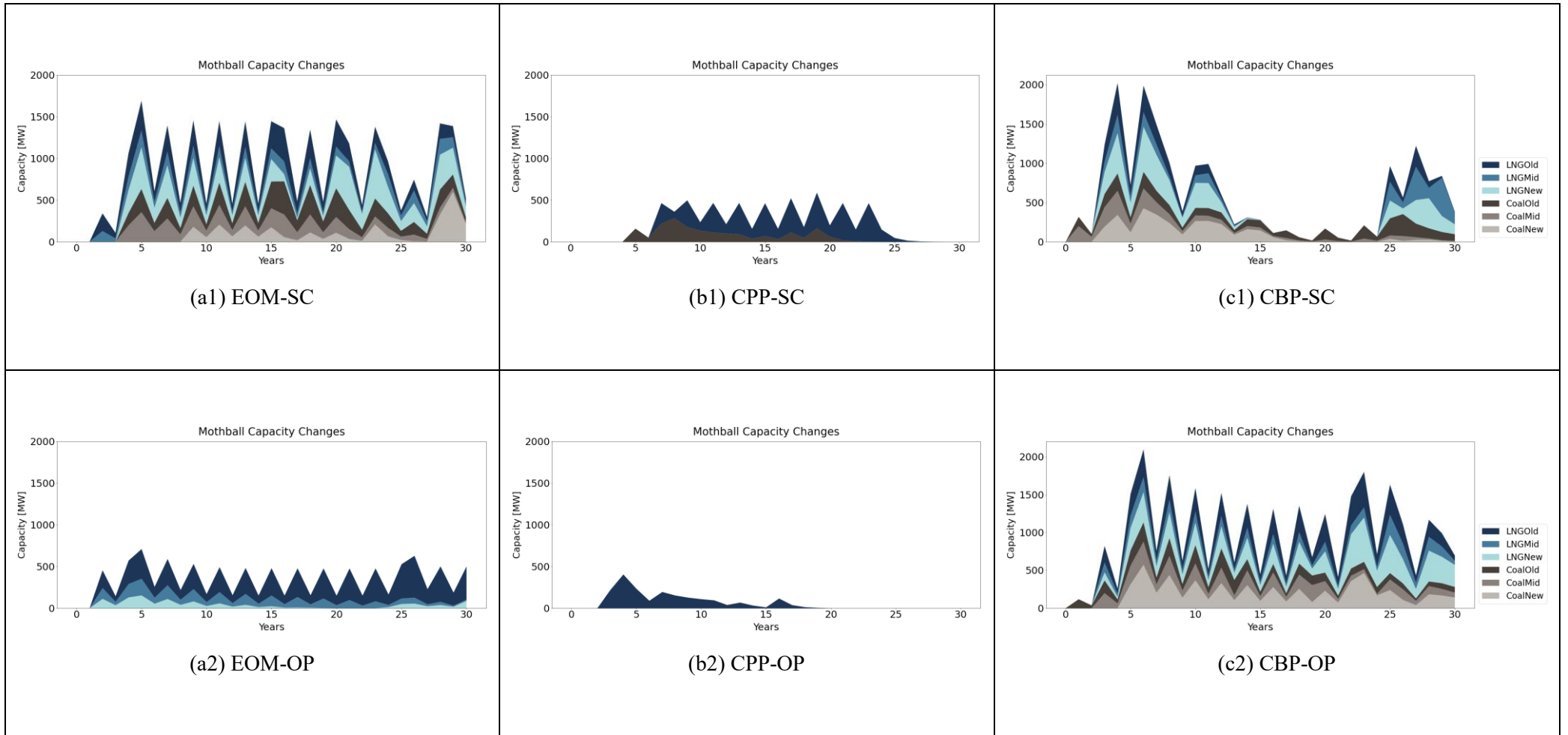


Figure 16. Mothballed capacity changes of all the cases

(Note: a, b, c represent energy only market case (EOM), capacity policy case (CPP), and carbon policy case (CBP), respectively. 1 and 2 represent screening curve (SC) method and optimization (OP) method)

Mothballing is the beginning of decommissioning. A large amount of mothballing only temporarily changes the market supply and demand balance without affecting the overall installed capacity, only a long period of negative income will change investors' expectations and take the mothballed capacity off the market. Fig. 17 shows further details of the capacity changes in terms of capacity retirement.

For the EOM case, the retirements are concentrated in the early and late stages. The early-stage retirements are due to the increase in VRE squeezing the generation space of thermal powers, while the reasons for late-stage retirements are more complex. From the results of capacity changes in the previous chapter, the generation decrease by VRE deterioration triggers the fluctuation of electricity price, which brings new thermal power plants to cover the declines, in the meantime, these new plants squeeze out the space of old thermal plants resulting in retirements. Comparing the SC and the OP, although the retirements in the OP are also concentrated in the early and late stages, the volume is much smaller than SC and only LNG instead of coal retirement. This is because in the OP, coal is more difficult to change the output, these technical characteristics lead to coal generation not easily declining, thereby ensuring a certain degree of its revenue. However, the more flexible technology LNG, which contributes to a higher level of VRE integration, lost its own generation opportunities, even having to withdraw from the market without sufficient compensation in EOM. This phenomenon cannot be observed in the cases of SC, where LNG and coal retirements are basically the same.

For the Capacity Policy Case, the flat curve of capacity changes due to the capacity policy, bringing the lowest retirements among all the cases, with only a portion of old thermal plants retired due to the large deployment of VRE in the early stage. It is noteworthy that in the SC case, this portion of retired thermal plants is old coal, while in the OP case, it is old LNG. The reason is that the increase of VRE squeezes the flexible technologies to reduce outputs, and among them, the costliest technologies lose the most and thus exit from the market. Since the old coal plants are still assumed to be fully flexible in the SC, therefore they have to reduce generation, and are squeezed out. But in the OP case, old coal is among the least flexible of all technologies due to its deterioration, making it difficult to change the output, while old LNG is the costliest option among flexible resources, thus it is retired from the market.

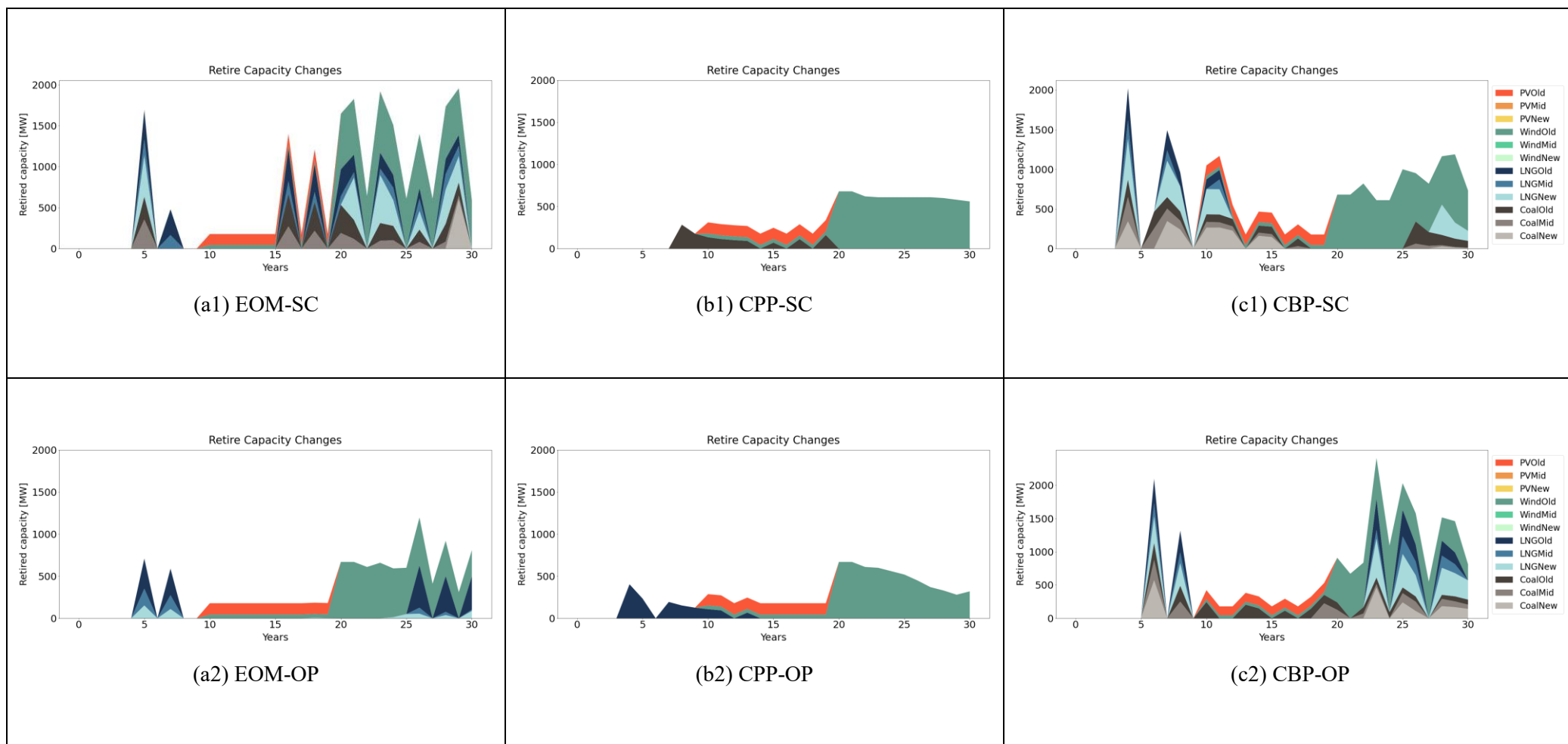


Figure 17. Retired capacity changes of all the cases.

(Note: a, b, c represent energy only market case (EOM), capacity policy case (CPP), and carbon policy case (CBP), respectively. 1 and 2 represent screening curve (SC) method and optimization (OP) method)

For the Carbon Policy Case, compared to EOM, retirements are also concentrated in the early and late stages, but the early stage has more retirements. This is due to the implementation of carbon policy with a floor price in the early stage providing a clear price signal, which amplifies the emission reduction effect from VRE deployments. Comparing the SC and the OP, SC has more early retirements and few late retirements, while the OP has the opposite result. The reason is that only a small number of thermal plants in the late stage of SC is sufficient to meet the required flexibility of integrating all the VRE, allowing the system to operate under lower emissions and lower carbon prices, with only a few emergency import events and more stable electricity prices. Nevertheless, in the OP, as mentioned earlier, the interaction of electricity price spikes due to insufficient flexibility in the system with the increasingly stringent carbon prices puts the thermal power plants in the investment boom and bust cycle in the late stage of OP, causing fluctuating retirement capacity as well.

For all cases, the reason for the VRE decommissioning is different from that of thermal power. Since the marginal cost of VRE is zero, and the FIP provides stable revenues, there is only lifetime retirement of VRE once the investment is made and no decommissioning occurs due to economic reasons. It can be observed that the retirement of VRE begins in the 10th year, which consists of the gradual retirement of the previous installed capacity 10 years ago before the simulation starts. Since there is no new investment in PV, it has all been retired from the market after 20 years, while the growing deployment of wind in the early stage brings a large number of retirements that occur after 20 years. The deployed wind capacity in SC is higher than the OP in all the cases, thereby the corresponding wind retirements in SC are also larger than the OP.

4. Conclusions

This study elaborates a common modeling defect, the Screening Curve in System Dynamics, which is a widely used method in modeling the liberalized electricity market. It further proposes an optimization-embedded hybrid method as a solution and compares the results of this solution with typical Screening Curve method. The capacity mechanism related to the electricity market and emission trading mechanism related to environmental issues are chosen as examples of market-based policies. A typical profits-based investment principle was applied to simulate decision-making in the liberalized electricity market. Real data from Hokkaido, Japan, from 2019 were used as a case study to test the model and compare the results from two methods. The results include installed capacity, power generation, CO₂ emissions, capacity retirements, and VRE integration and curtailment for the 30 years

simulation period.

The comparison of results shows that the SC method may overestimate the installed capacity and emission reduction effect of VRE, with an optimistic estimation of the overall age of the power plants. Therefore, the carbon price and the effect of the overall carbon policy are overestimated in SC, and this exaggeration increases as the installed capacity and output of VRE increase in the system. Nevertheless, when the proportion of VRE in the system is small, the difference between the two methods is neglectable. The exact number of the tipping point depends on the assumptions of models. In the current study, the results are similar when VRE share is roughly below 40% of total power generation. For the VRE share below 40%, while the two methods are interchangeable, the SC is even more convenient due to its fast and easy calculations. However, the SC method cannot distinguish the impact of different power mixes on the VRE integration level because it ignores technical factors.

This study uses sample hours with scaling factors to reduce the annual simulation calculations, but this method amplifies the impact of extreme events in certain hours on the system compared to a full hourly simulation. Future studies could focus on how to improve the performance and solving time of the optimization model, including more technologies, or upgrading the SC model to include more technical factors and the properties of VRE.

References

- [1] Dehghan H, Amin-Naseri MR, Nahavandi N. A system dynamics model to analyze future electricity supply and demand in Iran under alternative pricing policies. *Util Policy* 2021;69:101165.
- [2] Dai H, Xie X, Xie Y, Liu J, Masui T. Green growth: The economic impacts of large-scale renewable energy development in China. *Appl Energy* 2016;162:435–49.
- [3] Batinge B, Musango JK, Brent AC. Sustainable energy transition framework for unmet electricity markets. *Energy Policy* 2019;129:1090–9.
- [4] Zhou P, Jin RY, Fan LW. Reliability and economic evaluation of power system with renewables: A review. *Renew Sustain Energy Rev* 2016;58:537–47.
- [5] Roques FA. Market design for generation adequacy: Healing causes rather than symptoms. *Util Policy* 2008;16:171–83.
- [6] Cramton P. Electricity market design. *Oxf Rev Econ Policy* 2017;33.
- [7] Markard J. The next phase of the energy transition and its implications for research and policy. *Nat Energy* 2018;3:628–33.
- [8] Kraan O, Kramer GJ, Nikolic I, Chappin E, Koning V. Why fully liberalised electricity markets will fail to meet deep decarbonisation targets even with strong carbon pricing. *Energy Policy* 2019;131:99–110.
- [9] Blazquez J, Fuentes R, Manzano B. On some economic principles of the energy transition. *Energy Policy* 2020;147:111807.
- [10] Blazquez J, Fuentes-Bracamontes R, Bollino CA, Nezamuddin N. The renewable energy policy Paradox. *Renew Sustain Energy Rev* 2018;82:1–5.
- [11] Luo Y, Ahmadi E, McLellan BC, Tezuka T. Will Capacity Mechanisms Conflict with Carbon Pricing? *Energies* 2022;15:9559.
- [12] Sovacool BK, Geels FW. Further reflections on the temporality of energy transitions: A response to critics. *Energy Res Soc Sci* 2016;22:232–7.
- [13] Fouquet R. Lessons from energy history for climate policy: Technological change, demand and economic development. *Energy Res Soc Sci* 2016;22:79–93.
- [14] Borenstein S, Bushnell J. The US Electricity Industry After 20 Years of Restructuring. *Annu Rev Econ* 2015;7:437–63. <https://doi.org/10.1146/annurev-economics-080614-115630>.
- [15] Walter O, Tremel A, Prenzel M, Becker S, Schaefer J. Techno-economic analysis of hybrid energy storage concepts via flowsheet simulations, cost modeling and energy system design. *Energy Convers Manag* 2020;218:112955. <https://doi.org/10.1016/j.enconman.2020.112955>.
- [16] Barone G, Buonomano A, Forzano C, Palombo A, Vicidomini M. Sustainable energy design of cruise ships through dynamic simulations: Multi-objective optimization for waste heat recovery. *Energy Convers Manag* 2020;221:113166. <https://doi.org/10.1016/j.enconman.2020.113166>.
- [17] Calise F, Dentice d'Accadia M, Figaj RD, Vanoli L. Thermoeconomic optimization of a solar-assisted heat pump based on transient simulations and computer Design of Experiments. *Energy Convers Manag* 2016;125:166–84. <https://doi.org/10.1016/j.enconman.2016.03.063>.
- [18] Mefteh W. Simulation-based design: overview about related works. *Math Comput Simul* 2018;152:81–97.
- [19] Catalano F, Perone C, Iannacci V, Leone A, Tamborrino A, Bianchi B. Energetic analysis and optimal design of a CHP plant in a frozen food processing factory through a dynamical simulation model. *Energy Convers Manag* 2020;225:113444. <https://doi.org/10.1016/j.enconman.2020.113444>.
- [20] Adamou A, Turner J, Costall A, Jones A, Copeland C. Design, simulation, and validation of additively manufactured high-temperature combustion chambers for micro gas turbines. *Energy Convers Manag*

- 2021;248:114805. <https://doi.org/10.1016/j.enconman.2021.114805>.
- [21] Riva F, Colombo E. System-dynamics modelling of the electricity-development nexus in rural electrification based on a Tanzanian case study. *Energy Sustain Dev* 2020;56:128–43.
- [22] Sterman J. *System Dynamics: systems thinking and modeling for a complex world* 2002.
- [23] Qudrat-Ullah H, Seong BS. How to do structural validity of a system dynamics type simulation model: The case of an energy policy model. *Energy Policy* 2010;38:2216–24.
- [24] Ahmad S, Tahar RM, Muhammad-Sukki F, Munir AB, Rahim RA. Application of system dynamics approach in electricity sector modelling: A review. *Renew Sustain Energy Rev* 2016;56:29–37.
- [25] Pereira AJC, Saraiva JT. A long term generation expansion planning model using system dynamics – Case study using data from the Portuguese/Spanish generation system. *Electr Power Syst Res* 2013;97:41–50. <https://doi.org/10.1016/j.epsr.2012.12.001>.
- [26] Ibanez-Lopez AS, Martinez-Val JM, Moratilla-Soria BY. A dynamic simulation model for assessing the overall impact of incentive policies on power system reliability, costs and environment. *Energy Policy* 2017;102:170–88. <https://doi.org/10.1016/j.enpol.2016.12.026>.
- [27] Saysel AK, Hekimoğlu M. Exploring the options for carbon dioxide mitigation in Turkish electric power industry: System dynamics approach. *Energy Policy* 2013;60:675–86. <https://doi.org/10.1016/j.enpol.2013.04.053>.
- [28] Aslani A, Helo P, Naaranoja M. Role of renewable energy policies in energy dependency in Finland: System dynamics approach. *Appl Energy* 2014;113:758–65. <https://doi.org/10.1016/j.apenergy.2013.08.015>.
- [29] Hary N, Rious V, Saguan M. The electricity generation adequacy problem: Assessing dynamic effects of capacity remuneration mechanisms. *Energy Policy* 2016;91:113–27. <https://doi.org/10.1016/j.enpol.2015.12.037>.
- [30] Esmaili M, Ahmadian M. The effect of research and development incentive on wind power investment, a system dynamics approach. *Renew Energy* 2018;126:765–73. <https://doi.org/10.1016/j.renene.2018.04.009>.
- [31] He Y, Zhang J. Real-time electricity pricing mechanism in China based on system dynamics. *Energy Convers Manag* 2015;94:394–405. <https://doi.org/10.1016/j.enconman.2015.02.007>.
- [32] Setiawan AD, Zahari TN, Purba FJ, Moeis AO, Hidayatno A. Investigating policies on increasing the adoption of electric vehicles in Indonesia. *J Clean Prod* 2022;380:135097. <https://doi.org/10.1016/j.jclepro.2022.135097>.
- [33] Elias AA. Energy efficiency in New Zealand’s residential sector: A systemic analysis. *Energy Policy* 2008;36:3278–85. <https://doi.org/10.1016/j.enpol.2008.05.005>.
- [34] Tang L, Guo J, Zhao B, Wang X, Shao C, Wang Y. Power generation mix evolution based on rolling horizon optimal approach: A system dynamics analysis. *Energy* 2021;224:120075. <https://doi.org/10.1016/j.energy.2021.120075>.
- [35] Hasani M, Hosseini SH. Dynamic assessment of capacity investment in electricity market considering complementary capacity mechanisms. *Energy* 2011;36:277–93. <https://doi.org/10.1016/j.energy.2010.10.041>.
- [36] Stoft S. *Power system economics: designing markets for electricity*. Piscataway, NJ: IEEE Press; 2002.
- [37] Petitet M, Finon D, Janssen T. Capacity adequacy in power markets facing energy transition: A comparison of scarcity pricing and capacity mechanism. *Energy Policy* 2017;103:30–46. <https://doi.org/10.1016/j.enpol.2016.12.032>.
- [38] Gillich A, Hufendiek K, Klemp N. Extended policy mix in the power sector: How a coal phase-out

- redistributes costs and profits among power plants. *Energy Policy* 2020;147:111690. <https://doi.org/10.1016/j.enpol.2020.111690>.
- [39] Lamont AD. Assessing the long-term system value of intermittent electric generation technologies. *Energy Econ* 2008;30:1208–31. <https://doi.org/10.1016/j.eneco.2007.02.007>.
- [40] Vidal-Amaro JJ, Østergaard PA, Sheinbaum-Pardo C. Optimal energy mix for transitioning from fossil fuels to renewable energy sources – The case of the Mexican electricity system. *Appl Energy* 2015;150:80–96. <https://doi.org/10.1016/j.apenergy.2015.03.133>.
- [41] Oree V, Sayed Hassen SZ, Fleming PJ. A multi-objective framework for long-term generation expansion planning with variable renewables. *Appl Energy* 2019;253:113589. <https://doi.org/10.1016/j.apenergy.2019.113589>.
- [42] Batlle C, Rodilla P. An Enhanced Screening Curves Method for Considering Thermal Cycling Operation Costs in Generation Expansion Planning. *IEEE Trans Power Syst* 2013;28:3683–91. <https://doi.org/10.1109/TPWRS.2013.2249540>.
- [43] Zhang T, Baldick R. Consideration of Existing Capacity in Screening Curve Method. *IEEE Trans Power Syst* 2017;32:3038–48. <https://doi.org/10.1109/TPWRS.2016.2633399>.
- [44] Pratama YW, Mac Dowell N. Screening Curve for Valuing Power Generation and Storage Technologies in the 21st Century Grid. *SSRN Electron J* 2021. <https://doi.org/10.2139/ssrn.3821841>.
- [45] Flores-Quiroz A, Palma-Behnke R, Zakeri G, Moreno R. A column generation approach for solving generation expansion planning problems with high renewable energy penetration. *Electr Power Syst Res* 2016;136:232–41. <https://doi.org/10.1016/j.epsr.2016.02.011>.
- [46] Belderbos A, Delarue E. Accounting for flexibility in power system planning with renewables. *Int J Electr Power Energy Syst* 2015;71:33–41. <https://doi.org/10.1016/j.ijepes.2015.02.033>.
- [47] Xu J, Li X. Using system dynamics for simulation and optimization of one coal industry system under fuzzy environment. *Expert Syst Appl* 2011;38:11552–9.
- [48] Seyis S, Ergen E. A decision making support tool for selecting green building certification credits based on project delivery attributes. *Build Environ* 2017;126:107–18.
- [49] Pereira AJ, Saraiva JT. Generation expansion planning (GEP)—A long-term approach using system dynamics and genetic algorithms (GAs). *Energy* 2011;36:5180–99.
- [50] Yigit S, Ozorhon B. A simulation-based optimization method for designing energy efficient buildings. *Energy Build* 2018;178:216–27.
- [51] Morcillo JD, Franco CJ, Angulo F. Simulation of demand growth scenarios in the Colombian electricity market: An integration of system dynamics and dynamic systems. *Appl Energy* 2018;216:504–20.
- [52] Bazmi AA, Zahedi G. Sustainable energy systems: Role of optimization modeling techniques in power generation and supply—A review. *Renew Sustain Energy Rev* 2011;15:3480–500.
- [53] Poncelet K, Delarue E, D’haeseleer W. Unit commitment constraints in long-term planning models: Relevance, pitfalls and the role of assumptions on flexibility. *Appl Energy* 2020;258:113843.
- [54] Hemmati R, Hooshmand R-A, Khodabakhshian A. Reliability constrained generation expansion planning with consideration of wind farms uncertainties in deregulated electricity market. *Energy Convers Manag* 2013;76:517–26.
- [55] Olsina F, Garcés F, Haubrich H-J. Modeling long-term dynamics of electricity markets. *Energy Policy* 2006;34:1411–33.
- [56] Green R. Electricity and markets. *Oxf Rev Econ Policy* 2005;21:67–87.
- [57] Oyedepo SO, Fagbenle RO, Adefila SS, Adavbiele SA. Performance evaluation and economic analysis of a gas turbine power plant in Nigeria. *Energy Convers Manag* 2014;79:431–40.

- [58] Najjar YS, Abu-Shamleh A. Performance evaluation of a large-scale thermal power plant based on the best industrial practices. *Sci Rep* 2020;10:1–9.
- [59] Staffell I, Green R. How does wind farm performance decline with age? *Renew Energy* 2014;66:775–86.
- [60] Kim J, Rabelo M, Padi SP, Yousuf H, Cho E-C, Yi J. A Review of the Degradation of Photovoltaic Modules for Life Expectancy. *Energies* 2021;14:4278. <https://doi.org/10.3390/en14144278>.
- [61] Phalippou L. The hazards of using IRR to measure performance: The case of private equity. Available SSRN 1111796 2008.
- [62] Agency for Natural Resources and Energy. Past purchase price and period of FIT/FIP system 2021. https://www.enecho.meti.go.jp/category/saving_and_new/saiene/kaitori/kakaku.html (accessed February 7, 2023).
- [63] Organization for Cross-regional Coordination of Transmission Operators. Demand Curve Creation Procedure of Capacity Market Main Auction 2019. https://www.occto.or.jp/iinkai/youryou/kentoukai/2019/files/youryou_kentoukai_23_04.pdf (accessed December 1, 2022).
- [64] Byers C, Levin T, Botterud A. Capacity market design and renewable energy: Performance incentives, qualifying capacity, and demand curves. *Electr J* 2018;31:65–74. <https://doi.org/10.1016/j.tej.2018.01.006>.
- [65] Agency for Natural Resources and Energy, Ministry of Economy, Trade and Industry. Power Survey Statistics Table n.d. https://www.enecho.meti.go.jp/statistics/electric_power/ep002/results_archive.html (accessed February 20, 2023).
- [66] Hokkaido Power Company. Supply and demand results in the Hokkaido area n.d. https://www.hepco.co.jp/network/renewable_energy/fixedprice_purchase/supply_demand_results.html (accessed December 1, 2022).
- [67] Japan Electricity Power Exchange n.d. <http://www.jepx.org/market/index.html> (accessed February 20, 2023).
- [68] Schill W-P, Pahle M, Gambardella C. Start-up costs of thermal power plants in markets with increasing shares of variable renewable generation. *Nat Energy* 2017;2:17050. <https://doi.org/10.1038/nenergy.2017.50>.
- [69] Agency for Natural Resources and Energy, Ministry of Economy, Trade and Industry, Japan. Generation Cost Verification Working Group Report n.d. https://www.enecho.meti.go.jp/committee/council/basic_policy_subcommittee/ (accessed February 20, 2023).
- [70] Hokkaido Electric Power Company. About CO2 Emission Results in 2019 n.d. https://www.hepco.co.jp/info/info2020/1251006_1845.html (accessed February 20, 2023).
- [71] Oliver Grasl. System Dynamics and Agent-based Modeling in Python n.d. <https://pypi.org/project/BPTK-Py/> (accessed December 1, 2022).
- [72] Bynum ML, Hackebeil GA, Hart WE, Laird CD, Nicholson BL, Sirola JD, et al. *Pyomo - optimization modeling in Python*. Third edition. Cham, Switzerland: Springer; 2021. <https://doi.org/10.1007/978-3-030-68928-5>.
- [73] Hou Q, Du E, Zhang N, Kang C. Impact of High Renewable Penetration on the Power System Operation Mode: A Data-Driven Approach. *IEEE Trans Power Syst* 2020;35:731–41. <https://doi.org/10.1109/TPWRS.2019.2929276>.

- 916 [74] Kojima S, Asakawa K. Expectations for Carbon Pricing in Japan in the Global Climate Policy Context. In:
917 Arimura TH, Matsumoto S, editors. Carbon Pricing Jpn., Singapore: Springer Singapore; 2021, p. 1–21.
918 https://doi.org/10.1007/978-981-15-6964-7_1.
- 919 [75] Abani AO, Hary N, Rious V, Saguean M. Considering power plants mothballing in long-term simulation
920 models for liberalized power markets. 2017 14th Int. Conf. Eur. Energy Mark. EEM, Dresden, Germany:
921 IEEE; 2017, p. 1–6. <https://doi.org/10.1109/EEM.2017.7981984>.
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