A STUDY ON THE LINKAGE BETWEEN CAPACITY PRICING AND CARBON PRICING IN ELECTRICITY MARKET

Yilun Luo, Kyoto University, +81-75-753-4739, luo.yilun.48s@st.kyoto-u.ac.jp
Dr. Benjamin C. McLellan, Kyoto University, +81-75-753-4739, b-mclellan@energy.kyoto-u.ac.jp
Dr. Seiichi Ogata, Kyoto University, +81-75-753-4739, ogata@energy.kyoto-u.ac.jp
Dr. Tetsuo Tezuka, Kyoto University, +81-75-753-4739, tezuka@energy.kyoto-u.jp

Overview

This study intends to raise and answer a question: what is the interaction between capacity remuneration mechanism and carbon pricing in a liberalized electricity market, and how it ultimately affects the trajectory of power mix change? This study firstly constructs a conceptual model to explain the interactions between carbon pricing and capacity pricing. Secondly, a semi-quantitative dynamic simulation model based on the System Dynamics method is proposed based on the conceptual model to investigate the question. At last, choose Hokkaido Japan as a case study, several scenarios including energy only, carbon pricing only, capacity pricing only, and carbon price with capacity pricing are simulated through the semi-quantitative model. The results show that carbon price will promote the introduction of wind power as well as the reduction of 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 the lower floor also indirectly squeezes the generation space of flexible power plants. We propose that if the capacity price focus on subsidizing flexible power plants coupled with a higher floor carbon price, thereby form a consistent incentive and promote the decommissioning of carbon-intensive base-load power plants and significantly reduce CO_2 emissions with relatively stable electricity prices during the transition period.

Introduction

In the liberalized electricity market, the investments and decommissions of power generation capacity are made by many profit-driven companies as commercial decisions. These market participants' plans for power generation technology capacity depend on the impacts from price signals. In order to guide market participants' behavior, some policy-based markets are designed to evaluate the electricity commodities and bring appropriate price signals, as well as to resolve the market failures that have occurred during the liberalization process. Meanwhile, to deal with climate change issues, the current electricity industry is undergoing a paradigm transition from fossil fuel-based technologies to low CO_2 emissions technologies in a very limited time. Carbon pricing which is a powerful policy instrument is designed to internalize the environmental cost of CO_2 emissions, thereby driving and accelerating the transition of electricity system. During the transition of electricity system in the liberalized market, the increasingly complex designs may cause unexpected side effects through the interactions among policy instruments [1].

The capacity remuneration mechanisms are implemented as incentive tools for reliable investment, in order to ensure power adequacy in the liberalized electricity market. For the capacity pricing, there are mainly two objectives: first, providing subsidies for the fixed cost of the technologies which contribute to the security of electricity systems supply-demand balance operating [2], e.g. marginal power plants. Second, the price formation through auction based on the forecasted capacity demand, thereby ensure the electricity system adequacy and avoid the boom-bust investment phenomenon [3]. Meanwhile, carbon pricing is designed to handle climate change issues. 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 proportion of fossil fuel energy [4].

However, fossil fuel power plants are still dominating in most of the current electricity system, to provide system adequacy as well as flexibility, which lead to the CO_2 intensive power capacity be charged through carbon pricing while receiving payment from capacity pricing. Although both policies have achieved the direct goal, which is pricing certain objects through market-based policy instruments, the interaction between these two prices and the subsequent impacts on the electricity market is less investigated. Some previous qualitative studies [5-7] 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, capacity remuneration mechanism et. al. There is a growing number of studies have invested the interaction between VRE incentive and carbon pricing [8,9], increasing VRE share and capacity remuneration mechanism [10]. Nevertheless, there are few studies [11-13] that approach the unclear interaction between capacity pricing and carbon pricing, which may affect power generation investment decisions during the energy system transition.

In order to fill this knowledge gap and contribute to a better understanding of electricity system related policy design during the energy transition period. This study intends to raise and answer a question: what is the interaction between capacity pricing and carbon pricing in a liberalized electricity market during the low-carbon transition period, and how this interaction ultimately affects the trajectory of power mix change?

This study firstly constructed a subjective conceptual model to explain the interactions between carbon pricing and capacity pricing. Secondly, the System Dynamic approach is adapted to conduct the simulation of capacity changing based on the conceptual model. Thirdly, we use the real data from Hokkaido, Japan as a case study. Several scenarios including energy only, carbon pricing only. capacity pricing only and carbon pricing with capacity pricing are designed for the simulation. The results show the comparison among different scenarios of long-term capacity changing, CO_2 emission changing, carbon price changing, capacity pricing changing, and electricity pricing changing. At last, we discussed the impact of the interaction among policy-based markets on the energy system.

Methods

This study chooses System Dynamics as the modeling method in order to simulate the dynamic change of the complex system which including interaction among policy, technology, and economic factors. System Dynamics derived from control theory and systems thinking, provides concepts and semi-quantitative methods for analyzing feedback loops and non-linear interactions among system elements [1]. System Dynamics is a problem-oriented modeling method, which means all the factors and system boundaries are determined by focusing on the problem itself. Following this principle, this study focuses on the potential problem observed in the real world: the CO_2 intensive power capacity be charged through carbon pricing while receiving payment from capacity pricing.

The Causality Loop Diagram is the first step in System Dynamics, which consists of variables and arrows to demonstrate the causal links and influences. Through establishing the subjective conceptual models based on observation and causal inference, thereby understanding and clarifying the relationships among phenomena or behaviors. The positive link means if the cause increase or decreases, the effect increases or decreases compared to what it would have been, and the negative link is the opposite [1]. Figure 1 shows the Causality Loop Diagram of the conceptual model in this study, which is the basis of the long-term dynamic simulation model. The polarity of some arrows is not marked, due to their being purely data input or logic judgments.

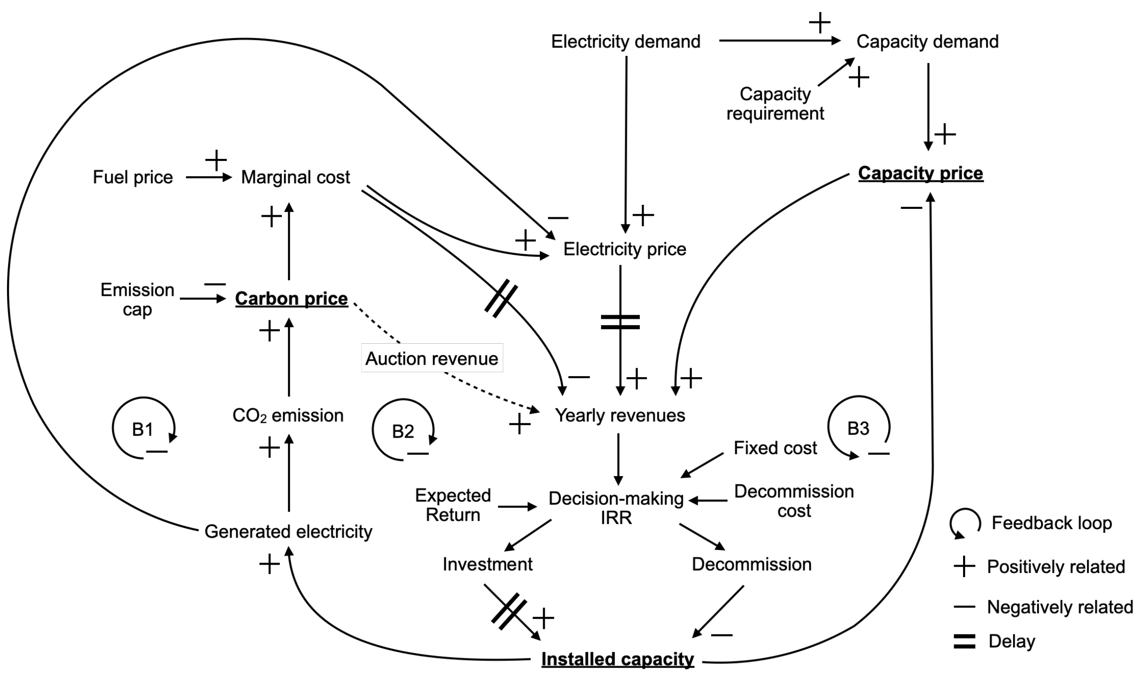

Figure 1 Causal loops diagram of the proposed simulation model

The model shown in Figure 1 consists of five modules, which are 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 renewable energy, coal as a representative of baseload fossil fuel power plants, and liquid natural gas (LNG) as a representative of flexible fossil fuel power plants. The comparison of the three technologies characteristics are 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. Due to space limitations, we have omitted the stock-flow diagram of the System Dynamics model. The stock-flow diagram is of great help to think about how to model, but the mathematical equations are more refined expressions. The equations of each module are listed below.

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: LNG	Flexible	Medium emission	High value

The capacity change module simulates the investment, decommissioning and retirement of different technologies. At the end of each year, the capacity ***CP*** of the current technology ***i*** consists of the new capacity ***NewIn*** join into the market, the deficit capacity ***Decom*** exits the market, and the life-expiring capacity ***Retire*** retires. As shown in Equation 1, where ***t*** is the number of weeks.

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

the new investment and decommission capacity are decided by market participants based on the profits, and the life-expire retirement does not relate to business, it only depends on the lifetime of the equipment. The newly added capacity takes construction time ***ConsTime*** after the investment decision, which is modeled as pipeline delay. The annual retirement capacity is modeled as the first-order delay of the technology lifetime ***lifetime***, as shown 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 time. As shown in Figure 2, the VRE has priority scheduling since its marginal cost is almost zero. The dispatch of coal and LNG depends on the order of their marginal cost.

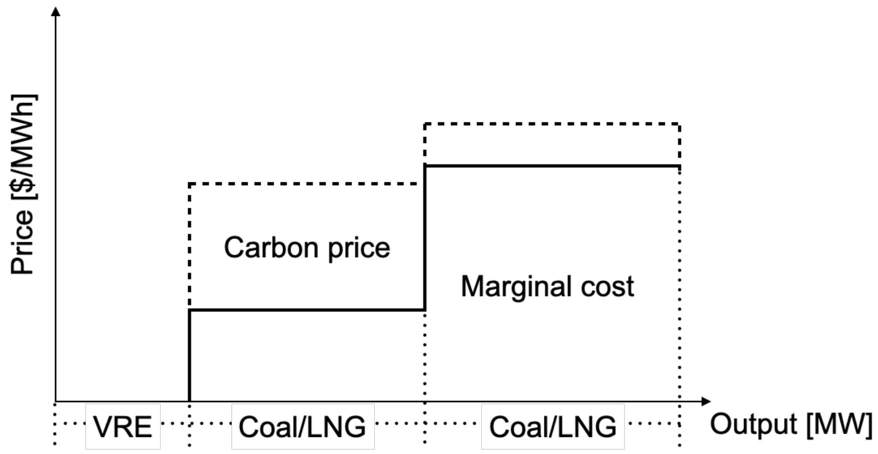

Figure 2 Concept of merit-order electricity pricing

As the equations below, the marginal fuel cost ***MarFuel*** is calculated through the power plant thermal efficiency ***Heff*** and heating value of fossil fuel ***Hval*** and the average fuel price ***Fuelprice*** as exogenous variables. The marginal cost of a thermal power plant is equal to the sum of the marginal fuel cost and carbon price ***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 plants since the ramp rate, which is the speed of adjusting output is slower and the cost is higher compared with other technologies. Therefore, we assume that power generation ***Generate*** of coal has a fixed output, which equals to the product of its capacity, annual operating factor ***OF***, and weekly hours. 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 input into the model as exogenous variables.

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

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

LNG is the representative of flexible power sources in the model, its output is assumed to equal to the residual load ***ResidualLord***, that is, the total demand ***Demand*** minus the uncontrollable VRE generation which is the ***NetLord***, and then minus the fixed output of the baseload power plant, thereby maintaining the system supply and demand balance.

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

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

The balance of supply and demand ***SDbalan*** equals the total supply minus ***TotalSup*** the total demand, where the weekly electricity demands are input as exogenous variables of the model. The total supply is the sum of VRE, coal, and LNG power generation per unit time.

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

The electricity price is calculated by the following equations. The current state of the system is indicated by the balance of supply and demand, and whether the flexible power source LNG is generating electricity is indicated by the residual lord. When the supply and demand are loose and LNG generating, the electricity price is the highest marginal cost of thermal power plants. When the supply and demand are loose and LNG is not generating, the electricity price is the weighted average marginal cost of coal generation and VRE generation. When supply and demand are tight and LNG generating, the electricity price is the highest marginal cost of the thermal power plants multiplied by the scarcity electricity price coefficient $\boldsymbol{\alpha}$. When supply and demand are tight and LNG 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.

In a perfect competition liberalized power market, the electricity price 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 the most of time, and the fixed cost recovery depends on the scarcity price when the supply-demand balance is tight, or the capacity price [14]. Since this study considering the existence of capacity prices, the electricity price in our model has a relatively lower price ceiling.

	$SDbalan(t) \geqq 0$	$SDbalan(t) < 0$
$ResidualLoad(t) > 0$	$\max\{MarCost_{Coal}(t), MarCost_{LNG}(t)\}$	$\max\{MarCost_{Coal}(t) \times \alpha, MarCost_{LNG}(t) \times \alpha\}$
$ResidualLoad(t) \leqq 0$	$MarCost_{Coal}(t) \times \frac{NetLoad(t)}{Demand(t)}$	$MarCost_{Coal}(t) \times \frac{NetLoad(t)}{Demand(t)} \times \alpha$

(11)

The capacity remuneration mechanism subsidies 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, a full-price subsidy will be provided which is the difference between the fixed cost per MW capacity and the expected return per MW capacity of a new building LNG power plant. If the current capacity is higher than the requirement, the subsidy price will be reduced in proportion and become zero after exceeding a certain range of the 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 times with the average yearly capacity factor. Equation 12, 13 describes the changes in capacity prices, where γ is the sensitivity coefficient of capacity prices increase.

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

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

This study made very strong assumptions to simulate the capacity price. The real-world capacity price calculation involves the evaluation method 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 temporarily beyond the scope of this study. We focus on the mutual influence of the behavior of subsidizing capacity itself on other price mechanisms in the electricity market. The definition and evaluation of power system reliability are very important, this study includes the main factors that may affect the capacity price and simplified them for modeling. These strong assumptions are the major constraints of this study and will be improved in future work.

We model the carbon price mechanism as a cap-trade emission allowance trading system with floor prices that is limited to the power system in the target area. The annual quota emission allowance will be auctioned at the floor price at the beginning of the year. If the current annual cumulative emissions are less than the annual emissions cap, then the carbon price is the floor price. If the current cumulative emissions exceed the emissions cap, the carbon price will increase. Equation 14, 15 describes the changes in carbon prices, where β is the sensitivity coefficient of carbon prices increase.

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

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

The emission per time step is equal to the generation of thermal power plants multiplied by the corresponding fuel emission factor. The cumulative amount of emissions within a year is 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 of carbon allowances will be used to additionally subsidize the 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 to a certain extent.

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

The decisions of market participants in the free market are assumed as purely commercial behaviors, thereby their decisions depend on the profits from the project. When the expected profits of the project are higher than its costs, participants will choose to make new investments. 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. As shown in Equations 19, 20, 21, the calculation of NPV includes the fixed cost in the initial year and the decommissioning cost in the last year of the power plant lifetime. The annual cash flow is equal to the revenue per MW during the year minus the maintenance costs and variable cost per MW.

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

$$ECF_i(t) = UnitRev_i - UnitVar_i - UnitMainten_i \tag{20}$$

$$DecomC_i = FixCost_i \times DecomCostRatio_i \tag{21}$$

The previous research [15-17] chose to use trends 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, compared with stable policy subsidies, the changing of electricity prices from the market reflects more about the short-term supply and demand balance, thereby its fluctuation trend does not accurately reflect the long-term expectations of the policies-driven transition. For example, the investment of VRE driven by FIT/FIP mechanism assumes stable returns will be guaranteed during its lifetimes. 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 policies-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, make decision based on the price of the past year, assuming that the situation will be constant for the entire project lifetime, and there is no trend forecast for electricity price fluctuations. Similar assumptions have found in previous research [18] as well. More sophisticated investment strategies or cash flow calculation methods will be tested as part of future work.

The investments of new power plants 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 sensitivity coefficient, then the rounded integer result is multiplied by the minimum size of generator sets, as shown in Equation 22.

$$NewInvest_i(t) = \left[\frac{npv_i(t) + FixCost_i}{FixCost_i} \times InvCoe_i\right] \times UnitCP_i \tag{22}$$

Equations 23 and 24 describe the decommission decision. The annual operating cash flow of all existing power plants includes revenue, variable costs, annualized fixed costs, and annualized decommission costs. 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 the constant status quo strategy, if the current revenue is less than the operating cost, it is considered this situation will be continuous in the future and there is no chance to recover the losses, thereby decommission is a rational decision. The decommissioned capacity is equal to the ratio of the annual loss to the annual revenue, multiplied by the decommission sensitivity coefficient and then times the minimum size of generator sets.

$$Cash_i(t) = UnitRev_i - UnitVar_i - UnitMainten_i - AnnulFixC_i - AnnulDecomC_i \tag{23}$$

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

Although the investment decisions in the real world are decentralized, in this study, we assume that all investors of the same technology make a unified decision within a year. This assumption allows the model to ignore the risk. 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 expected returns.

Based on this assumption, we calculate the annual revenue of thermal power plants as the accumulation of power generation multiplied by the electricity price, and the annual revenue of wind power generation is the power generation multiplied by the FIT price. The annual revenue per MW is calculated by Equations 27 and 28. Wind power has additional revenue from the emission trading system, as well as the thermal power plant receives a subsidy of the capacity market. Wind power is excluded from the capacity market due to the FIT subsidy.

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

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

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

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

Similarly, the annual variable cost is calculated as the accumulation of the 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 extremely low marginal cost.

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

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

Figure 3 is a more detailed causality diagram to clarify the relationship among all the modules and identified the endogenous and exogenous variables of the model.

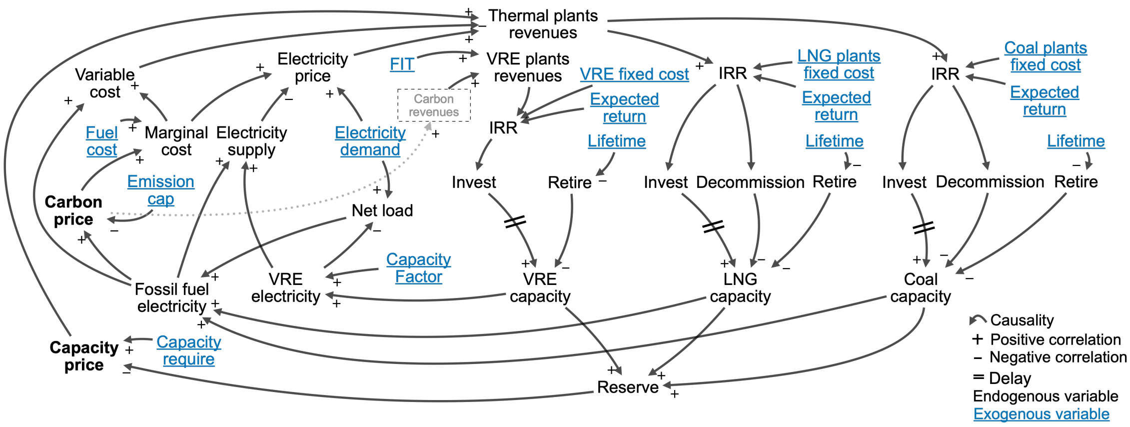

Figure 3 a more detailed causality diagram based according to the modeling equations

We choose Hokkaido as a case study to simulate the capacity changing. Hokkaido is isolated from the main state and only has few connections with the main grid, which means it more dependent on its own generation capacity to meet the demand. The initial installed capacity of each technology is the real data of Hokkaido in 2019. LNG capacity also includes a part of biomass thermal power plants which fit well into the flexible power characteristic.

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 simulation time period. The real supply-demand data in 2019 [19] is chosen as the input data of electricity demand as shown in Figure 4. We assume that the demand for each year in the future will be the same as in 2019. This is a very strong assumption that does not match the reality, but it helps us eliminate the less question-related factors from the complex reality to better focusing on the interactions among our main study targets.

Figure 4 the real electricity consumption data of Hokkaido 2019

Similarly, we use the real wind power data [19] and the installed wind power capacity of Hokkaido in 2019 to calculate the wind power factor as shown in Figure 5. We assume that the wind power factor for each year in the future is the same as in 2019. The excessive randomness will make the results from the model uninterpretable the data from real world with fixed fluctuations will improve the interpretability of the model and access better insight.

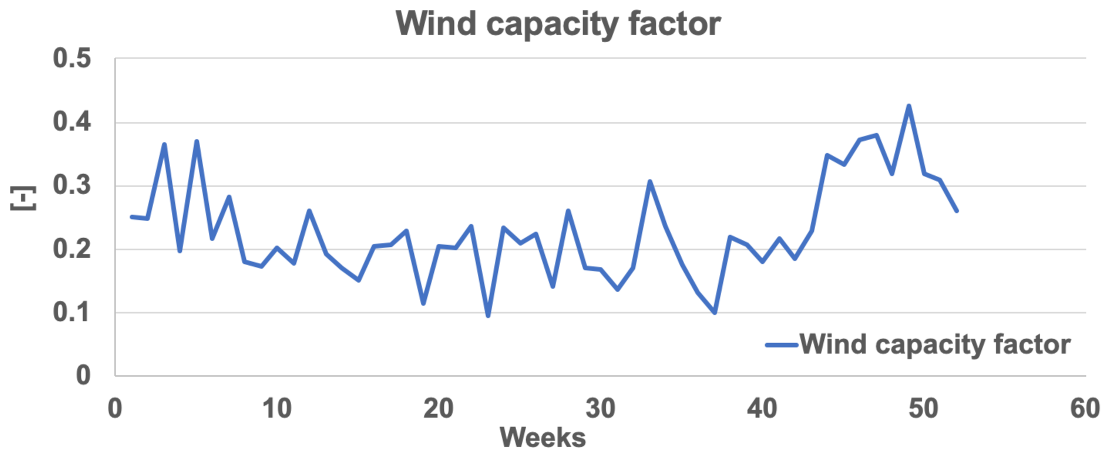

Figure 5 the capacity factor of wind generation in Hokkaido 2019

Since the Hokkaido Electric Power Company owns 87% of all thermal power plants in Hokkaido, we assume that the CO_2 emission factor of Hokkaido is the same as Hokkaido Electricity [20]. The total CO_2 emission value of the power department 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 figure6, the fixed value of emissions will be reduced every year until the emissions become zero in 2050.

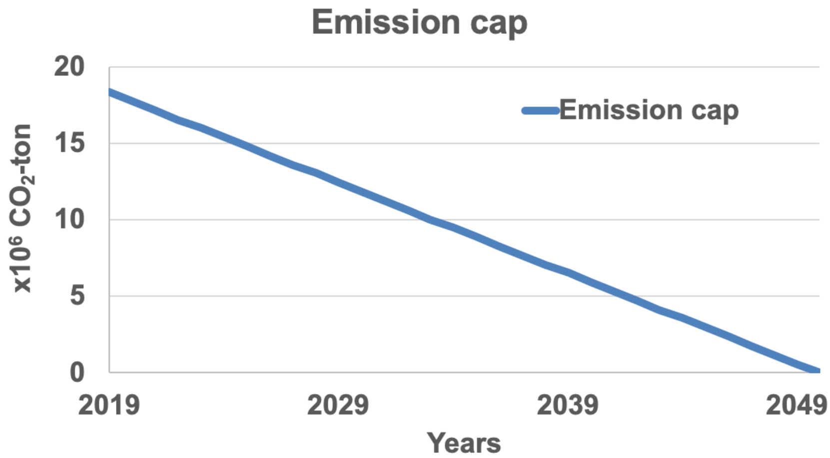

Figure 6 the emission allowance during the simulation period

Compare to the capital-intensive thermal power plants, the size of a single investment in wind power is much smaller, thereby the same return rate will stimulate more diversified investors in the market, thereby we assume that the sensitivity coefficient of wind power is much higher than other technologies. The wind power receives continuous FIT subsidies, so it will only retire when life-expired instead of decommissioning due to losses, so the sensitivity coefficient of decommission of the wind power is zero. We assume the expected return rate on investment of market participants cannot be lower than the interest rate. The detailed parameter as well as input data is shown in the table below:

Table 2 Main assumptions and input data of case study [21-24]

	Wind	Coal	LNG
Initial Capacity [MW]	534	2520	3507
Minimum size of generators set [MW]	5	100	200
Construction time [yr]	1	3	3
Sensitivity coefficient of new investment [-]	40	1	1
Sensitivity coefficient of Decommission [-]	-	1	1
Wind capacity value factor [-]	0.236	1	1
Mean Fuel Price in 2019 [$/ton]	-	108.58	512.99
Marginal Fuel Cost [$/MWh]	-	35.84	67.14
Emission Factor [ton-CO_2/MWh]	-	0.943	0.474
Heat value[MJ/ton]	-	25970	55010
Heat effiency [-]	-	0.42	0.5
Fixed Cost [$/MWh]	2590476	2380952	1142857
Maintance Cost [$/MW/yr]	2590	119047	57142
Decommission Cost Ratio [-]	0.01	0.07	0.07
Lifetime [yr]	20	40	40

Table 3 the assumptions and input data of economic related coefficients of case study [21-24]

Item	Value
Interest rate [-]	0.03
Sensitivity coefficient of carbon price	1
Sensitivity coefficient of capacity price*	130725.8
Sensitivity coefficient of electricity price	10
Sensitivity coefficient of decommission	1
FIT [$/MWh]	95
CO_2 floor price [$/ton-$CO_2$]	30
Capacity price cap** [$/MW]	134647.6
Electricity price cap [$/MWh]	1905
Exchange rate [JPY/$]	105

*the coefficient is calculated to ensure zero capacity price when total capacity are over 5% of requirement

**the cap is the difference between fixed cost and expected revenue for a new LNG power plant

In order to investigate the linkage between carbon pricing and capacity pricing, five scenarios are designed. The basic scenario, assuming that there is no capacity pricing nor carbon pricing in the electricity market. The capacity scenario, assuming that only capacity pricing exists in the electricity market. The carbon scenario assuming that only carbon pricing exists in the electricity market. The interaction scenario assuming that both capacity pricing and carbon pricing exist in the electricity market. The advance scenario assuming that high floor price carbon prices and flexible power source only capacity pricing, which means that all capacity contributes to the adequacy are counted, but only the capacity which provides flexibility are subsidized. The model simulates the long-term capacity changing, CO_2 emission changing, carbon price changing, capacity pricing changing, and electricity pricing changing of all scenarios. The simulation period is from 2019 to 2050, with weeks as the time unit. The model is built in the python environment using BPTK-Py packages [25], which provided the basic modeling framework of System Dynamics model.

Results

Figure 7 shows the simulation results of the capacity change of coal power plants in five scenarios. It can be observed that without the introduction of the carbon price, coal power plant capacity will maintain in the range of 3000MW to 4000MW. The capacity scenario has the highest coal capacity, followed by the base scenario. By comparing the results of the interaction scenario and carbon 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 higher floor in the early stage, as well as cut the capacity subsidy of inflexible power source, which leads to the investment of coal stopped. As a result of coaction, coal is not subject to additional capacity subsidies and bears the high carbon price, thereby decommissioned early.

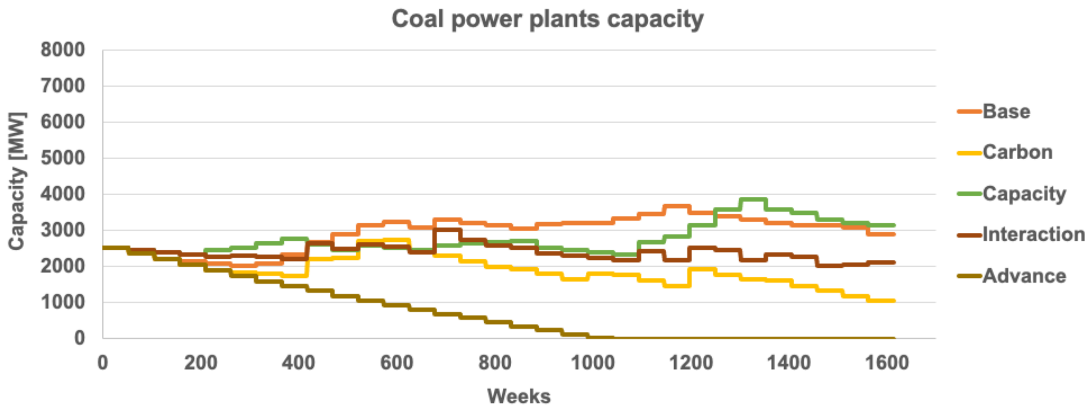

Figure 7 The trajectory of coal power plants capacity changing

Figure 8 shows the simulation results of the capacity change of LNG power plants in five scenarios. In all scenarios without capacity price, the capacity changing of LNG power plants show clear cyclical fluctuations, especially in the base scenario, where the maximum capacity is about 7 times the minimum. This reflecting the restraint of the capacity price on investment fluctuations.

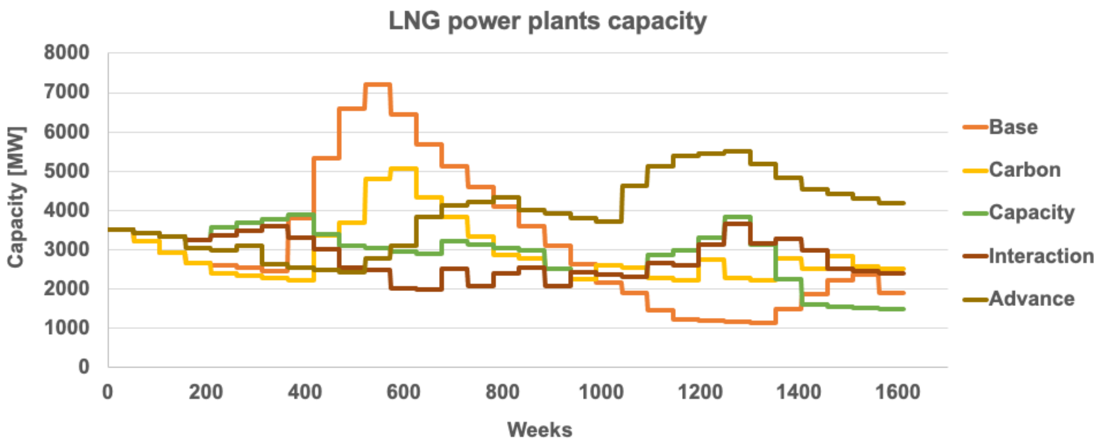

Figure 8 The trajectory of LNG power plants capacity changing

Compared with the base scenario, the introduction of carbon prices reduced the installed capacity of LNG in the early period before the base scenario starts to enter the bust cycle, however, the advance scenario is an exception, it has the highest installed capacity of LNG at the end of the simulation period. This is because the higher floor carbon price changed the order of marginal costs of coal and gas, which promote the decommission of coal, and the gas has entered the market as a substitute. The point is that carbon price needs to be high enough to cover the marginal cost gap between coal and gas thereby internalizing the cost of emissions and correctly distinguish the price of coal and gas from the perspective of CO_2 emissions.

Nevertheless, except for the capacity scenario, all scenarios with capacity prices bring higher LNG capacity. It looks contradictory but the reason is that in the capacity 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 LNG leads to the decrease of revenue and eventually capacity. From the results of the advance scenario, it shows that distinguish the subsidy of flexible power sources in the capacity price will promote each other with the high floor carbon price, which increases the capacity of flexible and relatively less emission LNG power plants.

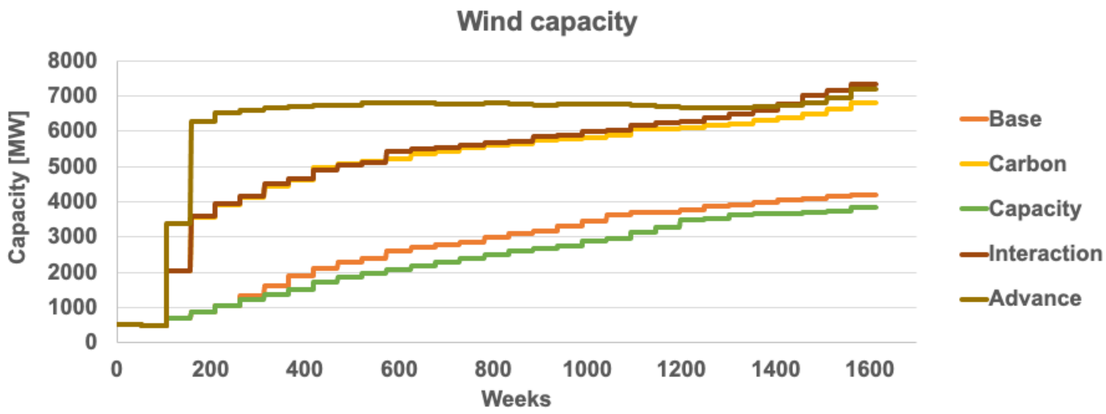

Figure 9 The trajectory of wind power plants capacity changing

Figure 9 shows the simulation results of wind capacity change in five 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 FIT subsidy alone, only with the additional revenue from the carbon price, the installed capacity of wind power significantly can exceed either one of the fossil fuel power plants.

Moreover, the growth rate of wind power in the early stage is significantly higher than that in the later stage. This is due to the fact that although the carbon price is higher in the late stage when the cap getting low, the carbon emissions are lower than it in the early stage, resulting in the subsidies derived from the emission trading system become less and less along with the cap decreases. The same reason also explains why the wind capacity in advance scenario is lower than the interaction 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 interaction scenario.

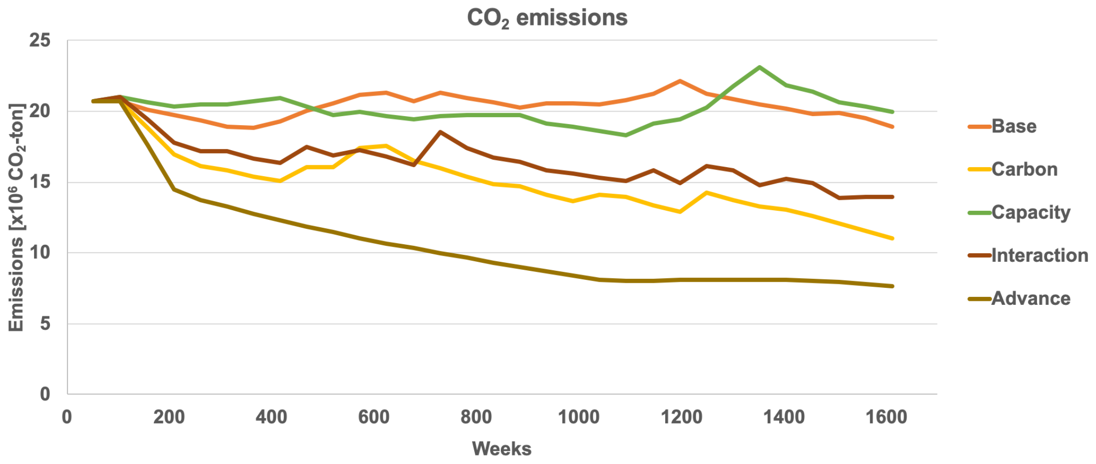

Figure 10 The trajectory of total CO_2 emission changing

Figure 10 shows the simulation results of the CO_2 emissions change in five scenarios. The capacity scenario has the highest CO_2 emissions, even higher than the base scenario, due to its subsidies for fossil fuels. The advance scenario achieved about 65% of emission reductions compares with the beginning at the end of simulation period. This is due to the consistent incentive from high floor carbon price with flexibility focusing capacity price promotes the decommissioning of coal while retaining the LNG power plants to maintain the system's supply and demand balance.

Comparing the carbon scenario, the capacity scenario, and the interaction scenario shows that the existence of the unreformed capacity price in the interaction scenario weakens the emission reduction effect from the carbon price. Although the wind capacity in the interaction scenario is higher than it in the advance scenario, capacity price and carbon price offsetting each other and end up with a large number of coal power plants, which squeezes the power generation of flexible gas resources with relatively lower carbon emissions, resulting in the scenario with highest wind capacity still cannot reduce CO_2 emissions.

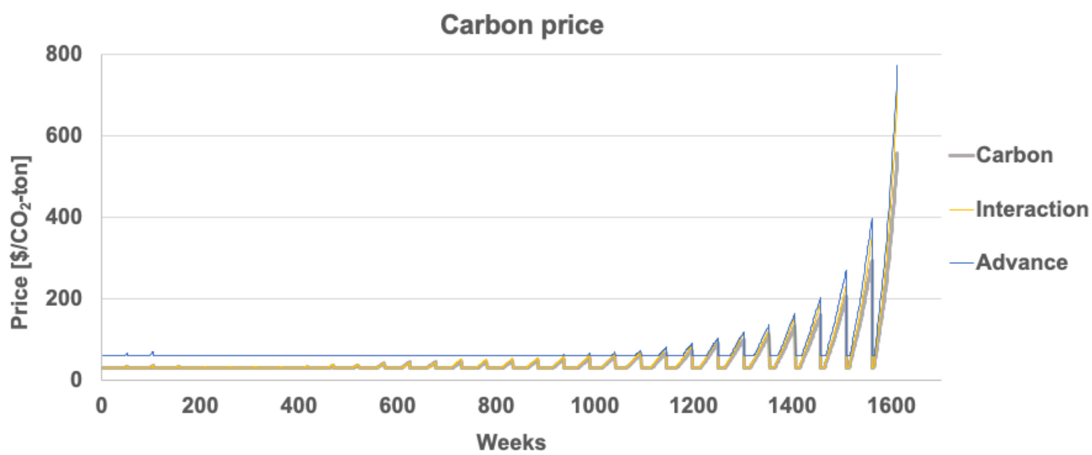

Figure 11 The changing of carbon price

Figure 11 shows the simulation results of carbon price change in three scenarios with carbon prices. The results of the three scenarios have similar trends, besides although the two scenarios have the same carbon floor price, the price of the interaction scenario is higher than the carbon 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 in the power mix of the interaction scenario, which causes an increase in carbon prices.

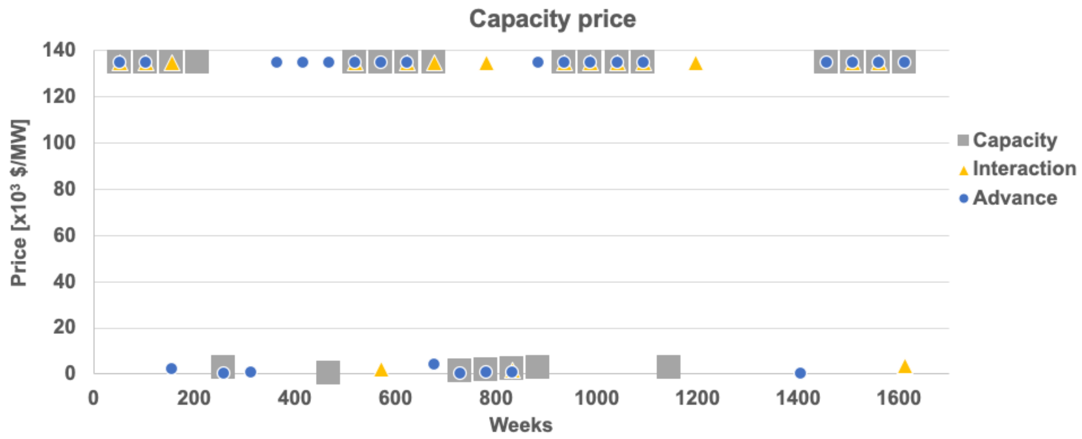

Figure 12 The changing of capacity price

Figure 12 shows the simulation results of capacity price change in 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 signal due to the massive promotion of LNG to replace the decommissioned coal.

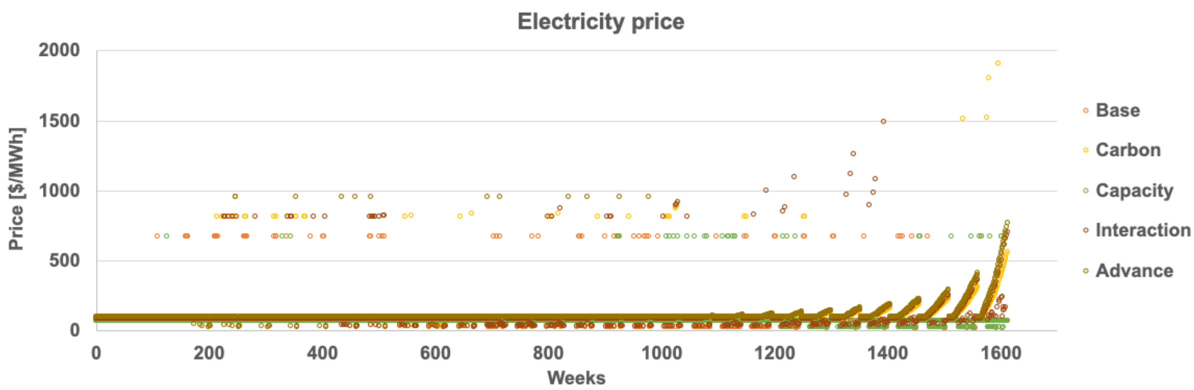

Figure 13 The changing of electricity price

Figure 13 shows the simulation results of electricity price changes in five scenarios. Compare with the base scenario, the capacity prices in the capacity scenario significantly reduces the number of electricity prices spike. Scenarios with a carbon price are affected by carbon prices, the prices, especially spike prices, are higher than the base scenario. Similarly, compare to the interaction scenario and the advance scenario, the subsidy for flexible power sources has significantly reduced the number of electricity price spikes. Even if the carbon price is higher, the electricity price has remained at a relatively stable level.

Since carbon prices are directly transmitted to the wholesale electricity market, the impact of carbon prices on wholesale electricity prices is more significant. 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.

Conclusions

The increasingly complex designs of liberalized electricity market may cause unexpected side effects through the interactions among policy instruments during the energy system transition period. This study proposed that the design of capacity pricing needs to link with the carbon pricing, otherwise the offset of two mechanisms may lead to inefficiency and slow down the energy system transition.

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 the lower floor cannot achieve the complete retirement of coal, which leads to the relatively high carbon emissions, bring more investment of VRE from allowance auction instead. However, the carbon price is not high enough to distinguish the emission gap between coal and LNG in the merit order mechanism, eventually, increasing VRE squeezed the low emission flexible LNG out of the market, reduced the reliability of the system. Nevertheless, in the case of flexibility technology focusing on capacity pricing alone with a high floor carbon price will bring out consistent incentives, diverting the capacity payment from coal power plant to more flexible and low emission LNG, thereby accelerate the coal power plants decommissioning and reduce CO_2 emissions by 2050.

References

[1] J. Sterman, Business Dynamics: System Thinking and Modeling for a Complex World, McGraw-Hill/Irwin, Boston (2000)

[2] A. Bublitz et. al., A survey on electricity market design: Insights from theory and real-world implementations of capacity remuneration mechanisms, Energy Economics, Volume 80, 2019, Pages 1059-1078

[3] Arango S, Larsen E. Cycles in deregulated electricity markets: Empirical evidence from two decades. Energy Policy 2011;39:2457–66.

[4] Frank J., Redmond L, The European Union Emissions Trading Scheme: Issues in Allowance Price Support and Linkage, Annual Review of Resource Economics, Vol. 5:301-324

[5] D. Peng, R. Poudineh, Electricity market design under increasing renewable energy penetration: Misalignments observed in the European Union, Utilities Policy, Volume 61, 2019

[6] A. A. Parmar, B. P. Darji, Capacity market functioning with renewable capacity integration and global practices, The Electricity Journal, Volume 33, Issue 2, 2020

[7] J. Hu et. al., Identifying barriers to large-scale integration of variable renewable electricity into the electricity market: A literature review of market design, Renewable and Sustainable Energy Reviews, Volume 81, 2018, Pages 2181-2195

[8] Gillich, Annika & Hufendiek, Kai & Klempp, Nikolai, 2020. "Extended policy mix in the power sector: How a coal phase-out redistributes costs and profits among power plants," Energy Policy, Elsevier, vol. 147.

[9] Pablo del Río, Emilio Cerdá, The missing link: The influence of instruments and design features on the interactions between climate and renewable electricity policies, Energy Research & Social Science, Volume 33, 2017, Pages 49-58

[10] Özge Özdemir, Benjamin F. Hobbs, Marit van Hout, Paul R. Koutstaal, Capacity vs energy subsidies for promoting renewable investment: Benefits and costs for the EU power market, Energy Policy, 2020, Volume 137

[11] Oscar Kraan, Gert Jan Kramer, Igor Nikolic, Emile Chappin, Vinzenz Koning, Why fully liberalised electricity markets will fail to meet deep decarbonisation targets even with strong carbon pricing, Energy Policy, 2019, vol. 131, pages 99-110

[12] Paul L Joskow, 2019. Challenges for wholesale electricity markets with intermittent renewable generation at scale: the US experience, Oxford Review of Economic Policy, vol. 35(2), pages 291-331

[13] Ottmar Edenhofer, Lion Hirth, Brigitte Knopf, Michael Pahle, Steffen Schlömer, Eva Schmid, Falko Ueckerdt, On the economics of renewable energy sources, Energy Economics, Volume 40, Supplement 1, 2013, Pages S12-S23

[14] David Newbery, Missing money and missing markets: Reliability, capacity auctions and interconnectors, Energy Policy, Volume 94, 2016, Pages 401-410

[15] Fernando Olsina, Francisco Garcés, H.-J. Haubrich, Modeling long-term dynamics of electricity markets, Energy Policy, Volume 34, Issue 12, 2006, Pages 1411-1433

[16] Masoud Hasani, Seyed Hamid Hosseini, Dynamic assessment of capacity investment in electricity market considering complementary capacity mechanisms, Energy, Volume 36, Issue 1, 2011, Pages 277-293

[17] Marie Petitet, Dominique Finon, Tanguy Janssen, Capacity adequacy in power markets facing energy transition: A comparison of scarcity pricing and capacity mechanism, Energy Policy, Volume 103, 2017, Pages 30-46

[18] Ibáñez López, Antonio Santiago (2017). Prospective long-term overall economic and environmental impact of a country's electric power system policies: a behavioral dynamic systems thinking approach. Thesis (Doctoral), E.T.S.I. Industriales (UPM)

[19] Japan electricity power exchange, http://www.jepx.org/market/index.html

[20] About CO2 emission results in 2019, Hokkaido Electric Power Co.,Inc. https://www.hepco.co.jp/info/info2020/1251006_1845.html

[21] Power survey statistics table, Agency for Natural Resources and Energy, Ministry of Economy, Trade and Industry, Japan

[22] Generation cost verification working group, Agency for Natural Resources and Energy, Ministry of Economy, Trade and Industry, Japan

[23] Eiichi Imamura, Masanao Iuchi, Shigeru Bando, Comprehensive assessment of life cycle CO2 emission from power generation technologies in japan, Socio-economic research center rep. No Y06

[24] Demand curve creation procedure of capacity market main auction, Organization for Cross-regional Coordination of Transmission Operators, Japan

[25] BPTK-Py: System Dynamics and Agent-based Modeling In Python, MIT License, https://bptk.transentis.com/en/latest/index.html