energies

Article

Will Capacity Mechanisms Conflict with Carbon Pricing? †

Yilun Luo *, Esmaeil Ahmadi , Benjamin C. McLellan * and Tetsuo Tezuka

Department of Socio-Environmental Energy Science, Graduate School of Energy Science, Kyoto University, Kyoto 606-8501, Japan
* Correspondence: luo.yilun.r06@kyoto-u.jp (Y.L.); b-mclellan@energy.kyoto-u.ac.jp (B.C.M.)
† This paper is an extended version of our paper published in Energy, COVID, and Climate Change, Proceedings of the 1st IAEE Online Conference, Paris, France, 7–9 June 2021.

Abstract: Climate change and related national mitigation targets make the decarbonization of the power sector an urgent need. The power sector faces the challenge of considering the design and interaction between emission reduction policies, which can sometimes counteract each other. This study proposes a framework that can be used to quantitatively study the qualitative link between carbon pricing and capacity pricing. The framework is validated through a case study in Hokkaido, Japan, and used to further investigate the interaction between the two policies through a System Dynamics simulation model and scenario design. The results indicate that a carbon price would promote the introduction of wind power, as well as the reduction in fossil fuels, while the capacity price will mitigate the boom-and-bust investment cycle and stabilize electricity prices. However, when the two policy-based prices act on the power system simultaneously, the advantages will be offset by each other. The existence of the capacity price partially offsets the emission reduction effect of the carbon price, and the carbon price with a lower floor will also indirectly squeeze the generation space of flexible power plants. In order to address these inefficiencies, this study proposed a capacity price focused on subsidizing flexible power plants and also coupled with a higher floor carbon price, which results in a consistent incentive. It also promotes the decommissioning of carbon-intensive base-load power plants and reduces CO_2 emissions significantly.

Keywords: liberalized electricity market; carbon pricing; capacity pricing; system dynamics; decarbonization

Citation: Luo, Y.; Ahmadi, E.; McLellan, B.C.; Tezuka, T. Will Capacity Mechanisms Conflict with Carbon Pricing? *Energies* **2022**, *15*, 9559. https://doi.org/10.3390/en15249559

Academic Editor: David Borge-Diez

Received: 23 October 2022
Accepted: 12 December 2022
Published: 16 December 2022

1. Introduction

The power sector is highly dependent on fossil fuels, with global carbon emissions from fossil fuels approaching 37 Gt CO_2 per year, an average annual increase of 2.4% during this century [1]. Although countries are committed to reducing emissions and setting ambitious targets, CO_2 in the atmosphere has still reached a record high value, exacerbating the need to reduce fossil fuel consumption globally [2]. Decarbonization of the power sector has received much attention with the introduction of renewable energy sources, especially wind and solar, which have grown 20-fold over the past 15 years to account for 5% of global electricity generation [3]. To address climate change, a paradigm shift in the current power industry from fossil-fuel-based technologies to low-carbon emission technologies is urgent. In the meantime, in a liberalized electricity market, the investment and decommissioning of generation capacity are made as business decisions by multiple profit-oriented companies. The investment in different generation technologies by these market players depends on the impact of price signals. To guide the behavior of market participants, several market policies aim to apply appropriate price signals, while addressing environment issues and market failures that have arisen, such as carbon prices for climate change externalities, as well as capacity prices to avoid boom-and-bust investment cycles.

Current international carbon emission reduction policies mainly include energy efficiency and emission standards, public technology research and development, and carbon pricing tools (including carbon tax and carbon emissions trading systems). Policy analysts generally agree that an economy-wide carbon pricing tool will be necessary to achieve deep carbon reductions in a cost-effective manner [4–6]. Carbon pricing is a powerful policy tool designed to drive and accelerate the transformation of the power system by internalizing the environmental cost of CO_2 emissions. It has been implemented in many countries as a market-driven tool to reduce greenhouse gas emissions and combat climate change [7]. Given the diversity of sources of carbon emissions, the uniform design of energy efficiency and emission standards is challenging [8]. The key advantages of carbon pricing tools are flexibility and effective incentives, which can lead to the best overall cost-effectiveness of the economy [9]. In addition, carbon pricing can reduce long-term abatement costs by inducing climate-friendly technological change [10].

Capacity mechanisms have become the favored approach in the US and Canada for dealing with incentives to maintain levels of generating capacity that satisfy reliability criteria. These respond to a potential decline in flexible or high-cost generators that become uneconomic in highly competitive markets or potentially those with high levels of low-cost renewables. Capacity markets were intended to address the concern that a rise in variable renewables would increase the uncertainty of revenue for conventional dispatchable generation capacity through lower and more volatile wholesale prices [11]. Regarding the fixed cost recovery of thermal power, there is a linkage between scarcity pricing mechanisms that rely on electricity price spikes and capacity market mechanisms that rely on institutional subsidies [12]. The design and implementation of a capacity market mechanism involves the creation of aggregate systems, capacity targets, auction markets where generators can submit bids to commit to supply under capacity-constrained conditions, and the resulting forward capacity prices [13–15]. The capacity mechanism not only minimizes the risk of shortages, but also reduces the price volatility [16].

Capacity remuneration mechanisms are implemented as incentive tools for reliable investment, in order to ensure power adequacy in the liberalized electricity market. For capacity pricing, there are mainly two objectives: first, providing subsidies for the fixed cost of technologies which contribute to the security of electricity systems' supply–demand balance operation [17], e.g., marginal power plants. Second is the objective of price formation through auctions based on the forecast capacity demand, thereby ensuring the electricity system adequacy and avoiding the boom–bust investment phenomenon [18]. Meanwhile, the main objective of carbon pricing is to internalize the CO_2 environmental externality of fossil fuel, in order to promote the variable renewable energy penetration and gradually reduce the consumption of fossil fuel energy [19]. Therefore, during the transition of power systems in liberalized markets, increasingly complex policy designs may have unintended side effects through the interaction of policy instruments [20].

Fossil fuel power plants still dominate most current electricity systems to provide system adequacy as well as flexibility, which lead to the CO_2 intensive power capacity being charged through carbon pricing while receiving payments from capacity pricing. Although both policies have achieved their direct goals of pricing certain objects through market-based policy instruments, the interaction between these two prices and the subsequent impacts on the electricity market have been less investigated. Previous qualitative studies [21–23] focused on the barrier and misalignment of integration among electricity-system-related mechanisms such as variable renewable energy (VRE) incentives, CO_2 emission trading or taxing, and the capacity remuneration mechanism. A growing number of studies have investigated the interaction between VRE incentives and carbon pricing [24,25], increasing VRE's share and capacity remuneration mechanisms [26]. Nevertheless, previous studies focus on qualitative analysis, and there is a gap in the field of study for investigating the policy interactions between capacity pricing and carbon pricing quantitatively, which may affect power generation investment decisions during the energy system transition. In addition, considering that the electricity market is a complex system, the implementation of its policies has a relatively volatile impact on the market. With the development of the electricity market, the correlation between policies will become one of the issues worth studying, because if the correlation is ignored, there may be negative policy effects, while systemic frictions can invalidate reform proposals and lead to forward misalignments [21]. Therefore, we will delve into the relationship between capacity pricing and carbon pricing in the free electricity market, and the results will provide a reference for more efficient market design.

Electricity market modeling commonly exhibits four major trends: optimization models [27], equilibrium models [28], simulation models [29], and hybrid models [30]. Among them, bottom-up optimization models usually show the cost-optimal path of an energy transition and solve the problem of "how to design" the system [31,32]. The results of these studies help paint an "ideal" world in which central actors with control must actively implement these decades-old systems to achieve cost-optimized paths. However, with the liberalization of the electricity market, some democracies intend to move away from centralized planning. If we want to increase our understanding of these systems, we should therefore pay more attention to the combination of heterogeneous actors with bounded rationality and imperfect information [33]. Equilibrium models attempt to characterize market problems using algebraic or differential equations, which focus on the series of overall changes caused by linkages between sectors affected by policy changes [34]. However, when the problem is too complex to be solved within a formal equilibrium framework, a simulation model can be used as a substitute for the equilibrium model to a certain extent [35]. System Dynamics focuses on the continuous changes of variables affected by policies. As a representative method in simulation models, it has been widely used in various industries and fields since it was first proposed in 1958 [36]. It has been applied to problems in agriculture [37], manufacturing [38], the green hydrogen industry [39], the chemical industry [40], and so on. Simulation models have been developed and applied to operational and policy issues in the energy sector. Among them, System Dynamics models are built for policy analysis, exploration of possible future scenarios, and management purposes [41–44], and are widely used in the field of energy policy, for example, national energy policy assessment [45], energy efficiency analysis [46], energy nexus [47], and resource carrying capacity [48].

Unlike previous studies, this study proposes a framework that can be used to investigate the link between carbon pricing and capacity pricing. To confirm the validity of the framework, we constructed a System Dynamics simulation model using Hokkaido as an example based on the framework. The study aims to address the following: (i) what is the interaction between capacity pricing and carbon pricing in a liberalized electricity market during the low-carbon transition period? (ii) How does this interaction ultimately affect the trajectory of power mix change? This study contributes to the extant literature in the following aspects. Firstly, this study proposes a conceptual model as the framework for further quantitative analysis of the correlation between carbon policy and capacity policy; secondly, the simulation experiments identified potential conflicts which will offset the advantages of each other that may exist between two policies under certain designs. This study could provide a new research perspective for exploring the impacts of policy interactions on the electricity market and provide effective support for the future involvement of the electricity market.

The rest of the paper is structured as follows. Section 2 presents the method and data. Section 3 presents the simulation results of power mix changes for five scenarios with in-depth analysis, and the Section 4 summarizes findings and a discussion of possible future research directions.

2. Methodology and Data Sources

2.1. Conceptual Model as the Framework

System Dynamics has advantages in handling linear and nonlinear interactions, large-scale, long development cycles, and complex and dynamic systems [20,49]. The System

Dynamics method is based on the point of view of causality and structure determining behavior, which establishes a model from the internal microstructure of the system. It further analyzes the internal relationship between the structure and function of the system and dynamic behavior with the help of computer simulation technology, in order to find a solution to the problem [37]. Moreover, System Dynamics provides a convenient and scientific basis for decision-makers to simulate and test proposed policies through multi-scenario simulations and to see the long-term results of implementing each policy before making a final decision [50]. The most important procedure for establishing a System Dynamics model for policy simulation is to establish causal loops to describe the logic of the system and to build equations among the factors, in order to generate quantitative relationships [51].

A causal loop diagram (CLD) is an important tool to show the feedback structure of the system [52]. As mentioned above, based on previous research on carbon price and capacity price, this study summarizes the typical causal loop diagram of these prices and further proposes a framework that can be used for quantitative analysis of the qualitative relationship between the two prices. The framework is shown in Figure 1, where "positively related" means that if all else is equal, one value increases and then the other increases, or one decreases and then the other decreases as well; "negative related" means if all else is equal, one value increases then the other decreases, or one decreases then the other increases. There are three balanced feedback loops in it. (1) The first is balance loop B1, where the supply loop represents the overall long-term supply and demand balance of the power system, including installed capacity, generated electricity, electricity price, yearly revenues, and decision-making. It means that more installed capacity will bring more power generation capacity, thereby reducing electricity price, revenue, and investment in new capacity. For the installed capacity, if it is wind, then more capacity means more power generation without emissions. If it is coal, we assume that it is base-load capacity with fixed output, thereby more installation will bring more electricity from coal power, together with emissions. More installed capacity of NG power plants means that they need to increase the corresponding power generation to maintain their profits. (2) The second feedback loop is balance loop B2: the carbon loop is aimed at carbon pricing, including thermal capacity, fossil fuel electricity, CO_2 emission, carbon price, marginal price, electricity price, yearly revenues, and decision-making. It means that more thermal power installed capacity will bring more carbon emissions, resulting in a rise in carbon prices, along with marginal costs and higher electricity prices, which affects the final investment decision. Depending on the technique, this loop causes different effects, which is elaborated in the Section 2 in details. Put simply, for thermal power plants, the increase in electricity prices is also accompanied by an increase in the cost of carbon prices, while for renewable energy, while benefiting from an increase in electricity prices, they also get compensated from the carbon market. (3) Lastly, balance loop B3 is for capacity price, including installed capacity, capacity price, yearly revenues, and decision-making. It means that more thermal power installed capacity will bring more effective capacity to meet the capacity demand, determined by the system based on power demand, thereby reducing capacity prices and ultimately affecting investment decisions.

The model shown in Figure 1 consists of five modules, which are the capacity changing module, electricity price module, carbon price module, capacity price module, and investment decision module. We consider three power generation technologies in the model: wind power as a representative of variable (non-controllable) renewable energy, coal as a representative of baseload (non-load-following) fossil fuel power plants, and natural gas (NG) as a representative of flexible fossil fuel power plants. The comparison of the characteristics of the three technologies is summarized in Table 1. The unit time step of the model is a week. The weekly time resolution can reflect the short-term supply and demand balance and the long-term capacity changes simultaneously.

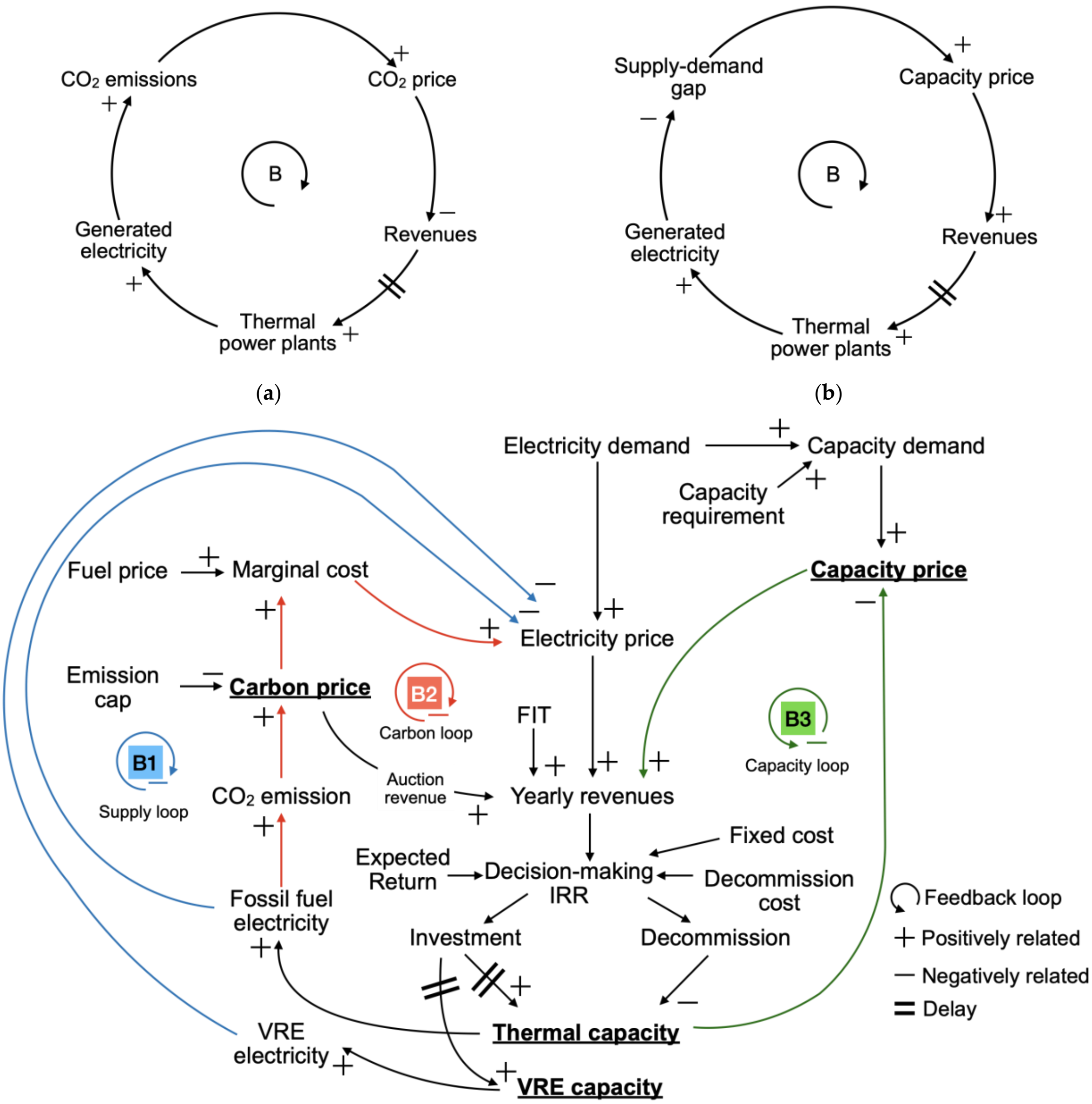


Figure 1. (**a**) Typical causal loop diagram of carbon price functioning; (**b**) Typical causal loop diagram of capacity price functioning; (**c**) Causal loop diagram of the proposed framework.

Table 1. Comparison of the three technologies characteristics.

	Power Output	CO_2 Emission	Capacity Value
VRE: Wind	Fluctuate	Zero emission	Low value
Fossil fuel: Coal	Stable	High emission	High value
Fossil fuel: NG	Flexible	Medium emission	High value

We conducted a further in-depth analysis of the causal relationship between the variables based on the proposed framework. After detailed separation of exogenous and endogenous factors and understanding of the positive and negative feedback relationship between each factor, we enriched the original conceptual model and determined a detailed causal cycle diagram. The proposed model represents the interaction relationship between factors in detail, clarifying the feedback mechanism and policy transmission mechanism of the system, as shown in Figure 2.

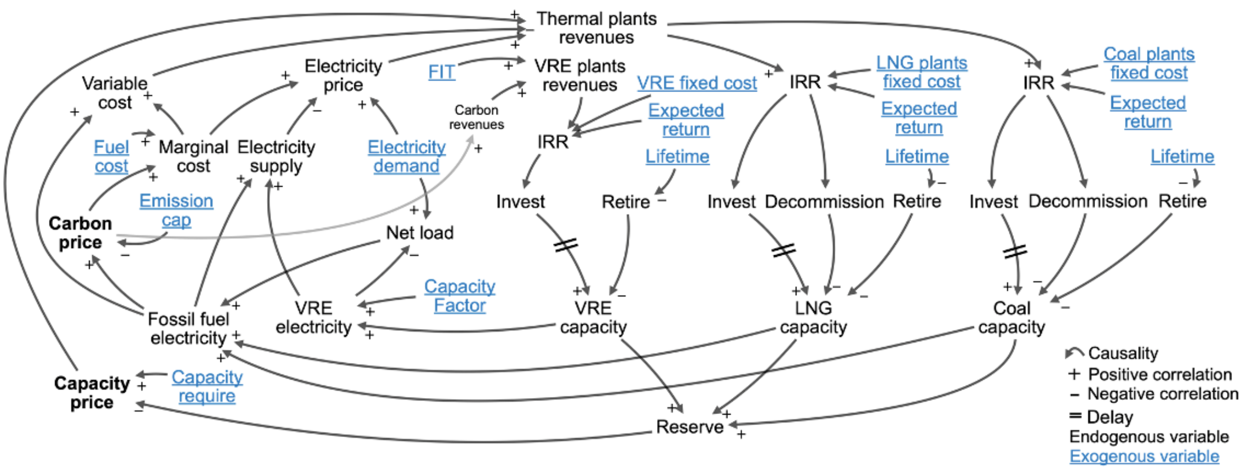


Figure 2. Detailed causal loop diagram of the proposed simulation model.

2.2. Quantitative Model Formulation

After completing the identification of the elements in the problem and the conceptual modeling of the causal loops, each element in the CLD start to be extended to a more concrete quantitative model, which is known as the stock-flow model. The stocks are altered by inflows and outflows; in other words, stocks are accumulations of the difference between the inflow to a process and its outflow, and they characterize the state of the system and generate information [20]. For instance, the capacity of generation technologies is a stock, and the new investment and the decommissioning of capacity are inflows and outflows. On the other hand, other elements in CLD may be modeled as variables and parameters, such as electricity price and the fixed cost of technologies.

The stock-flow model of capacity change is depicted in Figure 3. Due to the characteristics of the modeling of System Dynamics, the composition of each stock is homogeneous, that is, the capacity of one technology in the same stock is assumed as the same age, efficiency, etc. Therefore, in order to allow the new investment capacity to be included in the current existing capacity, we assume "0 age" of the existing power plant fleet, instead of having an average age. The capacity change module simulates the investment, decommissioning, and retirement of different technologies. At the end of each year, the capacity (MW) (*CP*) of each technology (*i*) consists of the following: the new capacity (MW) (*NewIn*) is added into the market, the decommission capacity (MW) (*Decom*) exits the market, and the life-expiring capacity (MW) (*Retire*) retires. This is described in Equation (1), where $\boldsymbol{t}$ is the number of weeks.

$$CP_i(t) = CP_i(t_0) + \int_{t_0}^{t} NewIn_i(t) - Decom_i(t) - Retire_i(t) \cdot dt \tag{1}$$

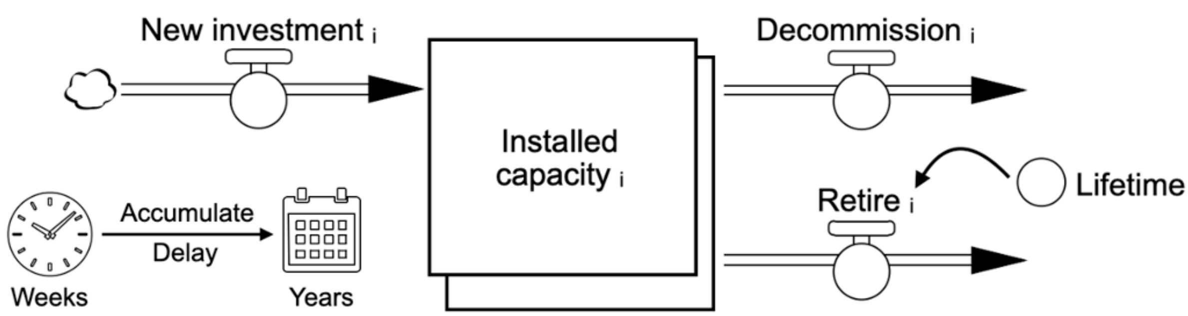


Figure 3. Stock-flow diagram of capacity change.

The new investment and decommission capacity are decided by market participants based on their profits. The life-expiring retirement does not relate to business, but only depends on the lifetime of the equipment for each specific technology, which is described in Table 2. The newly added capacity takes construction time (yr) (*ConsTime*) after the investment decision, which is modeled as pipeline delay in this study. The annual retirement capacity is modeled as the first-order delay of the technology lifetime (yr) (*lifetime*), as represented in Equations (2) and (3), where j is the number of years (a year is calculated as 52 weeks).

$$NewIn_i(j + ConsTime) = Delay(NewInvest(j), ConsTime) \tag{2}$$

$$Retire_i(t) = \frac{CP_i(t)}{Lifetime_i} \tag{3}$$

The electricity price module uses the concept of merit order to calculate electricity prices based on marginal costs, by simulating the balance of power supply and demand per unit of time. The import and export of electricity is not considered in the model setting, and at the same time, we assume that the demand is inelastic. As shown in Figure 4, the VRE has priority scheduling since its marginal cost is almost zero. The dispatch of coal and NG depends on the order of their marginal cost.

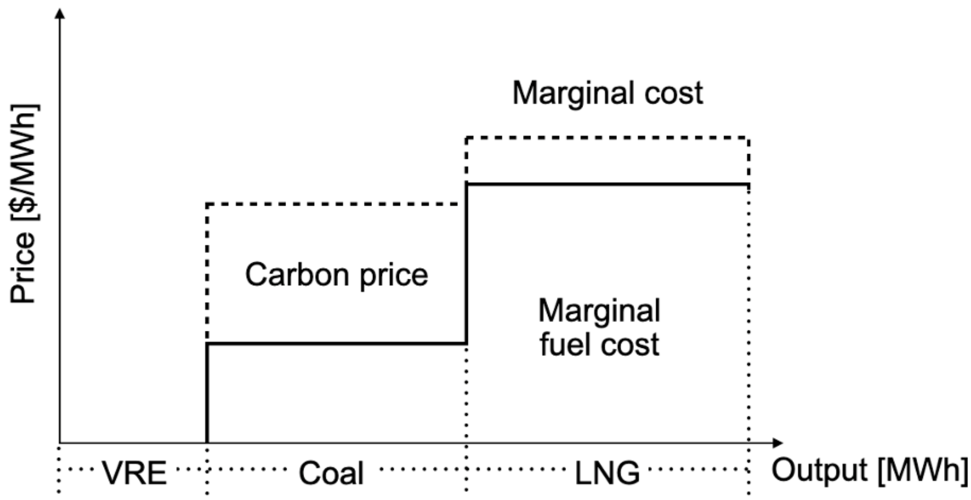


Figure 4. Concept of merit-order electricity pricing.

As represented in Equation (4), the marginal fuel cost (USD/MWh) (*MarFuel*) is calculated through the power plant thermal efficiency (*Heff*), heating value of fossil fuel (MJ/ton) (*Hval*), and the average fuel price (USD/ton) (*Fuelprice*) as an exogenous variable. In Equation (5), the marginal cost (USD/MWh) (*MarCost*) of a thermal power plant is equal to the sum of the marginal fuel cost and carbon price (USD/ton-CO_2) (*CarbonPrice*) multiplied by the unit emission coefficient (*EF*) of the fuel. Since fuel cost and emission intensity are exogenous variables, the calculated value of the marginal cost of two technologies in the model depends on the carbon price.

$$MarFuel_{Coal,LNG} = \frac{3600}{Heff_{Coal,LNG} \times Hval_{Coal.LNG}} \times Fuelprice_{Coal,LNG} \tag{4}$$

$$MarCost_{Coal,LNG}(t) = MarFuel_{Coal,LNG} + EF_{Coal,LNG} \times CarbonPrice(t) \tag{5}$$

The traditional coal power is mostly used as baseload power because its ramp rate, which is the speed of adjusting output, is slower and the associated cost is also higher compared to other technologies. Therefore, we assume that the power generation (MWh) (*Generate*) of coal is a fixed output, which equals the product of its capacity, annual operating factor (*OF*), and weekly hours. The 168 h in the model is one week (24 h for 7 days), and the OF coefficient is the average operating level (70%) of the Hokkaido baseload coal-fired power plant. We use OF as an exogenous variable to reflect the characteristics of coal power as base-load power generation, because in reality coal plants are rarely shut down throughout the year and are usually reluctant to alter production to meet minimum operating requirements. For the change in wind power installed capacity, we further assume that if the increment of wind power and coal power exceeds the total demand, then the oversupplied wind power will be curtailed to ensure the balance of the grid. The wind power is modeled as a constant weekly output with volatility, in which its capacity is multiplied by a capacity factor (*CF*) and weekly hours. The annual operating factor and the VRE capacity factor are inputs of the model as exogenous variables.

$$Generate_{Coal}(t) = CP_{Coal} \times OF_{Coal} \times 168\ hours \tag{6}$$

$$Generate_{Wind}(t) = CP_{Wind} \times CF_{Wind} \times 168\ hours \tag{7}$$

NG is the representative of flexible power sources in the model, and its output is assumed to be equal to the residual load (MWh) (*ResidualLoad*); that is, the total demand (MWh) (*Demand*) minus the uncontrollable VRE generation (MWh) (*NetLoad*), and then minus the fixed output of the baseload power plant, thereby maintaining the system supply and demand balance. Therefore, this study modeled the power grid dispatch according to a fixed priority order, with VRE first, coal second, and NG last. This ensures that the electricity generated from VRE can enter the grid as much as possible, coal as a base load does not need to change its output, and NG as a flexible resource is responsible for balancing the grid.

$$NetLoad(t) = Demand(t) - Generate_{Wind}(t) \tag{8}$$

$$ResidualLoad(t) = NetLoad(t) - Generate_{Coal}(t) \tag{9}$$

The balance of supply–demand (*SDbalan*) equals the total supply (MWh) (*TotalSup*) minus the total demand, where the weekly electricity demands are input as exogenous variables of the model, which is depicted as a stock-flow diagram in Figure 5. The total supply is the sum of VRE, coal, and NG power generation per unit of time.

$$SDbalan(t) = TotalSup(t) - Demand(t) \tag{10}$$

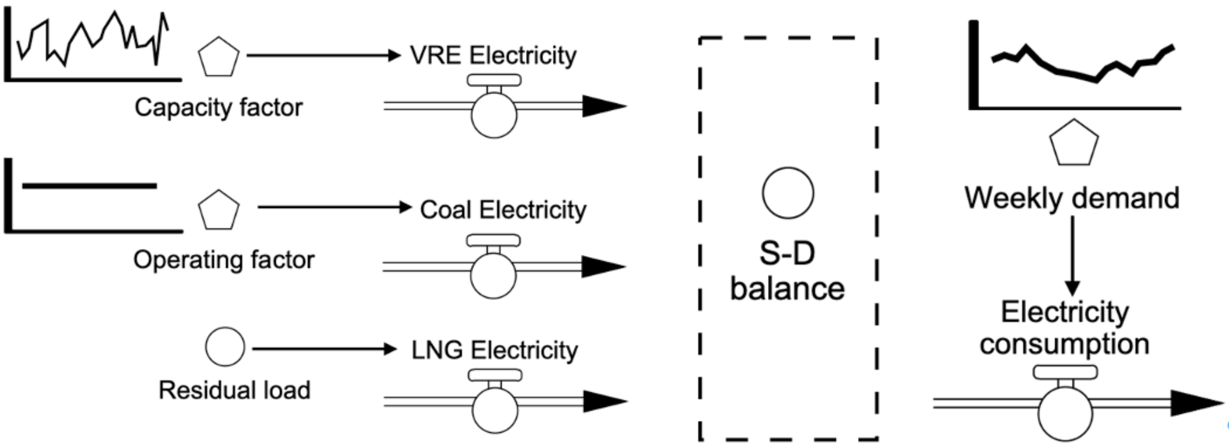


Figure 5. Stock-flow diagram of the balance of supply and demand.

The electricity price is calculated by the following Equation (11). The current state of the system is indicated by the balance of supply and demand, and whether the flexible power source, NG, is generating electricity, indicated by the residual load. When the hourly demand is less than the available supply capacity, which means it is loose, while NG is generating, the electricity price is the highest marginal cost of thermal power plants. When the supply and demand are loose and NG is not generating, the electricity price is the weighted average marginal cost of coal generation and VRE generation. When the hourly demand is more than the available supply capacity, which means it is tight, while NG is generating, the electricity price is the highest marginal cost of the thermal power plants multiplied by the scarcity electricity price coefficient (α). When supply and demand are tight and NG is not generating, the electricity price is the weighted average marginal cost of coal generation and VRE generation multiplied by the scarcity electricity price coefficient. We consider the weighted average to simulate the merit order effect, since the marginal cost of wind power generation is zero, and the average electricity price will continue to decrease after wind power generation increases. When the VRE capacity is extremely low, the marginal electricity price calculated using the weighted average is almost equivalent to the coal marginal electricity price. When the VRE continues to increase, the average electricity price will continue to drop to zero.

In a perfect competitive liberalized power market, the electricity price is equal to the highest marginal cost of the online generating technology. Therefore, the fixed cost of marginal power plants is not included in the electricity price most of the time, and the fixed cost recovery depends on the scarcity price when the supply–demand balance is tight, or the capacity price [53]. Since this study considers the existence of capacity prices, the electricity price ceiling in this model is set as the real price ceiling in Japan.

$$\begin{array}{lcc} & SDbalan(t) \geqq 0 & SDbalan(t) < 0 \\ ResidualLoad(t) > 0 & \begin{array}{c}\max\{MarCost_{Coal}(t),\\ MarCost_{LNG}(t)\}\end{array} & \max\{MarCost_{Coal}(t) \times \alpha, MarCost_{LNG}(t) \times \alpha\} \\ ResidualLoad(t) \leqq 0 & MarCost_{Coal}(t) \times \frac{NetLoad(t)}{Demand(t)} & - \end{array} \quad (11)$$

The capacity remuneration mechanism subsidizes the power plants which contribute to the adequacy of power generation capacity. In this study, we model the capacity remuneration mechanism as a capacity auction market. The total capacity is evaluated at the end of each year. If the current capacity is lower than the capacity requirement (MW) (*CPReq*), a full-price subsidy (USD/MW) (*MaxP*) will be provided, which is the difference between the fixed cost per MW capacity and the expected return per MW capacity of a new NG power plant. This expected return of a standard newly built NG power plant is decided by the regulatory agency based on the industry survey [54]. If the current capacity is higher than the requirement, the subsidy price (USD/MW) (*CapacityPrice*) will be reduced in proportion and become zero after exceeding a certain range of requirement. We use the traditional planning reserve margin method to calculate the capacity requirement, which is 15% higher than the yearly peak demand. Different power generation technologies have different weights of contributions to capacity adequacy. This study assumes the capacity value of VRE calculated by its installed capacity multiplied by the average yearly capacity factor. Equations (12) and (13) describe the changes in capacity price, where *CPRatio* is the ratio of existing capacity to capacity requirement, γ is the sensitivity coefficient of the capacity price increase. In addition, following the instruction from the regulatory agency of the case study area, which currently recognized all thermal power as 100% qualified capacity without further availability or minimum yearly output requirements [55], we thereby calculated the capacity in Formula (12) without the operating factor.

$$CPRatio(t) = \frac{CP_{Coal,LNG}(t) + CP_{Wind}(t) \times CF}{CPReq} \quad (12)$$

$$CapacityPrice(t) = \begin{cases} MaxP & CPRatio \leqq 1 \\ MaxP - CPRatio(t) \times \gamma & CPRatio > 1 \end{cases} \quad (13)$$

This study made assumptions to simulate the capacity price. The real-world capacity price calculation involves the evaluation of the reliability of the power system. In particular, how to calculate the capacity value of VRE's random output is a complicated topic. This part is considered initially to be beyond the scope of this study. We focus on the mutual influence of the behavior of subsidizing capacity on other price mechanisms in the electricity market.

We model the carbon price mechanism as a cap–trade emission allowance trading system with floor prices, with the pricing scope limited to the power system in the target area. The annual emission quota allowance will be auctioned at the floor price (USD/ton-CO_2) (*FLP*) at the beginning of each year. If the current annual cumulative emissions (ton-CO_2/yr)(*TotalEm*) are less than the annual emissions cap (ton-CO_2/yr) (*Emcap*), then the carbon price is the floor price. If the current cumulative emissions exceed the emissions cap, the carbon price will increase. Equations (14) and (15) describe the changes in carbon prices, where *EmRatio* is the ratio of emissions to allowances, β is the sensitivity coefficient of the carbon price increase.

$$EmRatio(t) = \frac{TotalEm(t)}{EmCap} \tag{14}$$

$$CarbonPrice(t) = \begin{cases} FLP & EmRatio \leqq 1 \\ FLP \times EmRatio(t) \times \beta & EmRatio > 1 \end{cases} \tag{15}$$

The emission per time step (ton-CO_2) ($CO_2emission$) is equal to the generation of fossil fuel thermal power plants multiplied by the corresponding fuel emissions factor. The cumulative emissions within a year from all plants are the total annual emissions.

$$CO_2emission(t) = Generate_{Coal,LNG}(t) \times EF_{Coal,LNG} \tag{16}$$

$$TotalEm(j) = \int_t^{t+52} CO_2emission(t) \cdot dt \tag{17}$$

The revenue from the auction (USD) (*CarbonRevenue*) of carbon allowances will be used to subsidize the additional introduction of VRE, where the annual carbon revenue is the annual accumulated CO_2 emissions multiplied by the weekly updating carbon price. In the real world, the carbon price revenue of the regulator is limited to the primary auction market, and the real-time carbon price arbitrage revenue belongs to the secondary market. We assume that, to a certain extent, the expectations generated by carbon prices in the secondary market will eventually be reflected back to the primary auction market. For example, if the demand for carbon allowances in the secondary market is strong, it will raise participants' bidding prices in the primary auction market. Therefore, rather than multiplying the total amount by the floor auction price, our calculation can reflect the impact of the auction price and secondary market revenue on the overall carbon price revenue.

$$CarbonRevenue(j) = \int_t^{t+52} CO_2emission(t) \times CarbonPrice(t) \cdot dt \tag{18}$$

The decisions of market participants in the free market are assumed as purely commercial behavior, thereby their decisions depend on their profits from investment. We use 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. When the expected profits of the investment are higher than its costs during the whole lifetime, participants will choose to build new capacity. Generally, in the whole lifetime of the project accounting, the lifetime is assumed to be 40 years for thermal and 20 years for wind. We set the threshold of the expected return rate equal to the interest rate, which is usually the lowest return acceptable to any rational investor. As shown in Equations (19)–(21), the calculation of NPV includes the fixed cost (USD/MW) (*FixCost*) in the initial year and the decommissioning cost (USD/MW) (*DecomC*) in the last year of the power plant's lifetime. The Decommissioning cost equals a ratio (*DecomCostRatio*) of the fixed cost. The annual cash flow (USD/MW)

(*ECF*) is equal to the revenue (USD/MW) (*UnitRev*) during the year minus the maintenance costs (USD/MW) (*UnitMainten*) and variable cost (USD/MW) (*UnitVar*).

$$NPV_i(t) = -FixCost_i + \sum_{n=1}^{Lifetime-1} \frac{ECF_{i,n}}{(1+IRR)^{Lifetime-1}} + \frac{ECF_{i,Lifetime} - DecomC_i}{(1+IRR)^{Lifetime}} \quad (19)$$

$$ECF_i(t) = UnitRev_i - UnitVar_i - UnitMainten_i \quad (20)$$

$$DecomC_i = FixCost_i \times DecomCostRatio_i \quad (21)$$

Previous research [56,57] chose to use trend prediction when estimating the future cash flow of NPV. The implicit assumption of this method is that future electricity prices will continue to develop in accordance with the fluctuation trend during the reference period. However, the current energy system is under a policy-driven fast transition period, and compared with stable policy subsidies, the changing in electricity prices from the market reflects more on the short-term supply and demand balance, thereby its fluctuation trend does not accurately reflect the long-term expectations of the policy-driven transition. For example, the investment in VRE driven by the FIT mechanism assumes stable returns will be guaranteed during its lifetime. Many power plants also tend to sign long-term power purchase agreements for a large amount of electricity trading to avoid risks, so as to ensure that there is a stable revenue every year.

Since this study focuses on the interaction between policy-based market pricing and the impact on the trajectory of long-term system transition, we adopt a constant status quo investment strategy that ignores fluctuation trends. That is, reviewing the current revenue and cost at the end of each year, decisions are made based on the price of the past year, assuming that the situation will be steady for the entire project lifetime, and there is no trend forecast for electricity price fluctuations. Similar assumptions are found in previous research [58]. It should be emphasized that this assumption is far from reality, but easy to model. It is undeniable that real-world investor behavior is far more complex than this simplifying assumption. For example, when an investment is profitable, everyone will actively participate until the profit continues to decline to a normal level. In the end, only the first mover will obtain more profit.

The investments in new power plants (stock-flow diagram as shown in Figure 6) are modeled as discrete investments in the number of generating units. The new investment is equal to the ratio of the expected return to the fixed cost multiplied by the investment coefficient (*InvCoe*), then the rounded integer result is multiplied by the minimum size of generator sets (MW) (*UnitCP*), as shown in Equation (22). The investment coefficient is the adjustment item for model calibration when it is required for future prediction; so far, this study focuses on the theoretical simulation of policy interaction, thereby we assume the coefficient qualitatively to emphasize the difference as 1 for thermal power and 40 for VRE, since the minimum unit sizes of those technologies are different. The basis of this assumption is to ensure that when thermal power and VRE receive the same degree of return, the capacity of their final investment is the same.

$$NewIn_i(t) = \left[\frac{NPV_i(t) + FixCost_i}{FixCost_i} \times InvCoe_i \right] \times UnitCP_i \quad (22)$$

Equations (23) and (24) describe the decommissioning decision. The annual operating cash flow (USD/MW) (*Cash*) of all existing power plants includes revenue, variable costs, fixed maintenance costs, annualized fixed costs (USD/MW) (*AnnulFixC*), and annualized decommission costs (USD/MW) (*AnnulDecomC*). When the operating cash flow is negative, that is, when the revenue is lower than its operating cost, the market participants will choose to close the power plant and exit the market. This is due to the assumption of a constant status quo strategy; if the current revenue is less than the operating cost, it is considered that this situation will be continuous in the future and there is no chance to recover the losses, therefore decommissioning is a rational decision. The decommissioned capacity is equal to the ratio of the annual loss to the annual revenue, multiplied by the decommissioning coefficient (*DecomCoe*) and then multiplied by the minimum size of generator sets. Similar to the investment coefficient, we assume the coefficient qualitatively as 1 for thermal power, to indicate the equal weight of investment and decommissioning for thermal power, and 0 for VRE, since no VRE exits the market due to continuous subsidization.

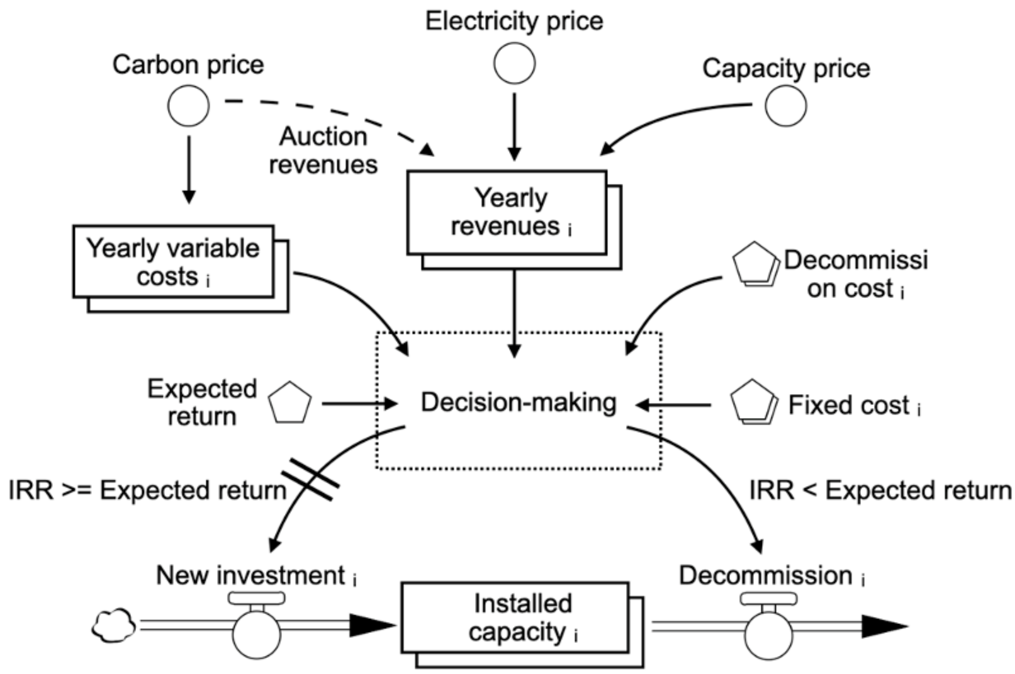


Figure 6. Stock-flow diagram of the balance of the investments of new power plants.

$$Cash_i(t) = UnitRev_i - UnitVar_i - UnitMainten_i - AnnulFixC_i - AnnulDecomC_i \quad (23)$$

$$Decom_i(t) = \left[\frac{UnitRev_i(t) - Cash_i(t)}{UnitRev_i(t)} \times DecomCoe_i\right] \times UnitCP_i \quad (24)$$

Although the investment decisions in the real world are decentralized, in this study, we assume that all investors in the same technology make the same decision within any year. This assumption allows the model to ignore risk. The actual decision of a single company highly depends on the decision-maker's own risk perception threshold [59], while the unified decision in a year after aggregation ignores the fluctuations of micro-individuals and reflects the overall changing of expected returns.

Based on this assumption, in Equations (25) and (26), we calculate the annual revenue (USD) (*Revenue*) of thermal power plants as the accumulation of power generation multiplied by the electricity price (USD/MWh) (*ElecPrice*), and the annual revenue of wind power generation is the power generation multiplied by the FIT price (USD/MWh) (*FIT*). The annual revenue per MW is calculated by Equations (27) and (28). Wind power has additional revenue from the emission trading system, while thermal power plants receive subsidies from the capacity market. Wind power is excluded from the capacity market as it cannot provide controllable power output. The current FIT policy in Japan is controlled by the regulatory agency, and users across the country are jointly responsible for the FIT subsidy, so we set it as an external variable. Due to the fixed income brought by FIT, wind power will have a certain degree of continuous growth in the future period. On this basis, we use the potential carbon price auction revenue to provide additional subsidies for wind power as a booster, so as to realize the simulation of the gradual substitution of wind power for thermal power generation. This setting is due to the following: (1) FIT is a mandatory policy launched by the regulatory agency, so it is an exogenous variable and will not be affected by simulation results; (2) the additional revenue from wind power brought by the carbon price auction can form dynamic constraints within the model with the withdrawal of thermal power generation. This part of the simulation combines the exogenous variables in the real world and the endogenous variables assumed in the model, and the results are still within a reasonable range.

$$Revenue_{Coal,LNG}(j) = \int_t^{t+52} Generate_{Coal,LNG}(t) \times ElecPrice(t) \cdot dt \tag{25}$$

$$Revenue_{Wind}(j) = \int_t^{t+52} Generate_{Wind}(t) \times FIT \cdot dt \tag{26}$$

$$UnitRev_{Wind}(t) = \frac{Revenue_{Wind}(j) + CarbonRevenue(j)}{CP_{Wind}} \tag{27}$$

$$UnitRev_{Coal,LNG}(t) = \frac{Revenue_{Coal,LNG}(j)}{CP_{Coal,LNG}} + CapacityPrice(t) \tag{28}$$

Similarly, in Equation (29), the annual variable cost (USD) (*VarC*) is calculated as the accumulated power generation times the marginal cost. The annual variable cost per MW is calculated by Equation (30). The variable cost of wind power is ignored due to the low marginal cost.

$$VarC_{Coal,LNG}(j) = \int_t^{t+52} Generate_{Coal,LNG}(t) \times MarCost_{Coal,LNG}(t) \cdot dt \tag{29}$$

$$UnitVarC_{Coal,LNG}(t) = \frac{VarC_{Coal,LNG}(j)}{CP_{Coal,LNG}} \tag{30}$$

2.3. Case Study

In order to verify the applicability and rationality of the framework, we intend to conduct simulations through case studies. Since the capacity mechanism is strongly influenced by electricity imports and exports, choosing a more isolated grid is more suitable for validating the proposed framework. Hokkaido is isolated from Japan's main island (Honshu), and its connection to Japan's main power grid is limited. At the same time, Hokkaido has a complete power generation, power supply, and transmission system, and its local electricity demand is objective. Therefore, we chose Hokkaido, an island in northern Japan, as a case study to simulate capacity changes. The initial installed capacity of each technology are the real data of Hokkaido in 2019. NG capacity also includes some biomass thermal power plants which perform similar to the flexible power characteristic of NG plants.

We assume that the initial state of the system is in equilibrium, and the lifetime of all power plants starts counting from the beginning of the simulation period. The real supply–demand data in 2019 [60] are used as the input data of electricity demand, as shown in Figure 7. We assume that the demand for each year in the future will be the same as in 2019. In reality it is usual to expect that due to electrification (as part or prerequisite of decarbonization), electricity demand will grow in the future. This assumption helps us to eliminate factors that are less relevant to the question under study from the complex reality, allowing a focus on the interactions among our main study targets.

Similarly, we use the real wind power data [60] and installed wind power capacity of Hokkaido in 2019 to calculate the wind power factor, as shown in Figure 8. We assume that the wind power factor for each year in the future is the same as in 2019. On the one hand, excessive randomness will make the results from the model become difficult to understand, but on the other hand, oversimplification can make the results directly dependent on the assumptions. Therefore, the input data of this study are from the real world with fixed fluctuations, which will improve the interpretability of the model and give better insights to be extracted.

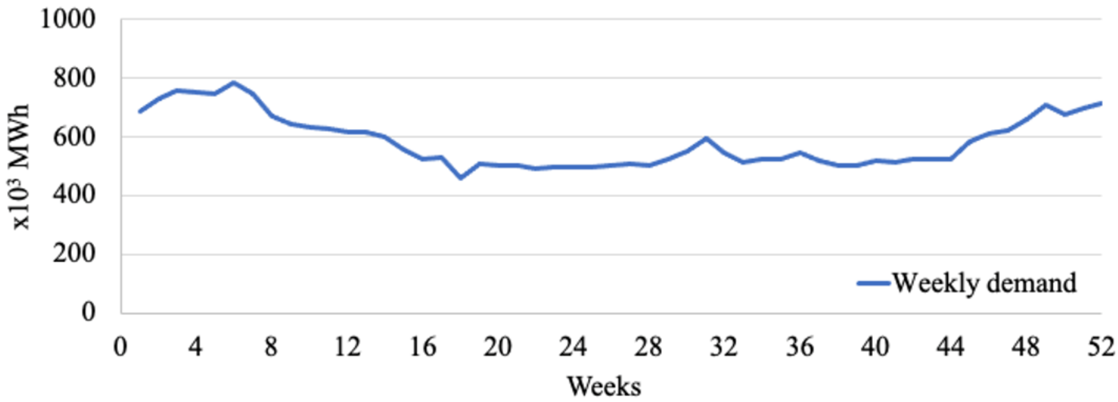


Figure 7. The real electricity consumption data of Hokkaido in 2019.

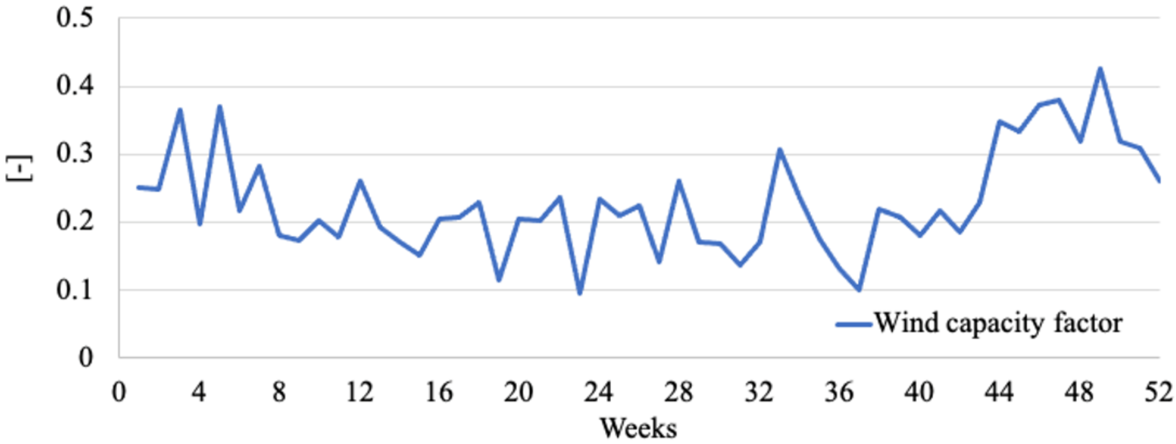


Figure 8. The capacity factor of wind generation in Hokkaido 2019.

Since the Hokkaido Electric Power Company owns 87% of all thermal power plants in Hokkaido, we calculated the CO_2 emissions of all thermal power plants in Hokkaido using the CO_2 emission factors of the Hokkaido Electric Power Company as a benchmark [61]. The total CO_2 emission value of the power sector in Hokkaido 2019 is calculated based on the actual power consumption multiplied by the emission factor. The annual emission allowance is calculated based on the total emission in 2019, as shown in the Figure 9, and the fixed value of the emissions will be reduced linearly every year until the emissions become zero in 2050. It is worth noting that the emission cap is an indicator rather than an effective cap, which is used to simulate the carbon price. We try to model a market-based policy instead of non-discretionary enforcement constraints. The regulatory agency sets emission targets and auctions the emission allowances accordingly, as different emission sources will choose to reduce their emissions or purchase more allowances regarding their own conditions. The price of emissions allowance is determined by both supply (the cap set by the agency) and demand (emitter willingness) sides. The price of allowances will rise when the supply from the emissions cap is continuously tightened, thereby forming a flexible means to promote emission reductions.

Compared to the capital-intensive thermal power plants, the size of a single investment in wind power is much smaller, thus the same return rate will encourage more diversified investors in the market, and therefore we assume that the investment coefficient of wind power is much higher than other technologies. Wind power receives continuous FIT subsidies, which means all the generated electricity will be sold to the grid as long as it is lower than the hourly demand, and since the supply–demand balance module assumes full flexibility of NG power, there will be no curtailment due to lack of flexibility. This stable income makes sure wind power will only retire when its life is expired instead of decommissioning due to losses, thereby the decommission coefficient of wind power is zero. We assume the expected return rate on investment of market participants cannot be lower than the interest rate.

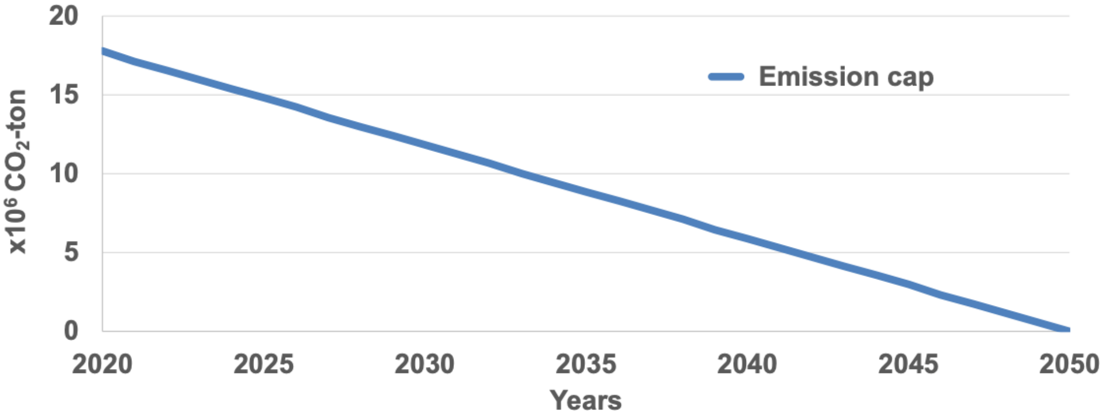


Figure 9. The emission allowance during the simulation period.

2.4. Data Sources

The data used here are from a number of key sources, including official statistical reports of the Ministry of Economy, Trade and Industry of Japan, survey reports of research institutions commissioned by the government, released reports of the power grid regulator, and the official records of power companies. The detailed parameters as well as input data are summarized in Table 2.

Table 2. Main assumptions and input data related to the case study [62–65].

Variables (Unit)	Wind	Coal	NG
Initial capacity (MW)	534	2520	3507
Minimum size of generators set [1] (MW)	5	100	200
Construction time (yr)	1	3	3
Investment coefficient (-)	40	1	1
Decommissioning coefficient (-)	-	1	1
Wind capacity value factor (-)	0.236	1	1
Mean Fuel Price in 2019 (USD/ton)	-	108.58	512.99
Marginal Fuel Cost (USD/MWh)	-	35.84	67.14
Emission Factor (ton-CO_2/MWh)	-	0.943	0.474
Heat value (MJ/ton)	-	25,970	55,010
Heat efficiency (-)	-	0.42	0.5
Fixed cost (USD/MW)	2,590,476	2,380,952	1,142,857
Maintenance cost (USD/MW/yr)	2590	119,047	57,142
Decommission cost ratio (-)	0.01	0.07	0.07
Lifetime (yr)	20	40	40
Interest rate (-)		0.03	
Sensitivity coefficient of carbon price		1	
Sensitivity coefficient of capacity price		130,725.8 *	
Sensitivity coefficient of electricity price		10	
FIT (USD/MWh)		95	
CO_2 floor price (USD/ton-CO_2)		30	
Capacity price cap (USD/MW)		134,647.6 **	
Electricity price cap (USD/MWh)		1905	
Exchange rate (JPY/USD)		105	

Note: * the coefficient is calculated to ensure zero capacity price when total capacity is over 5% of requirement; ** the cap is the difference between fixed cost and expected revenue for a new NG power plant [55]. [1] We set this minimum size based on the historical average size of one generator, since Hokkaido's coal power units are generally older, while the gas units were built in recent years. Therefore, the single unit size of a coal generator is smaller than that of a gas turbine generator.

3. Results and Discussion

3.1. Scenario Setting

As summarized in Table 3, in order to investigate the linkage between carbon pricing and capacity pricing, five scenarios were designed. The base scenario assumes that there is no capacity pricing nor carbon pricing in the electricity market. The capacity-only scenario assumes that only capacity pricing exists in the electricity market. The carbon-only scenario considers only carbon pricing in the electricity market. The capacity–carbon scenario represents both capacity pricing and carbon pricing in the electricity market. The advance scenario proposes a high carbon floor price with capacity pricing only for flexible power sources, which means that all capacity contributions to adequacy are counted, but only capacity which provides flexibility is subsidized. The model simulates the change in long-term capacity, CO_2 emissions, carbon price, capacity pricing, and electricity pricing for all the proposed scenarios. The simulation period is from 2019 to 2050, with weeks as the time unit. The model is coded into Python environment using the BPTK-Py package [66], which provided the basic modeling framework of the System Dynamics model.

Table 3. Scenarios settings summary.

Scenarios	Carbon Pricing	Capacity Pricing
Base	-	-
Carbon-only	USD 30/ton CO_2 floor price	-
Capacity-only	-	All fossil fuel power plants
Capacity–carbon	USD 30/ton CO_2 floor price	All fossil fuel power plants
Advance	USD 60/ton CO_2 floor price	Flexible power plants

3.2. Simulation Results

Figure 10 shows the simulation results of the capacity change of coal power plants in the scenarios. It can be observed that without the introduction of the carbon price, coal power plant capacity will be maintained in the range of 3000 MW to 4000 MW. The capacity-only scenario has the highest coal capacity, followed by the base scenario. By comparing the results of the capacity–carbon scenario and carbon-only scenario, the subsidy from capacity price has significantly weakened the emission reduction effect from the carbon price. Among all the scenarios, only the advance scenario achieved complete decommissioning of coal. This is due to the strong price signal generated by the carbon price with a higher floor in the early stage, as well as cutting the capacity subsidy of the inflexible power source, which put a stop to the investment in coal plants. As a result of coaction, coal is not subject to additional capacity subsidies and bears the high carbon price, thereby is decommissioned in early stages.

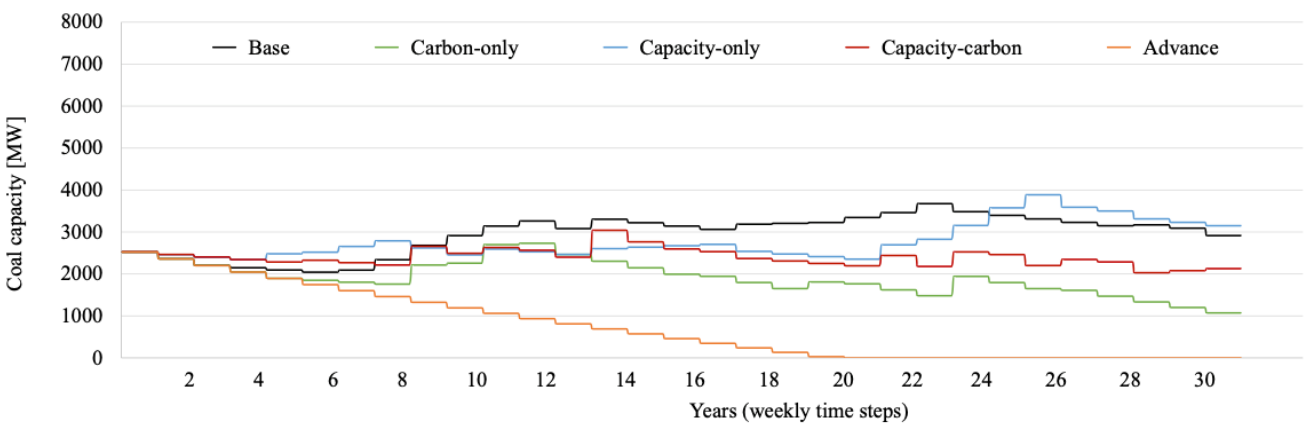


Figure 10. The trajectory of coal power plants' capacity change.

Figure 11 shows the simulation results of the capacity change of NG power plants in the proposed scenarios. In all scenarios without capacity price, the capacity change of NG power plants indicates clear cyclical fluctuations, especially in the base scenario, where the maximum capacity is about seven times the minimum. This reflects the restraint of the capacity price on investment fluctuations. In the liberalized electricity market, due to the lack of overall information and construction cycle, there will inevitably be a cycle of rise and fall. However, because NG power plants play the role of flexible resources in the power system, they are responsible for constantly regulating their own output to meet the balance between supply and demand of the power grid. Therefore, NG power plants, as flexible resources, are more significantly affected by the boom–bust cycle. Judging from the simulation results of the capacity-only and advance scenarios, the introduction of capacity policy has significantly suppressed the volatility of investment. Sustained and stable capacity revenue greatly reduces the boom-and-bust cycle. This is the oscillation behavior brought about by the goal seeking structure in a typical free market [49].

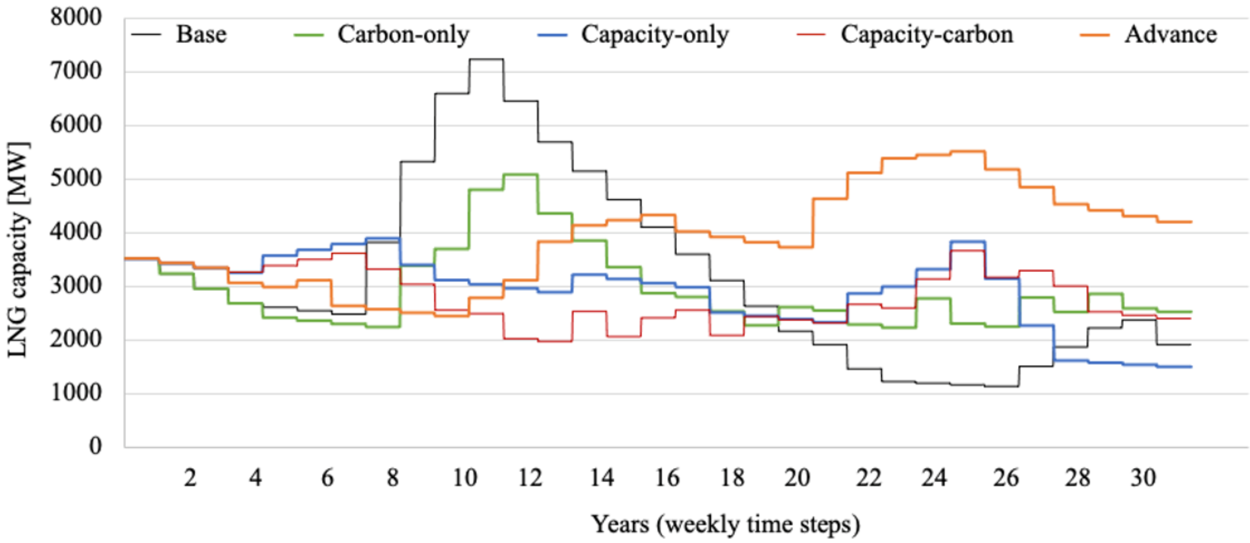


Figure 11. The trajectory of NG power plant capacity change.

Compared with the base scenario, the introduction in carbon prices reduced the installed capacity of NG in the early period before the base scenario started to enter the boost cycle; however, the advance scenario is an exception, as it has the highest installed capacity of NG at the end of the simulation period. This is because the higher floor carbon price promotes the decommissioning of coal, and the gas has entered the market as a substitute. The point is that the carbon price needs to be high enough to cover the fuel cost gap between coal and gas, thereby internalizing the cost of emissions and correctly distinguishing the price of coal and gas from the perspective of CO_2 emissions.

Nevertheless, except for the capacity-only scenario, all scenarios with capacity prices bring higher NG capacity. It looks contradictory but the reason is that in the capacity-only scenario, the capacity subsidy guarantees the fixed output of coal power plants, thereby reducing the use of flexible power sources. The limited power generation space of NG leads to the decrease in revenue and eventually capacity. The results of the advance scenario show that distinguishing the subsidy of flexible power sources in the capacity price with the high floor carbon price will promote the effectiveness of both carbon pricing and capacity pricing, which increases the NG capacity as flexible plants with relatively lower emissions factors.

Figure 12 shows the simulation results of wind capacity change in the scenarios. Wind power has ensured revenue due to FIT subsidies, so its capacity steadily increases during the simulation period. Furthermore, since wind power also receives the auction revenue from the emission trading system, the wind power capacity in the scenario with carbon prices greatly improved. If we take a closer look by comparing the capacity of wind power and other fossil fuel power, during the simulation period, wind power can barely reach the same capacity as fossil fuels with the FIT subsidy alone, and only with the additional revenue from the carbon price can the installed capacity of wind power significantly exceed either one of the fossil fuel power plant types.

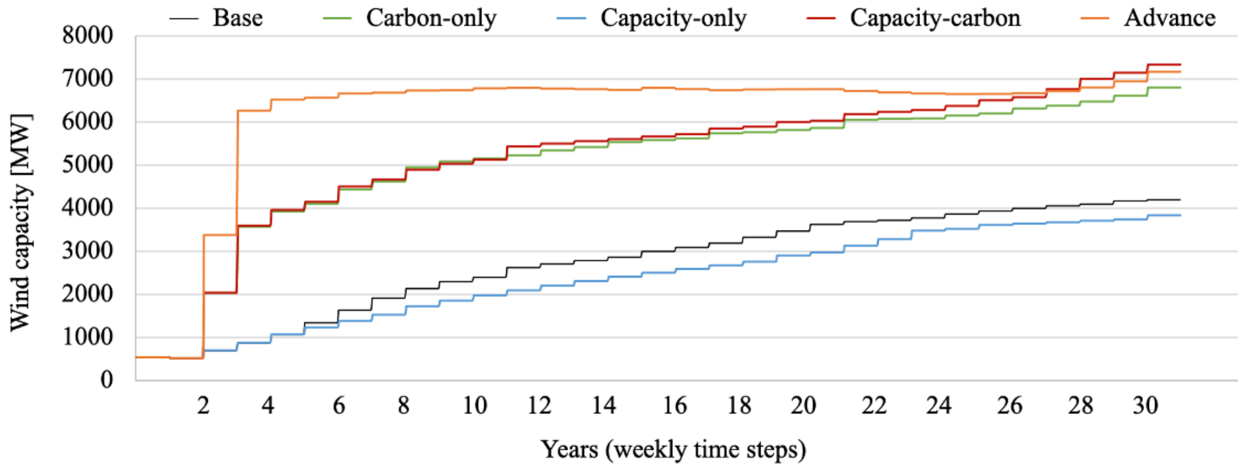


Figure 12. The trajectory of wind power plants' capacity change.

Moreover, the growth rate of wind power in the early stage is significantly higher than that in the latter stages. This is because although the carbon price is higher in the latter stages, when the cap is reduced significantly, the carbon emissions are lower than in the early stage, resulting in the subsidies derived from the emission trading system becoming less and less as the cap decreases. For the same reason, the wind capacity in the advance scenario is lower than the capacity–carbon scenario. In the advance scenario, carbon emissions are less, so the carbon price source subsidy for wind is less, which leads to the rapid introduction of wind power in the early stage, but the final value is slightly lower than the capacity–carbon scenario.

Figure 13 shows the simulation results of the CO_2 emission change in the scenarios. The capacity-only scenario has the highest CO_2 emission, even higher than the base scenario, due to its subsidies for fossil fuels. The advance scenario achieved about 65% of emission reductions at the end of the simulation period compared to the starting point. This is due to the consistent incentive from the high carbon floor price with flexibility. Focusing on capacity price promotes the decommissioning of coal, while retaining the NG power plants to maintain the system's supply and demand balance.

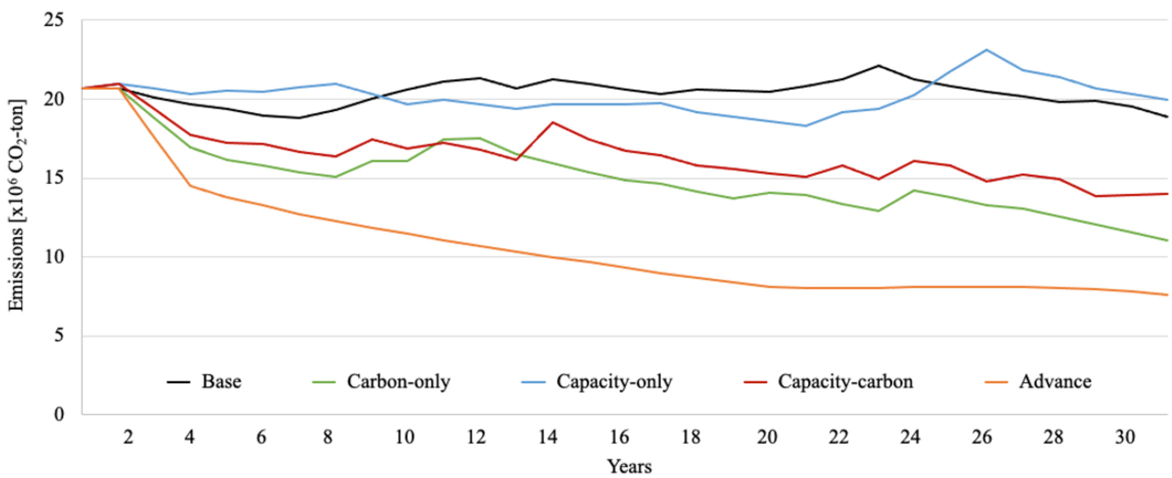


Figure 13. The trajectory of total CO_2 emission change.

Compared to the carbon-only scenario and the capacity-only scenario, the capacity–carbon scenario shows that the existence of the unreformed capacity price weakens the emission reduction effect from the carbon price. Although the wind capacity in the capacity–carbon scenario is higher than in the advance scenario, the capacity price and carbon price offset each other and we end up with a large number of coal power plants, which squeezes the power generation of flexible gas resources with relatively lower carbon emissions, causing the scenario with the highest wind capacity to still be unable to reduce CO_2 emissions to zero, even higher than the other two carbon-only and advance scenarios. Even though the emission cap reaches zero, no scenarios can achieve zero CO_2 emissions, since NG is the only flexible resource in this model. Moreover, the emissions cost of NG is passed on to the electricity price, and we assume that the demand side is nonelastic; therefore, in order to guarantee the supply of electricity, the bill will be paid no matter how high the price is.

Figure 14 shows the simulation results of carbon price change in three scenarios with carbon prices. We can observe annual cycles of the carbon price, and as the simulation approaches the end, the price peak becomes significantly higher. The reason for the periodic price peak is that the allowances have the characteristics of periodic supply. Therefore, when the emission allowances are renewed at the beginning of the year, sufficient supply will reduce the carbon price. However, as the allowances are gradually auctioned out, the reduction in supply will cause the rapid rise in the carbon price. The overall allowances will decrease over time, while the carbon price will increase significantly over time. Since the peak carbon price in the model is defined as the ratio of total emissions (including excess emissions) to the allowance for the year, a linear decline in allowances has a significant impact on the exponential rise in carbon prices.

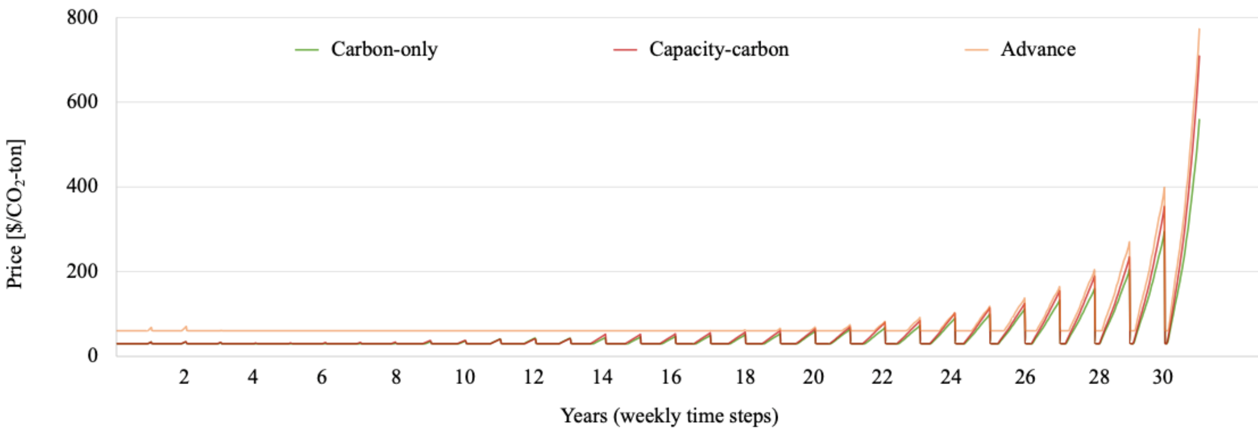


Figure 14. The changes in carbon price.

The results of the three scenarios have similar trends, although the two scenarios have the same carbon floor price, and the price of the capacity–carbon scenario is higher than the carbon-only scenario at the end of the simulation period. The reason is that when facing the same amounts of carbon allowance at the end, the mutual offset of the capacity price and carbon price leads to more CO_2 emissions from the power mix of the capacity–carbon scenario, which causes an increase in carbon prices.

Figure 15 illustrates the simulation results of capacity price change in the three scenarios with capacity price. Since the capacity price will quickly drop to zero after the capacity reaches the requirement, the price shows scatter. Because the new investment capacity has a delay of construction time, the unsatisfied capacity requirement often takes four to five years to be reflected, and then the capacity price starts to change. The advance scenario generates the most capacity price signals due to the massive promotion of NG to replace the decommissioned coal.

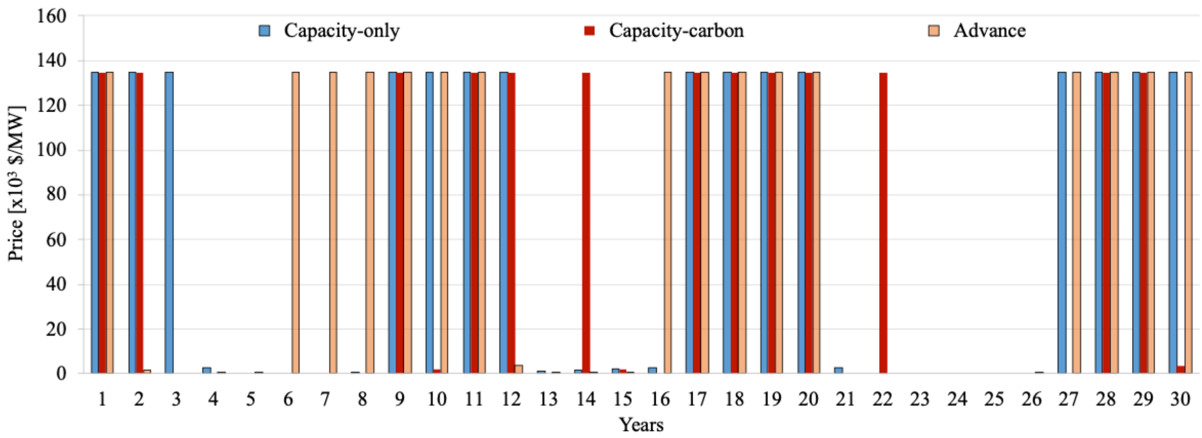
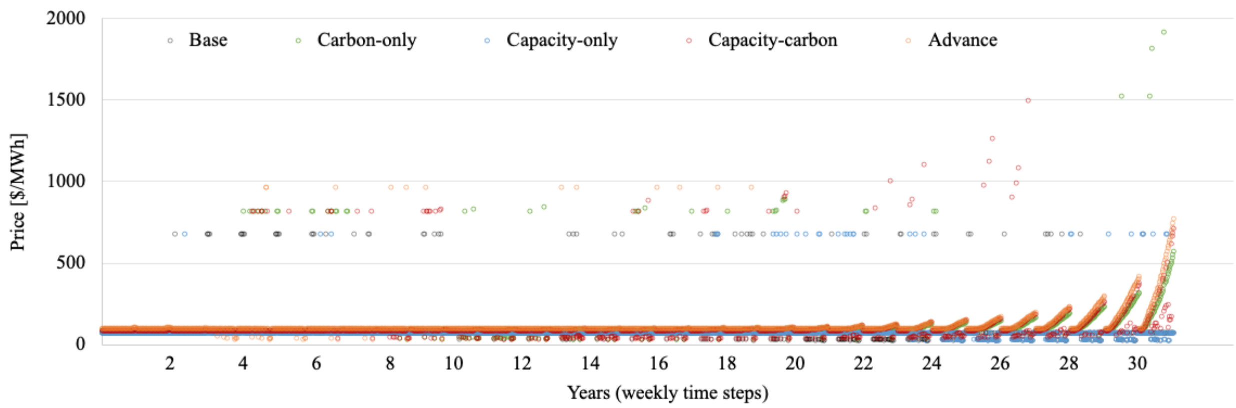
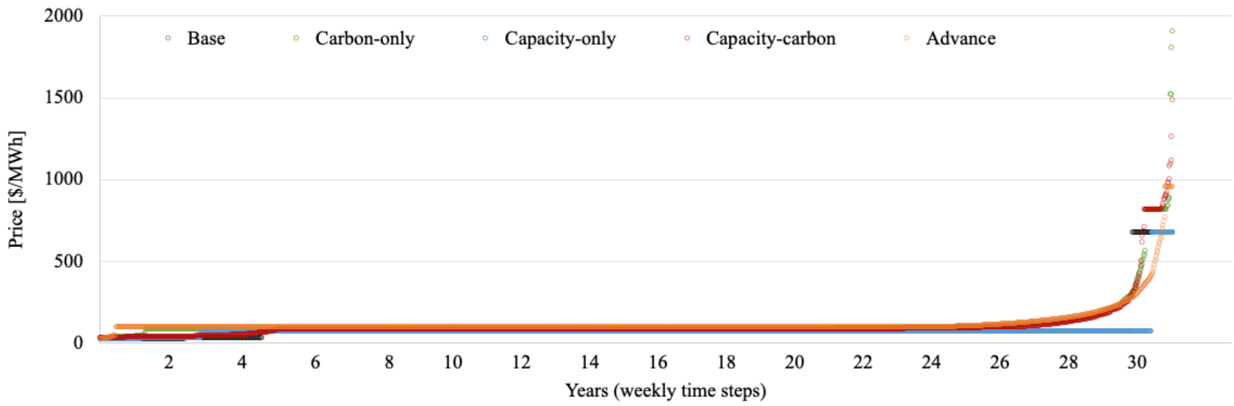


Figure 15. The change in capacity price.

Figure 16a shows the simulation results of electricity price changes in the proposed scenarios. Compared with the base scenario, the capacity price in the capacity-only scenario reduces the number of electricity price spikes significantly. Scenarios with a carbon price are affected by carbon prices, and the prices, especially spike prices, are higher than the base scenario. Similarly, compared to the capacity–carbon scenario and the advance scenario, the subsidy for flexible power sources significantly reduces the number of electricity price spikes. Even if the carbon price is higher, the electricity price has remained at a relatively stable level.



(**a**)



(**b**)

Figure 16. (**a**) The change in electricity price; (**b**) the sorted electricity price.

Since carbon prices are directly transmitted to the wholesale electricity market, the impact of carbon prices on wholesale electricity prices is more significant. Due to the Section 4 of emissions from the only flexible resource, this cost pass-through also indirectly curbs the possibility of achieving zero emissions for the entire system, and forces consumers to bear the high environmental costs while paying for grid balancing costs. Although the introduction of capacity prices reduces the number of electricity price spikes which may benefit the electricity retailers who face the risk of price changes, the cost of capacity subsidies is not directly reflected in the wholesale electricity price, and end-users will eventually bear it in the retail electricity price implicitly.

Figure 16b shows the sorted electricity prices from smallest to largest. The above discussion can be more easily understood from this figure. Electricity prices are stable at marginal plant fuel costs most of the time. There are only minor price spikes in the capacity-only scenario, and the rest of the scenarios also have about 200 weeks of price spikes over the 1612-week simulation period. Therefore, the capacity-only scenario has the most stable electricity price, and the carbon-only scenario has the highest electricity spike price. The advance scenario clearly reduces several extreme electricity prices compared with the capacity–carbon scenario.

3.3. Policy Implications

Based on the simulation results, we proposed that the design of capacity pricing needs to be linked with the carbon pricing, otherwise the offset of two mechanisms may lead to inefficiency and slow down the energy system transition, which addressed the two research questions in the Section 1. When the design of capacity pricing only focuses on fossil fuel power plants without any distinction between emissions or flexibility among different technologies, then the payment from capacity pricing will partially counteract the incentives from carbon pricing. Furthermore, the carbon prices with a lower floor cannot achieve the complete retirement of coal, which leads to the relatively high carbon emissions, and brings more investment in VRE from allowance auctions instead. However, the carbon price is not high enough to distinguish the emission gap between coal and NG in the merit order mechanism; eventually, increasing VRE squeezed the low emission flexible NG out of the market, reducing the reliability of the system. Nevertheless, in the case of flexible technology, focusing on capacity pricing alone with a high floor carbon price will bring out consistent incentives, diverting the capacity payment from a coal power plant to more flexible and lower emissions of NG, thereby accelerating the coal power plant decommissioning and reducing CO_2 emissions by 2050.

The increasingly complex designs of liberalized electricity markets may cause unexpected side effects through the interactions among policy instruments during the energy system transition period. Facing such complex systems, simulation-based design can provide references for policy-makers. Although the simulation model and results are limited by assumptions and preconditions, powerful computers can bring many options, thereby helping decision-makers think holistically and avoid unanticipated results. It should be emphasized that the model in this study only simulates a potential conflict of one of the certain policy designs we modeled, rather than targeting all the policies currently conducted in general. For instance, the emission trading system represented by Europe is the current mainstream carbon policy, nevertheless, there is a controversy over the design of the capacity mechanism, as different countries and regions have their own considerations according to the local context. Therefore, the proposed mitigation in this study is also focused on the design of the capacity mechanism, which brings more variability and possibilities due to its diversified design and provides a reference for real-world policy design.

4. Conclusions

This study constructed a framework of the link between carbon pricing and capacity pricing and investigated the interaction between carbon pricing and capacity pricing in a liberalized electricity market through a System Dynamics model in order to contribute a better understanding of the two research questions. We confirm the effectiveness of the conceptual model-based analysis framework in specific scenarios. The conclusions can be summarized as follows.

(i) Although carbon pricing is helpful for CO_2 emission reductions and a capacity mechanism is helpful for stabilizing electricity prices, there may be a phenomenon of offsetting advantages when the two policies are applied at the same time. (ii) The current capacity mechanism inevitably increases CO_2 emissions while increasing system reliability, because non-differentiated capacity pricing will maintain the proportion of coal in the system, thus weakening the emission reduction effect of carbon pricing. (iii) A carbon price will generally reduce system reliability while reducing CO_2 emissions, because carbon prices will reduce the revenue of coal and natural gas, so that they will be withdrawn from the market, which will reduce the system reliability to a large extent in the case of non-controllable renewables such as PV and wind power filling the gap, and with no further measures to counteract it (e.g., grid scale storage or controllable non-carbon emitting power). (iv) A lower carbon price setting would squeeze out natural gas plants, while a higher carbon price setting could fill the marginal cost gap between coal and natural gas, forcing coal plants to retire earlier with less impact on system reliability. Therefore, we recommend that the interaction of capacity pricing and carbon pricing should be considered as a whole and rationally designed. The impact of capacity mechanisms should be considered when designing carbon pricing. Similarly, the impact of carbon pricing should be considered when designing capacity mechanisms. Capacity prices that focus on flexible sources would align the incentives with carbon pricing, thereby accelerating the retirement of coal power plants as well as reducing CO_2 emissions.

This study effectively validates the rationality of the proposed framework for researching policy interactions by taking Hokkaido as a case. The framework can be used to quantitatively analyze the impact of the interaction between two or more policies on the electricity market, but there are still some limitations, which need to be further reflected on and improved in future research. First of all, the verification framework can be further improved. Specifically, it can involve more scenario designs, more research case comparisons, and more indicators to measure the simulation results, such as adding energy security indexes to measure reliability, etc. This could include a broader set of technologies or technology types (for example, controllable zero-carbon generators). Second, due to the limited results of real-world policy implementation, the mapping of the research framework to the real world remains to be explored. Next, further study should focus on more technical factors of power grid operation, since the deployments of VRE increase the uncertainty of grid dispatch as well as the requirements of generators to adjust their output power over a short period, which means the validity of the current assumption of full flexibility in the System Dynamics model regarding supply–demand balancing is challenged. Finally, a single method has certain limitations for the study of policy interaction, and it is difficult to fully consider micro and macro implications. Therefore, more uncertainties brought by renewable energy should be considered in the setting of quantitative research framework influences.

Author Contributions: Conceptualization, Y.L; methodology, Y.L.; software, Y.L.; validation, Y.L.; writing—original draft preparation, Y.L.; writing—review and editing, E.A., B.C.M. and T.T.; supervision, B.C.M. and T.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Quéré, C.; Andrew, R.M.; Friedlingstein, P.; Sitch, S.; Hauck, J.; Pongratz, J.; Pickers, P.A.; Korsbakken, J.I.; Peters, G.P.; Canadell, J.G.; et al. Global carbon budget 2018. *Earth Syst. Sci. Data* **2018**, *10*, 2141–2194. [CrossRef]
2. Peters, G.P.; Le Quéré, C.; Andrew, R.M.; Canadell, J.G.; Friedlingstein, P.; Ilyina, T.; Jackson, R.B.; Joos, F.; Korsbakken, J.I.; McKinley, C.A.; et al. Towards real-time verification of CO_2 emissions. *Nat. Clim. Chang.* **2017**, *7*, 848–850. [CrossRef]
3. Wilson, I.A.; Staffell, I. Rapid fuel switching from coal to natural gas through effective carbon pricing. *Nat. Energy* **2018**, *3*, 365–372. [CrossRef]
4. Metcalf, G.E.; Weisbach, D. The design of a carbon tax. *Harv. Envtl. L. Rev.* **2009**, *33*, 499. [CrossRef]
5. Kaplow, L. Why (ever) define markets? *Harv. Law Rev.* **2010**, *124*, 437–517.
6. Borenstein, S.; Bushnell, J.; Wolak, F.A.; Zaragoza-Watkins, M. Expecting the unexpected: Emissions uncertainty and environmental market design. *Am. Econ. Rev.* **2019**, *109*, 3953–3977. [CrossRef]
7. Barnett, M.; Brock, W.; Hansen, L.P. Pricing uncertainty induced by climate change. *Rev. Financ. Stud.* **2020**, *33*, 1024–1066. [CrossRef]
8. Newell, R.G.; Stavins, R.N. Cost heterogeneity and the potential savings from market-based policies. *J. Regul. Econ.* **2003**, *23*, 43–59. [CrossRef]
9. Davis, L.W.; Knittel, C.R. Are fuel economy standards regressive? *J. Assoc. Environ. Resour. Econ.* **2019**, *6*, S37–S63. [CrossRef]
10. Newell, R.G.; Jaffe, A.B.; Stavins, R.N. The induced innovation hypothesis and energy-saving technological change. *Q. J. Econ.* **1999**, *114*, 941–975. [CrossRef]
11. Lockwood, M.; Mitchell, C.; Hoggett, R. Incumbent lobbying as a barrier to forward-looking regulation: The case of demand-side response in the GB capacity market for electricity. *Energy Policy* **2020**, *140*, 111426. [CrossRef]
12. Joskow, P.L. Challenges for wholesale electricity markets with intermittent renewable generation at scale: The US experience. *Oxf. Rev. Econ. Policy* **2019**, *35*, 291–331. [CrossRef]
13. Cramton, P.; Stoft, S. A capacity market that makes sense. *Electr. J.* **2005**, *18*, 43–54. [CrossRef]
14. Léautier, T.O. The visible hand: Ensuring optimal investment in electric power generation. *Energy J.* **2016**, *37*, 89–109. [CrossRef]
15. Keppler, J.H. Rationales for capacity remuneration mechanisms: Security of supply externalities and asymmetric investment incentives. *Energy Policy* **2017**, *105*, 562–570. [CrossRef]
16. De Vries, L.J. Generation adequacy: Helping the market do its job. *Util. Policy* **2007**, *15*, 20–35. [CrossRef]
17. Bublitz, A.; Keles, D.; Zimmermann, F.; Fraunholz, C.; Fichtner, W. A survey on electricity market design: Insights from theory and real-world implementations of capacity remuneration mechanisms. *Energy Econ.* **2019**, *80*, 1059–1078. [CrossRef]
18. Arango, S.; Larsen, E. Cycles in deregulated electricity markets: Empirical evidence from two decades. *Energy Policy* **2011**, *39*, 2457–2466. [CrossRef]
19. Convery, F.J.; Redmond, L. The European Union Emissions Trading Scheme: Issues in allowance price support and linkage. *Annu. Rev. Resour. Econ.* **2013**, *5*, 301–324. [CrossRef]
20. John, S. *Business Dynamics: Systems Thinking and Modeling for a Complex World*; Irwin McGrawHill: New York, NY, USA, 2000.
21. Peng, D.; Poudineh, R. Electricity market design under increasing renewable energy penetration: Misalignments observed in the European Union. *Util. Policy* **2019**, *61*, 100970. [CrossRef]
22. Parmar, A.A.; Darji, B.P.B. Capacity market functioning with renewable capacity integration and global practices. *Electr. J.* **2020**, *33*, 106708. [CrossRef]
23. Hu, J.; Harmsen, R.; Crijns-Graus, W.; Worrell, E.; van den Broek, M. Identifying barriers to large-scale integration of variable renewable electricity into the electricity market: A literature review of market design. *Renew. Sustain. Energy Rev.* **2018**, *81*, 2181–2195. [CrossRef]
24. Gillich, A.; Hufendiek, K.; Klempp, 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. [CrossRef]
25. del Río, P.; Cerdá, E. The missing link: The influence of instruments and design features on the interactions between climate and renewable electricity policies. *Energy Res. Soc. Sci.* **2017**, *33*, 49–58. [CrossRef]
26. Özdemir, Ö.; Hobbs, B.F.; van Hout, M.; Koutstaal, P.R. Capacity vs. energy subsidies for promoting renewable investment: Benefits and costs for the EU power market. *Energy Policy* **2020**, *137*, 111166. [CrossRef]
27. Alahyari, A.; Ehsan, M.; Mousavizadeh, M.S. A hybrid storage-wind virtual power plant (VPP) participation in the electricity markets: A self-scheduling optimization considering price, renewable generation, and electric vehicles uncertainties. *J. Energy Storage* **2019**, *25*, 100812. [CrossRef]
28. Cheng, L.; Yu, T. Nash equilibrium-based asymptotic stability analysis of multi-group asymmetric evolutionary games in typical scenario of electricity market. *IEEE Access* **2018**, *6*, 32064–32086. [CrossRef]
29. Fang, D.; Zhao, C.; Yu, Q. Government regulation of renewable energy generation and transmission in China's electricity market. *Renew. Sustain. Energy Rev.* **2018**, *93*, 775–793. [CrossRef]
30. Wang, J.; Wu, J.; Che, Y. Agent and system dynamics-based hybrid modeling and simulation for multilateral bidding in electricity market. *Energy* **2019**, *180*, 444–456. [CrossRef]
31. Sarıca, K.; Kumbaroğlu, G.; Or, I. Modeling and analysis of a decentralized electricity market: An integrated simulation/optimization approach. *Energy* **2012**, *44*, 830–852. [CrossRef]

32. Ma, T.; Nakamori, Y. Modeling technological change in energy systems–from optimization to agent-based modeling. *Energy* **2009**, *34*, 873–879. [CrossRef]
33. Kraan, O.; Kramer, G.J.; Nikolic, I. Investment in the future electricity system-An agent-based modelling approach. *Energy* **2018**, *151*, 569–580. [CrossRef]
34. Jia, Z.; Lin, B. CEEEA2. 0 model: A dynamic CGE model for energy-environment-economy analysis with available data and code. *Energy Econ.* **2022**, *112*, 106117. [CrossRef]
35. Ventosa, M.; Baıllo, A.; Ramos, A.; Rivier, M. Electricity market modeling trends. *Energy Policy* **2005**, *33*, 897–913. [CrossRef]
36. Forrester, J.W. Industrial dynamics. *J. Oper. Res. Soc.* **1997**, *48*, 1037–1041. [CrossRef]
37. Bacenetti, J.; Duca, D.; Negri, M.; Fusi, A.; Fiala, M. Mitigation strategies in the agro-food sector: The anaerobic digestion of tomato puree by-products. An Italian case study. *Sci. Total Environ.* **2015**, *526*, 88–97. [CrossRef]
38. Adane, T.F.; Bianchi, M.F.; Archenti, A.; Nicolescu, M. Application of system dynamics for analysis of performance of manufacturing systems. *J. Manuf. Syst.* **2019**, *53*, 212–233. [CrossRef]
39. Li, C.; Zhang, L.; Ou, Z.; Ma, J. Using system dynamics to evaluate the impact of subsidy policies on green hydrogen industry in China. *Energy Policy* **2022**, *165*, 112981. [CrossRef]
40. He, Z.; Weng, W. A dynamic and simulation-based method for quantitative risk assessment of the domino accident in chemical industry. *Process Saf. Environ. Prot.* **2020**, *144*, 79–92. [CrossRef]
41. Gass, S.I. Decision-aiding models: Validation, assessment, and related issues for policy analysis. *Oper. Res.* **1983**, *31*, 603–631. [CrossRef]
42. Sterman, J.D. Testing behavioral simulation models by direct experiment. *Manag. Sci.* **1987**, *33*, 1572–1592. [CrossRef]
43. Oliva, R. Model calibration as a testing strategy for system dynamics models. *Eur. J. Oper. Res.* **2003**, *151*, 552–568. [CrossRef]
44. Shore, B. Information sharing in global supply chain systems. *J. Glob. Inf. Technol. Manag.* **2001**, *4*, 27–50. [CrossRef]
45. Aslani, A.; Helo, P.; Naaranoja, M. Role of renewable energy policies in energy dependency in Finland: System dynamics approach. *Appl. Energy* **2014**, *113*, 758–765. [CrossRef]
46. Arias-Gaviria, J.; Valencia, V.; Olaya, Y.; Arango-Aramburo, S. Simulating the effect of sustainable buildings and energy efficiency standards on electricity consumption in four cities in Colombia: A system dynamics approach. *J. Clean. Prod.* **2021**, *314*, 128041. [CrossRef]
47. Naderi, M.M.; Mirchi, A.; Bavani, A.R.M.; Goharian, E.; Madani, K. System dynamics simulation of regional water supply and demand using a food-energy-water nexus approach: Application to Qazvin Plain, Iran. *J. Environ. Manag.* **2021**, *280*, 111843. [CrossRef]
48. Hu, G.; Zeng, W.; Yao, R.; Xie, Y.; Liang, S. An integrated assessment system for the carrying capacity of the water environment based on system dynamics. *J. Environ. Manag.* **2021**, *295*, 113045. [CrossRef]
49. Kunc, C. System dynamics: A soft and hard approach to modelling. In Proceedings of the 2017 Winter Simulation Conference (WSC), Las Vegas, NV, USA, 3–6 December 2017; pp. 597–606. [CrossRef]
50. Bastan, M.; Abdollahi, F.; Shokoufi, K. Analysis of Iran's dust emission with system dynamics methodology. *Tech. J. Eng. Appl. Sci.* **2013**, *3*, 3515–3524.
51. Yunna, W.; Kaifeng, C.; Yisheng, Y.; Tiantian, F. A system dynamics analysis of technology, cost and policy that affect the market competition of shale gas in China. *Renew. Sustain. Energy Rev.* **2015**, *45*, 235–243. [CrossRef]
52. Yao, L.; Liu, T.; Chen, X.; Mahdi, M.; Ni, J. An integrated method of life-cycle assessment and system dynamics for waste mobile phone management and recycling in China. *J. Clean. Prod.* **2018**, *187*, 852–862. [CrossRef]
53. Newbery, D. Missing money and missing markets: Reliability, capacity auctions and interconnectors. *Energy Policy* **2016**, *94*, 401–410. [CrossRef]
54. Olsina, F.; Garcés, F.; Haubrich, H.-J. Modeling long-term dynamics of electricity markets. *Energy Policy* **2006**, *34*, 1411–1433. [CrossRef]
55. Agency for Natural Resources and Energy, METI. About the Capacity Market, Page 30, 25 April 2022. Available online: https://www.meti.go.jp/shingikai/enecho/denryoku_gas/denryoku_gas/seido_kento/pdf/064_03_00.pdf (accessed on 1 December 2022).
56. Hasani, M.; Hosseini, S.H. Dynamic assessment of capacity investment in electricity market considering complementary capacity mechanisms. *Energy* **2011**, *36*, 277–293. [CrossRef]
57. 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. [CrossRef]
58. López, I.; Santiago, A. Prospective Long-Term Overall Economic and Environmental Impact of a Country's Electric Power System Policies: A Behavioral Dynamic Systems Thinking Approach. Ph.D. Thesis, E.T.S.I. Industriales (UPM), Polytechnic University of Madrid, Madrid, Spain, 2017.
59. Gotoh, R.; Tezuka, T.; McLellan, B.C. Study on Behavioral Decision Making by Power Generation Companies Regarding Energy Transitions under Uncertainty. *Energies* **2022**, *15*, 654. [CrossRef]
60. Japan Electricity Power Exchange. Available online: http://www.jepx.org/ (accessed on 1 December 2022).
61. About CO_2 Emission Results in 2019, Hokkaido Electric Power Co., Inc. Available online: https://www.hepco.co.jp/info/info2020/1251006_1845.html (accessed on 1 December 2022).

62. *Power Survey Statistics Table*; Agency for Natural Resources and Energy, Ministry of Economy, Trade and Industry: Tokyo, Japan, 2019. Available online: https://www.enecho.meti.go.jp/statistics/electric_power/ep002/results_archive.html (accessed on 1 December 2022).
63. Generation Cost Verification Working Group, Agency for Natural Resources and Energy, Ministry of Economy, Trade and Industry, Japan. Available online: https://www.enecho.meti.go.jp/committee/council/basic_policy_subcommittee/mitoshi/cost_wg/2021/data/08_06.pdf (accessed on 1 December 2022).
64. Imamura, E.; Iuchi, M.; Bando, S. *Comprehensive Assessment of Life Cycle CO_2 Emission from Power Generation Technologies in Japan*; Report No Y06; Socio-Economic Research Center: Tokyo, Japan, 2016.
65. *Demand Curve Creation Procedure of Capacity Market Main Auction*; Organization for Cross-regional Coordination of Transmission Operators: Tokyo, Japan, 2019. Available online: https://www.occto.or.jp/iinkai/youryou/kentoukai/2019/files/youryou_kentoukai_23_04.pdf (accessed on 1 December 2022).
66. BPTK-Py: System Dynamics and Agent-based Modeling in Python, MIT License. Available online: https://pypi.org/project/BPTK-Py/ (accessed on 1 December 2022).