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Analysis of Carbon Taxation under Fuel Price Uncertainty in Japanese Energy System

Pongsak Krukanont[1,*] and Tetsuo Tezuka[2]

[1] The Thailand Research Fund, 14th Floor, SM Tower, 979 Phaholyothin Rd., Samsaen-nai, Phayathai, Bangkok 10400, Thailand

[2] Graduate School of Energy Science, Kyoto University, Yoshida-honmachi, Sakyo-ku, Kyoto 606-8501, Japan.

*Author to whom correspondence should be addressed, email: pongsak@trf.or.th

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Abstract: In this paper, we use optimization modeling and Monte Carlo simulation to study the implications of fuel price uncertainty on the analysis of carbon taxation in Japan, covering projection to 2025. Based on a multi-period linear programming, the model provides the expected minimum cost of total energy system and measures the risk on the optimal allocation of investment for capacity expansion. The risk was measured by the variance of Monte Carlo runs. Under unpredictable prices of fossil fuels, simulation results indicated that the risk on the expected system cost does not vary proportionally with the carbon tax rates. However, this risk could be mitigated by the optimal diversifications of renewable energy and other clean technologies (e.g., nuclear power and hydroelectric), if the carbon tax rate was properly set. It was found that a carbon tax rate of around 200 US$/ton C is an efficient tax rate that imposes the lowest risk on the expected system cost. Wind power was also found to be an important part of a least-cost/low-risk portfolio of renewable energy sources. This study offers an improvement over the more ad hoc judgments used in traditional models for energy planning and policy such as sensitivity and worst-case scenario analyses.

Keywords: Fuel Price Uncertainty, Carbon Taxation, Optimization Model, Linear Programming, Monte Carlo Simulation, Japan

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Introduction

System modeling has become an increasingly important tool for developing national energy and environmental policies. One of the most popular models is integrated resource planning (IRP), which identifies the optimal portfolio of resource uses and technology deployments over time. However, the model usually assumes perfect information about the characteristics of the energy-economic system. This is difficult and poses risks for decision makers, especially in long-term analyses that involve large uncertainties in the decision-making process**1**. In general, uncertainty is handled by making ad hoc judgments about sensitivity, comparing scenarios, performing worst-case analyses, etc. Furthermore, in more comprehensive analyses, important uncertainties are different according to what decision makers define and what they need for the robust decision. As a result, many uncertainty analyses are inevitably subjective and require different modeling approaches**2**. For these reasons, the analysis of national energy planning and policies is still an area of active research, particularly since each country has its own characteristic of energy resources, economic structures, environmental restrictions and uncertainty concerns, which produce dissimilar optimum planning/policy strategies. For instance, Birge and Rosa [3] used the stochastic Global 2100 model, which is based on the United States economy to analyze CO2 emission policy. Their analysis considered the uncertain returns on new technology investment. The MARKAL (MARKet ALlocation) model has been used to analyze greenhouse gas abatement policies in Québec and India [4,5]. In these cases, important uncertainties were considered by a macroeconomic growth, a mitigation level and a tax on carbon emissions.

In Japan, energy security is a major public policy concern. Japanese energy consumption is among the highest in the world, but the country lacks domestic energy resources. In 2002, it was reported that the country imports 99% of its primary energy fossil fuels [6]. This leaves the Japanese energy supply highly vulnerable to disruptions in the international energy markets. Fig. 1 shows the fuel price trends in Japan from 1975 to 2002, during which the annual growth rates were somewhat unpredictable. Besides, recent awareness of global warming has increased the policy dilemma for Japan because of the conflicting goals of energy security and CO_2 emissions control (e.g., a carbon taxation policy). Therefore, Japanese energy planning and policy analysis seem to be conducted within two major perspectives: 1) efficient policies and their impacts on the economy, and 2) future alternative of energy system. For example, Goto and Sawa [7] investigated the macroeconomic costs of various policies for controlling CO_2 emissions, including a trade off relationship between these costs and the sectoral impacts of carbon taxation [8]. An outlook for Japan's energy supply and demand with projection to 2015 was also proposed, in which structural changes in the economy and society were taken into consideration [9]. Nakata and Lamont [10] conducted an impact analysis of energy and carbon taxes on Japanese energy systems. They concluded that the energy tax would be a more stable approach to maintaining a diversity of energy resources. Using the same modeling approach, the impact of nuclear phase-out was also analyzed [11]. Recently, Hunt and Ninomiya [12] conducted an empirical analysis of the relationship between energy demand, gross national product (GNP) and the real energy price in Japan in order to investigate various future scenarios for primary energy demand and CO_2 emissions in the context of the Kyoto reduction target. Although these analyses have been well-documented in Japan's future energy planning and policies, they do not explicitly account for the fuel price uncertainty that is one of the most important uncertainties in the country's energy security concerns. **1**

It should be noted that, in this paper, uncertainty and risk are used interchangeably in a manner not consistent with some discussions in the literature, where the risk usually assumes that decision makers know the distribution of the future outcome (e.g., probability distributions). This assumption is not true in the case of uncertainty because the situation under consideration is in highly unusual (see also Knight [1]). Whenever, we discuss uncertainty or risk, we assume that the distribution is known. **2** See also Kann and Weyant [2] for a unifying framework for comparing the different types of uncertainty analyses.

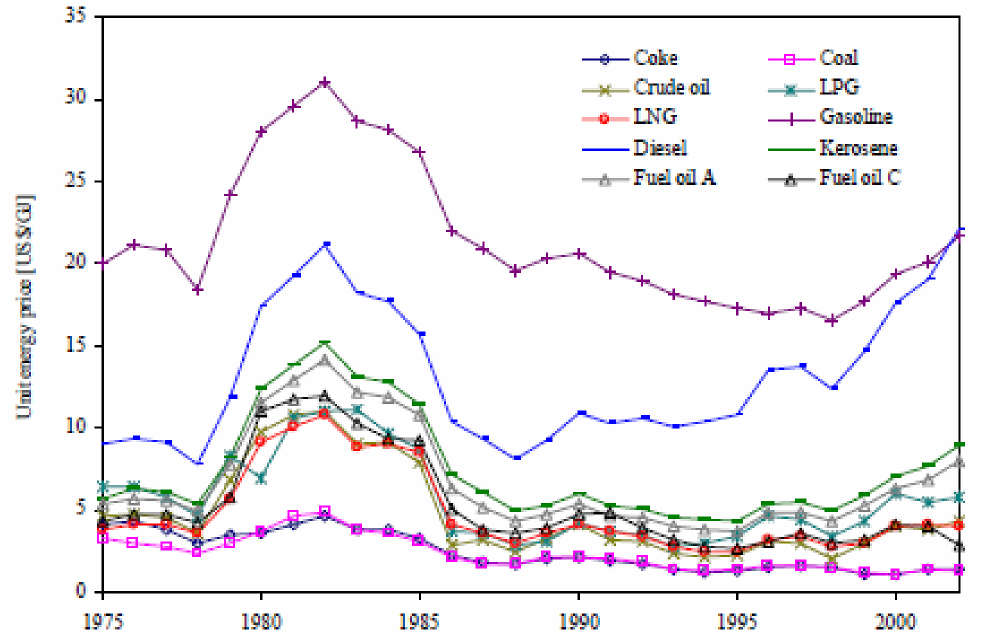

Fig.1 Historical trends of fuel price in Japes

Building on reviews of literature related to fuel price risk [13-16], this paper focuses on the implications of fuel price uncertainty on the the analysis of carbon taxation in Japan, covering projection to 2025. Using an integrated resource planning approach, we developed an optimization model incorporating the Monte Carlo technique simulation to measure this fuel price risk and to explore how it influences the decision-making process for the optimal allocation of investment. The proposed model offers, not only an improvement over the more ad hoc decisions required in traditional analyses, but a better understanding of how to design efficient planning/policy instruments that impose the lowest risk.

Descriptions and Model Framework

As shown in Fig. 2, the model framework is constructed using multi-period linear programming and Monte Carlo simulation to determine not only the expected minimum cost of the total system under the uncertainty of fuel prices but also the optimal allocation of investment under carbon taxation. The energy–economic system (data inputs) was constructed based on a bottom-up modeling approach since it can analyze into the details of technology potential and their future development. The Monte Carlo simulation technique was incorporated in order to ascertain the impacts of fuel price uncertainty on the expected system cost, the decisionmaking process of capacity expansion and the level of CO2 emissions. This approach consists of simultaneously varying the fuel price parameters using random sampling and then running the optimization model for each discrete set of random parameters in search of variables in the model. The results of Monte Carlo simulation are based on statistical interpretation. The process of Monte Carlo simulation is terminated after checking the accuracy of the objective function (by observing the convergence of standard deviation); otherwise it is necessary to increase the size of random samples. In the following subsections, we provide a brief of mathematical formulations of the objective function, followed by model specifications and important of model assumptions.

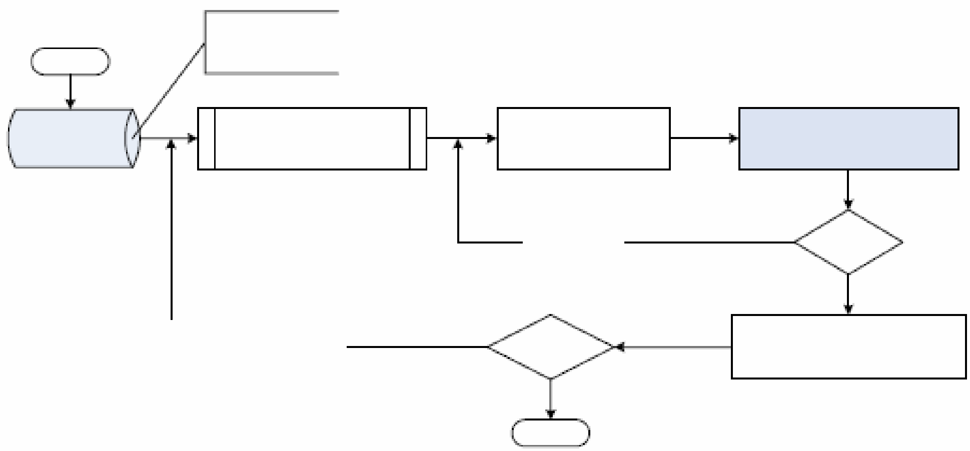

Fig. 2 Model framework for analysis of fuel price uncertainty

Mathematical formulations

Unpredictable fossil fuel prices are taken into account by using the Monte Carlo simulation technique to represent the stochastic environment of fossil fuel prices. These random parameters are assumed to enter the model in the form of annual growth rates. Under this system framework, the probability density function of the annual growth rate of fuel price is assumed to be known3 (e.g., normal distribution). Thus, historical data on fuel price trends is helpful to prescribe these distribution functions. To be compatible with a linear programming model, we formulated the fuel price uncertainty for various fossil fuels based on conversion technologies. For a given of sample size, random fossil fuel prices can be generated by Eq. (1).

$$EP_{j,t+1} = EP_{j,t}\left(1 + GR^{random}_{j,t+1}\right) \qquad (1)$$

Where

Set indices

j	Set of conversion technologies
t	Set of time frame

Parameters

$EP_{j,t}$	Specific energy price based on j technology in the t time fr:
$GR^{random}_{j,t}$	Annual random growth rate of fuel price based on j technol

Within the framework of multi-period linear programming, the objective function is the least present value of total system costs for technologies chosen to satisfy end-use energy demands, environmental and other constraints. This total present cost consists of capital investments, fixed operation and maintenance (O&M) costs, fuel costs and associated environmental costs for carbon taxation. A simplified form of the objective function can be written as follows:

$$\text{Minimize} \quad \sum_{t=1}^{T}\frac{1}{(1+i)^{t}}\left[\sum_{j=1}^{J} CI_{j,t}NEWCAP^{cumulative}_{j,t}\frac{i(1+i)^{l_j}}{(1+i)^{l_j}-1} + \sum_{j=1}^{J} CF_{j,t}NEWCAP^{cumulative}_{j,t} + \sum_{j=1}^{J} EP_{j,t}FCONS_{j,t}NEWGEN^{cumulative}_{j,t} + TOTEMIS_{t}TAX\right] \qquad (2)$$

Where

Parameters

$CI_{j,t}$	Specific investment cost of j technology in the t time frame
$CF_{j,t}$	Specific O&M costs of j technology in the t time frame
$FCONS_{j,t}$	Unit fuel consumption of j technology in the t time frame
i	Discount rate
l_j	Lifetime of j technology
TAX	Carbon tax rate

Decision variables

$NEWCAP_{j,t}^{cumulative}$	Cumulative capacity expansion provided by j technology in the t time frame
$NEWGEN_{j,t}^{cumulative}$	Cumulative operation of the new capacity provided by j technology in the t time frame
$TOTEMIS_t$	Total CO_2 emissions in the t time frame

Model specifications and assumptions

In this paper, we analyzed two future scenarios. The reference scenario is the "business as usual" (BAU) scenario, in which there was no planning or policy action (as constraints). The second scenario is the "carbon taxation" (TAX) scenario. In this scenario, a penalty cost was assessed on technologies that emit CO_2 emissions. Two carbon tax rates—100 US$/ton C and 350 US$/ton C—were emphasized to represent "a little less" and "a little more" control of CO_2 emissions, respectively. This scenario also assumes that the revenues from carbon taxation were not used to subsidize for energy programs. In addition, we assume that the annual growth rates of fuel prices vary independently according to the normal (Gaussian) distribution function[4]. By using the mean value and standard deviation derived from the historical data shown in Fig. 1, the random growth rates of fuel prices can be generated, in which 2,000 random samples were used in Monte Carlo simulation. Greater accuracy could be achieved, but the computing costs are significant. This sample size was selected because of the limited computation. The reference system for energy supply-demand was recently updated with energy-economic statistics of Japan as a case study [6]. The time frame for simulation starts from 2001 to 2025. The energy-economic system covers 15 end-use sectors and 55 conversion technologies of various types. The database of various energy technologies was created using data from many publications [19-29]. Since the techno-economic characterizations of various energy technologies (e.g., specific investment cost, specific O&M cost, conversion efficiency and lifetime) are individually dependent upon the location and scope of the study, some of the original references are hyperlinked to the internet.

The optimization model is written in GAMS (General Algebraic Modeling System) code and uses the CPLEX package to solve linear programming problems [30]. The complete model comprises of 9,004 constraints and 9,152 variables, and takes a few hours (including Monte Carlo simulation) to execute on a standard PC. The mathematical details and complete computer code are available from the corresponding author.

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[3]Although an assumption to know a probability distribution may seem limiting, for evaluating energy planning and policy decision makers may not need to know the whole probability distribution and the future outcome accurately because the focus is mainly about the impact of fuel price uncertainty on some decision variables. Hence, a subjective specification of the probability distribution can give useful information, although it may exclusively be plausible for some decision makers and be implausible for others.

[4] It is not our intention here to prescribe the most suitable probability distributions for the parameter growth rates. Hence, we use the normal distribution since it is commonly employed to represent the uncertainty resulting from unbiased measurement error. The issue of using alternative distributions (non-normality) had been extensively studied in regard to electric utility resource decisions [17]. In addition, Morgan and Henrion [18] provide methods for estimating other probability distributions from observed data and evaluating the fit of a distribution.

Results and Discussion

Optimal allocation of investment

To confine our discussion, the simulation results related to the optimal allocation of investment for capacity expansion are first presented using the expected (mean) value of Monte Carlo runs[5]. As shown in Fig. 3, the cumulative capacity expansion under the BAU scenario relies heavily on coal technology as the lowest fuel price compared to other fossil fuels. This result indicates that the higher price and greater variation in the growth rate of natural gas make it uncompetitive in the long run, although the specific cost of investment in natural gas is lower than that of coal technology. As for renewable energy, wind and biomass (biomass co-firing) also penetrate the market. It is clear that, for wind energy, the decisions to expand capacity are made since the early stages of the planning period, while for biomass co-firing, they are made at the end of the planning period. This is because there is no fuel cost for wind turbines, whereas biomass co-firing operations have a biomass cost. Hence, the decisions to expand capacity for these technologies are optimally made at different points in the planning period. However, wind and biomass together have only a small market share under the BAU scenario since they are still too expensive (as wind energy has a low resource availability, while biomass has a high fuel cost compared to its heating value).

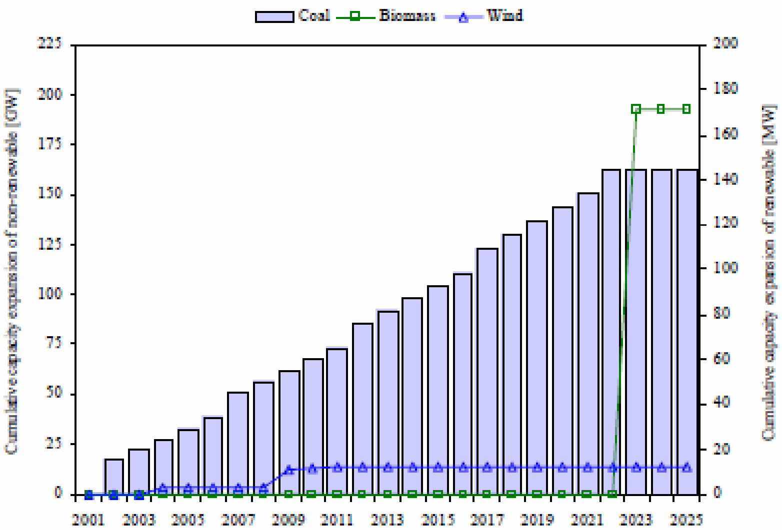

Fig.3 Cumulative capacity expansion under the BAU scenario

Under the carbon taxation (TAX) scenario, Figs. 4 and 5 show the cumulative capacity expansion at carbon tax rates of 100 US$/ton C and 350 US$/ton C, respectively. It is obvious that the cumulative capacity of coal technology under the low carbon tax rate (100 $/ton C) is slightly decreased by 7% compared to the BAU scenario. The decision on this coal reduction is allocated among cleaner technologies, including nuclear power, hydroelectric and renewable energy. This result reveals that natural gas and oil technologies mostly are not competitive for "a little less" control of CO_2 emissions as they share a small market penetration at the end of the planning period. Under the high carbon tax rate (350 US$/ton C), however, the cumulative capacity of coal at the end of the planning period is reduced by up to 38% as compared to the BAU scenario. Natural gas technology is inevitably required for "a little more" control of CO_2 emissions, including the more market penetration of nuclear power, hydroelectric plant and renewable energy.

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5 It is possible to choose other solution options of Monte Carlo simulation for discussion, for example the solutions at quartiles or any percentile. However, we discuss the mean value of Monte Carlo runs since it can imply that decision makers who choose this mean value are fairly hedging against fuel price uncertainty.

Although the average price of natural gas is about three times higher than that of coal, switching from coal to natural gas (with the same amount of primary energy input) can reduce CO_2 emissions by up to 43% [23]. Natural gas is then selected as a cleaner fossil fuel since the penalty for CO_2 emissions would control the consumption of coal fuel. It is worth noting that the decision on natural gas expansion is made with a small amount at the early of the planning period, but this capacity expansion is significantly increased after 2017. This implies that natural gas technology is somehow exposed to fuel price risk, and it would be thus avoided to invest with a large capacity at the early of the planning period. This underlying reason yields the same behavior for the power generation fuelled by oil.

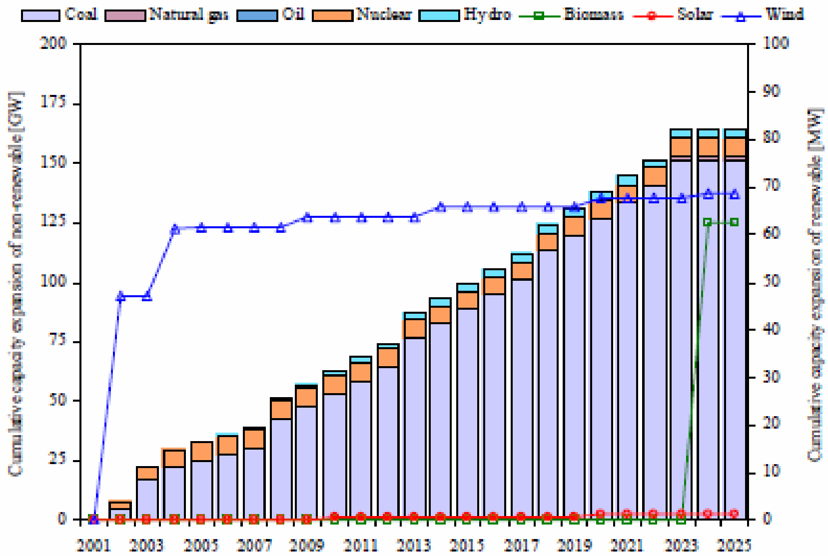

Fig.4 Cumulative capacity expansion at the carbon tax rare of 100 US&/ton C

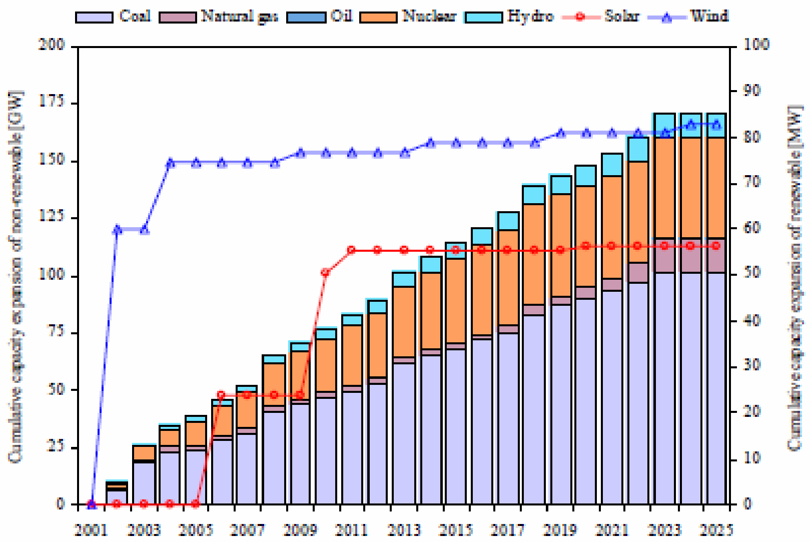

Fig.5 Cumulative capacity expansion at the carbon tax rate of 350 100 US&/ton C

Correlation of cost-risk-emissions

In this section, we roll back to the objective function in which Monte Carlo simulation is used to estimate the minimum cost of the total system under fuel price uncertainty. Table 1 summarizes the expected total system costs under different scenarios and calculates the probabilities of a normal (Gaussian) distribution. These values show the distribution of the random samples that fall within a single and double standard deviations of the mean value. For example, under the BAU scenario, approximately 68% of the samples will fall within one standard deviation of the mean value, and over 95% will fall within two standard deviations. Based on 2,000 of random samples, it is clear that the BAU scenario imposes the lowest risk (as measured by the variance), followed by TAX (100 US$/ton C) and TAX (350 US$/ton C) scenario. These results imply that the expected total system cost under the BAU scenario is the least exposed to the fuel price risk as the decision of capacity expansion is certain to be in favor of coal technology, while the carbon taxation scenarios are somewhat sensitive to fuel price uncertainty as they adopt more capacities on natural gas technology to control CO_2 emissions. Although it can be concluded that the scenarios related to the control of CO_2 emissions are exposed to the uncertainty of fuel prices, the optimal combination of renewable and other clean technologies in some instances may reduce this vulnerability. The implications of this issue are complicated by the interplays among technology decisions, operating decisions and system dynamics in that the carbon taxation scenario is described in detail.

Table 3 Results of Monte Carlo simulation on expected total system cost

Expected Total System Cost* [US$ Billion]	Future Scenarios		
	BAU	TAX (100 US$/ton C)	TAX (350 US$/ton C)
Maximum value	172.923	187.885	277.052
Minimum value	159.522	164.630	217.327
Mean value	166.285	176.622	230.215
Variance	***4.802***	***10.686***	***47.230***
Standard deviation	2.191	3.269	6.872
Probability within one standard deviation	0.680	0.720	0.869
Probability within two standard deviations	0.959	0.943	0.946

* Excluded revenue from carbon taxation.

Under carbon taxation, one of the difficult policy dilemmas is a decision about the carbon tax rate that should be a trade off between controlling the level of CO_2 emissions and choosing clean technologies for investment allocation. For this reason, additional simulation experiments were performed at various carbon tax rates in order to measure the risks for both the expected total system cost and the expected level of CO_2 emissions. These risks were measured by the variance of Monte Carlo runs. Fig. 6 shows the expected total system cost and expected CO_2 emissions in 2025 under different carbon tax rates. The error bars are plotted with their variances from Monte Carlo simulation. It is obvious that the risk on the expected system cost (vertical error bars) does not vary proportionally with the carbon tax rates. This can be explained by the decision-making process for capacity expansion, in which the decision made under a low carbon tax rate (as "a little less" control of CO_2 emissions) is mainly based on coal technology and a small amount of clean technologies, including natural gas, nuclear power, hydroelectric and renewable energy. When the carbon tax rate increases (as "a little more" control of CO_2 emissions), clean technologies must take a greater share of the market. In other words, the capacity expansion of these technologies can mitigate the fuel price risk for coal technology. Among the clean technologies, however, natural gas is the most exposed to fuel price uncertainty. Therefore, if nuclear power, hydroelectric and renewable energy were properly mixed to control CO_2 emissions, the price risk of fossil fuels on the expected total system cost can be mitigated. It can also be implied (from Figs. 4 and 5) that wind power can be viewed as the least-cost/low-risk option among renewable energy. In such a case study of Japan, a carbon tax rate of around 200 US$/ton C was found as an efficient tax rate that provides the lowest risk on the expected total system cost. This is useful information for policy makers, in which the capacity expansion on natural gas technology should be optimally invested and a decision about the carbon tax rate (for controlling the level of CO_2 emissions) should properly be set in order to mitigate the fuel price risk on the expected minimum cost.

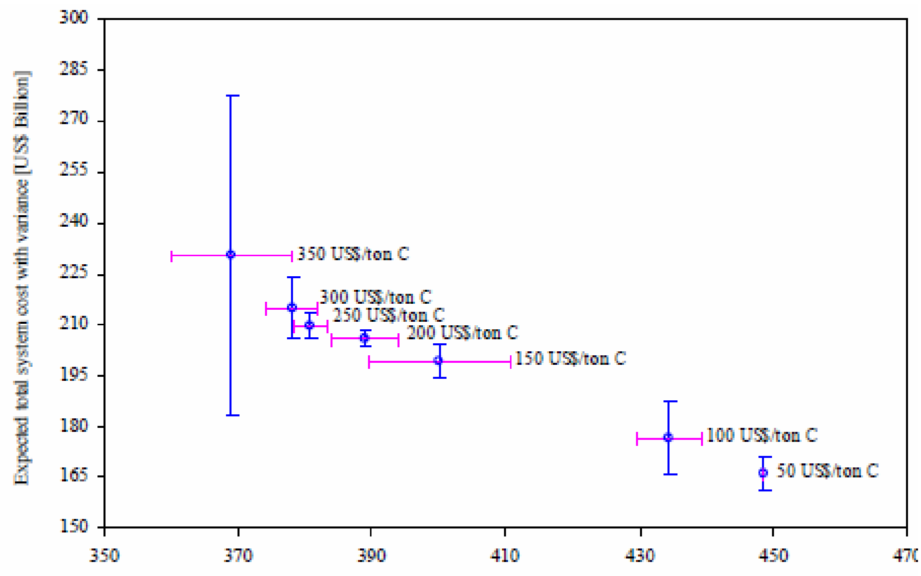

Fig. 6 Expected total system cost and expected CO_2 emissions in 2025 plotted with variance under different carbon tax rates

From the viewpoint of CO_2 emissions, it is also obvious that the risk on expected CO_2 level in 2025 (horizontal error bars) does not vary proportionally with the carbon tax rates. Although the higher carbon tax rate can better reduce CO_2 emissions, the fuel price uncertainty may yield a greater dispersion of expected CO_2 level. These results indicate that at the very high carbon tax rate the decision of capacity expansion is somewhat sensitive to fuel price uncertainty, which in turn yields a greater dispersion of the expected of CO_2 level.

Therefore, a decision on the carbon tax rate can be analyzed quantitatively through tradeoffs among cost, risk and emission reduction. These decision variables can be considered as attributes of the decision-making process, and the result of the trade off is dependent upon the decision makers' preference for each attribute. This analysis requires the application of Multiple Criteria Decision-Making (MCDM) techniques (e.g., compromise programming and lexicographic optimization), which is beyond the scope of this study. However, it can be concluded that optimal diversification using clean technologies can help not only to reduce CO_2 emissions, but also to mitigate the volatile price of fossil fuels in a quantitative way. By applying Monte Carlo simulation techniques, such technologies were found to be important parts of a least-cost/low-risk portfolio for designing long-term energy planning/policy under uncertainty fuel prices. In addition, it can provide better understanding and support for the decision-making process when developing efficient policy instruments, such as the range of plausible carbon tax rates.

Conclusion

This paper has presented a linear programming model incorporating the Monte Carlo simulation technique. The model was used to study the implications of fuel price uncertainty for the analysis of carbon taxation in Japan. Fuel price risks embodied in the expected minimum system cost and the expected level of CO_2 emissions can be quantitatively measured. Under carbon taxation, the model can identify a least-cost/low-risk portfolio for the optimal allocation of investment and the range of plausible carbon tax rates. This information is valuable for policy decision supports. Consequently, the proposed model offers an improved way to make decisions over the more ad hoc judgments required by traditional methods such as sensitivity and worst-case analyses. It is worth noting that the aim of model is not to recommend future energy planning and policy options, but to provide decision makers with a better understanding of how to design efficient policy instruments that impose the lowest risk, especially for a carbon taxation policy.

Acknowledgments

This paper was supported in part by Kyoto University 2st COE "Establishment of COE on Sustainable Energy System". COE stands for Center of Excellence, a program under the Ministry of Education, Culture, Sports, Science and Technology, Japan.ping efficient policy instruments, such as the range of plausible carbon tax rates.

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