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Jungwoo Lee
Moon Soul Graduate School of Future Strategy, KAIST

Jae-Suk Yang
Moon Soul Graduate School of Future Strategy, KAIST

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Jungwoo Lee [a, b], Jae-Suk Yang[a]

[a] Moon Soul Graduate School of Future Strategy,
Korea Advanced Institute of Science and Technology, Daejeon 34141, Republic of Korea

[b] Center for R&D Technology Policy, Korea Institute of Energy Technology Evaluation and Planning, Seoul 06175, Republic of Korea

Corresponding author

Jae-Suk Yang

Telephone Number: +82 42 350 4031

E-mail address: yang@kaist.ac.kr

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Abstract

For governments that prioritize R&D investment, future decision-making depends on performance-based budgeting. Governments evaluate outputs and outcomes of R&D programs regularly and budget for next year on the basis of program assessment. However, existing assessment methodology disregards long-term technology development; in sectors such as the energy sector, it takes a long time for technologies to progress from R&D to commercialization. This paper is a comparative analysis of existing R&D assessment models and the new foresight model developed from the point of view of government. A regression analysis is conducted using probit and ordinary least squares (OLS) models to analyze the performance of projects completed based on past R&D investment. The foresight model, which is based on the levelized cost of electricity (LCOE), is discussed in comparison. Results of the regression analysis show that government investment in market expansion of renewable energy technologies is minimal in Korea. In contrast, the LCOE foresight model results show that renewable energy technologies are appropriate targets for government R&D investment. The foresight model should be utilized for government R&D decision-making in the energy sector because it brings to light hidden information, including learning rates and technology dynamics, which remains unaddressed when analyzing using existing R&D assessment models.

Keywords: R&D assessment; Government R&D; LCOE foresight; R&D decision-making; R&D investment

1. Introduction

In the late 1980s, performance-based budgeting was introduced to government-supported programs in accordance with the demand for greater efficiency in the public finance sector during the global recession. Performance-based budgeting entails evaluation of outcomes as compared to resources and activities, as opposed to the previous administrative focus on inputs and processes. Performance-based budgeting has since been applied to government-supported R&D programs [1–4]. Governments assess the performance of R&D programs annually, and, based on these assessments, the budget for next year is determined. Assessment of government-supported R&D programs has been analyzed in previous studies focusing on: (1) R&D logic models, (2) analytical methodology, and (3) empirical analysis (certain countries only). The main topic and research questions of these studies are listed in Table 1.

Insert Table 1 about here

Previous methods of assessment of government-supported R&D programs have advantages in terms of data collection and apparent correlations between investment and performance. However, future trends in technology and commensurate R&D investment cannot be predicted using these methods[1].

In the energy sector, three key factors have been identified as predicting trends in technological development. First, performance improves in accordance with lowering costs

[1] From the perspective of performance evaluation related to R&D investment, forward-looking assessments are mostly qualitative analyses. Representative methods are AHP, Delphi, and matrix analysis. Unlike preceding research, this research was conducted within the analytical framework called performance-based R&D budgeting using quantitative analysis. Thus far, no study has been conducted from this viewpoint.

through the learning process [5–14]. Second, market entry in the energy technology sector is determined by competition in the energy industry [15–18]. Third, technological interdependence results in characteristic patterns of technological co-evolution such as natural gas power generation or ESS for load shaping and intermittent generation of renewable energy power plants [15,19,20]. With these factors in mind, we can identify six stages of technological development (Table 2) [8,15,20-21].

Insert Table 2 about here

From the government's standpoint, the timing of investment and which technologies to support must be considered. Government-supported R&D investment must be distinguished from private R&D investment that focuses on profit-seeking. In the past, researchers have concluded that governments are wise to engage where social welfare is high and the private sector has avoided investing due to lack of incentive [25,26]. In many cases, governments must focus on development of technologies that require huge budgets and long-term investment and involve changes in infrastructure [27–29]. Another rationale for government engagement is to overcome market inefficiencies and outdated practices [30,31]. Thus, investment is often made in new technologies ranging from inventions to niche market commercialization rather than pervasive or saturation technologies.

This paper is a comparative analysis of the effectiveness of the regression and levelized cost of electricity (LCOE) foresight models from the point of view of government-assisted R&D programs. Of course, not all countries evaluate the performance of government R&D investments using a regression method. Depending on the country, the insight of experts is valued when it comes to R&D investment. In many cases, the "informal and consultative" method is adopted, especially in EU countries, while the "formal and technical" method based on quantitative evaluation is used in other cases [32]. However, among the top five countries in terms of size of government R&D, the U.S., Japan, Germany, and Korea, all (with the exception of France) have adopted regression-based econometrics as a default evaluation method [33–36]. Regression analyses focus on correlations between past government R&D investment and sales of beneficiary companies. However, using the LCOE foresight model, we predict changes in future energy technologies based on the learning curve, market share, and their interaction. In our comparative analysis, we show that the LCOE foresight model provides information about technological trends that cannot be obtained in a regression analysis. Finally, we discuss the political implications of our results for decision-making by governments regarding R&D investment.

2. Research Methodology

2.1. Technologies included in the analysis

In this study, six technologies are analyzed: solar PV, wind, fuel cell, new coal, new gas combined cycle gas turbine (CCGT) and nuclear energy. The Korean government concentrated support on these power-generating technologies from 2008 to 2014. The technologies subjected to analysis are shown in Table 3. The regression analysis included data about past R&D investment by the Korean government and the sales of beneficiary companies. All data included in the LCOE foresight model, such as fixed costs and operating costs, was predicted on the basis of the environment in Korea.

Insert Table 3 about here

2.2. Research process

We conducted a comparative analysis of the results of a regression analysis and an analysis using the LCOE foresight approach. The process is illustrated in Figure 1.

Insert Figure 1 about here

2.2.1. Regression analysis

We conducted a survey including companies that received R&D assistance from the government in the period from 2008 to 2014 to determine the correlation between government support and the sales of beneficiary companies. Survey subjects included application technologies with TRL(Technology Readiness Level) between 4 and 6 at the beginning of the process of R&D investment by the government, and commercialization technologies between TRL 7 and 9 as the final technology development target. Survey items represented variables expected to affect the sales of beneficiary companies. The definitions of the variables are listed in Table 4.

Insert Table 4 about here

We explored the correlation between government R&D investment and sales of beneficiary companies by conducting a regression analysis with sales of beneficiary companies as the dependent variable and all other variables as independent variables. The reason for defining the sales of beneficiary companies as the dependent variable is that the priority of technological investment in the application stage in the power generation sector is realization of the energy mix presented in the national plan. Most countries with medium- and long-term energy plans, including OECD members, regard the application stage of R&D development and its correlation with performance in the field as important indicators of investment success [37,38]. A probit model was used to investigate the relationship between government R&D investment and successful sales in different technical fields including all companies. For all companies included in the model in which sales were generated from the R&D project, the value was set to be 1. For companies in which no sales were generated from the R&D project, the value was set to be 0. Then, an ordinary least squares (OLS) analysis was conducted to verify the association between government R&D investment and sales growth in beneficiary companies in which sales were generated from the R&D project.

2.2.2. LCOE foresight model

Two scenarios were established for estimation of the LCOE foresight model. The baseline scenario is the current policy scenario, in which current energy policies and levels of government R&D investment are maintained, as announced by the government. The enhanced R&D scenario is the one in which the technical performance matches the targets proposed in the National R&D Roadmap due to increased government R&D investment, in contrast with the baseline scenario [39]. Comparing these two scenarios makes it possible to confirm the effects of investment in technical development by the government.

The LCOE foresight model consists of three steps. First, we derive the cost reduction potential by segregating key components of the system and expect its performance to reflect R&D investment by the government. Then, based on the future performance of the system, we calculate the amount of electricity generated in the development of new technologies, also considering interactions among them. In the final step, we examine all six technologies in the LCOE foresight model using cost reduction potential data and electricity generation data obtained in the previous steps.

All data used to predict the cost reduction potential and the amount of electricity generated was gathered by a technical committee composed of 43 domestic experts [40]. This committee estimated the technical specifications for six energy-generating technologies over the course of several meetings. We also reviewed the technical specifications published in previous research, using data from these studies to validate the committee's estimates [41–44].

First step: Derive cost reduction potential

Costs of generating power can be divided into capital, operating, and fuel expenditures. In order to predict capital expenditure, key parameters affecting cost reduction were identified and the overall cost of generating power was determined. Then, the cost reduction potential was derived according to changes in key performance-related parameters. Examples for predicting capital expenditure and cost reduction parameters and the process through which costs were reduced are shown in the Figure 2. For operating expenditure, future levels were predicted in contrast with a set standard through the convergence of expert opinions. For fuel expenditure, the predictions of the Energy Information Administration were utilized [45]. Details about key parameters for cost reduction, technology performance, system configuration cost are shown in the attached Appendix.

Insert Figure 2 about here

Second step: Calculate the amount of electricity generated

The TIMES model is used to calculate the amount of electricity generated for new technologies. The TIMES model enables us to analyze a combination of technologies that minimize the total cost of a system under the given constraints. The objective function minimizes the discounted cost of the energy system during the period of analysis. The objective function can be expressed as follows [46,47]:

$$NPV = \sum_{r=1}^{R} \sum_{t=1}^{NPER} \left(1 + \mathrm{d}\right)^{NYRS(1-t)} \cdot ANNCOST(r,t) \cdot (1 + \left(1 + d\right)^{-1} + \left(1 + d\right)^{-2} + \cdots + \left(1 + d\right)^{1-NYRS}$$

,

where *NPV* is the net present value of the total cost for all regions, *NPER* is the set of years included in the analysis, *NYRS* is the number of years in each period *t*, *r* is the set of regions, *ANNCOST(r;t)* is the total annual cost in region *r* and period *t*, and *d* is the general discount rate.

The following constraints are used to calculate electricity in the TIMES model of this study [48–50]. First, to satisfy the capacity transfer constraints, the total available capacity for each technology whose physical life has not yet ended, in region *r*, in period *t* is equal to the sum of investments calculated in the model at past and current periods, plus capacity in place prior to the modeling horizon that is still available. Second, capacity constraint is the amount of activity that for each technology, period t, region r, and timeslice s may not exceed its available capacity, as specified by a user-defined availability factor. Third, by commodity balance constraint, the production plus imports from other regions of each commodity must balance the amount consumed in the region or exported to other regions. The commodity consists of energy carriers such as electricity, energy services, and emissions that are either produced or consumed by energy sources, sinks, technologies, and demands.

The model is run over the 20-year period from 2015–2035 in accordance with the period in which the second Korea Energy Master Plan will be implemented [51]. The analysis was conducted for each successive five-year period from 2015. The discount rate was set at 5.5% to convert the future cost to the present value based on a reference value for the economic analysis on public investment projects in the Republic of Korea [52]. For this study, we gathered data for conventional electricity-generating technologies from the historical data on the Korean electric power system [53,54]. Also, we developed another data set for new technologies based on the results of a survey undertaken by the technical committee. The electricity demand during the time period follows the second Korea National Master Plan, and the government's plans to retire existing plants and build new power plants are incorporated into the model as constraints [51].

Third step: LCOE foresight

The LCOE reflects investments during the life of a technology in the power-generating facilities divided by the amount of power produced during the same period. It represents the per-kilowatt-hour cost in discounted real dollars of operating a generating plant over an assumed financial life and duty cycle [55]. Main inputs necessary to calculating LCOE include capital costs, fuel costs, and fixed and variable operations and maintenance (O&M) costs for each plant type. The availability of various incentives can also impact the calculation of LCOE. The LCOE is calculated as follows [44,56–58]:

$$\mathrm{LCOE} = \frac{\text{Total Expenditure}}{\text{Total Electricity Generation}} = \frac{\sum_{t=1}^{n} \frac{I_t + M_t + F_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+r)^t}},$$

where *LCOE = the levelized cost of generating electricity,* I_t *= investment expenditure in year t, CAPEX (capital expenditure),* M_t *= operations and maintenance expenditure in year t, OPEX (operating expenditure),* F_t *= fuel expenditure in year t,* E_t *= electricity generated, n = expected lifetime of a system, and r = discount rate*. LCOE was predicted by technology and year by including the cost reduction potential, determined in the first step, and the amount of electricity generated, calculated in the second step, in the LCOE formula.

3. Results

3.1. Regression analysis

The results of a probit analysis including all companies that received R&D funding from the government are shown in Table 5. These results confirm a significant effect of government investment only in firms specializing in conventional power plant-based technology. There was no correlation between government R&D investment and the sales of beneficiary companies specializing in renewable power-generating technology. Instead, a negative significant relationship was observed between R&D investment in beneficiary companies and the sales of those companies. This indicates that the private sector failed to commercialize, although they invested in renewable energy technologies in accordance with the government investment signals. The higher the technology level in the early support stage, the higher the success rate of commercialization of conventional power plant-based technology. This technology requires a high level of stability and reliability, but no significant relationship to renewable energy is evident. Regardless of the technology, higher values for TRL were observed for technologies that were closer to commercialization at the initial stage of R&D, and, for those firms in which investment increased further after R&D, the possibility of commercialization continues to increase. However, the most important result from the probit analysis is that a significant effect of government R&D investment is evident only in firms specializing in conventional power plant-based technology. For those specializing in renewable technologies, no significant relationship to government R&D investment is observed.

Insert Table 5 about here

Second, the results of the OLS analysis including those companies that succeeded in commercialization are listed in Table 6. We extracted data for these successful companies from among all companies that received government R&D funding and applied the logarithm to the amount variable to satisfy the normal distribution assumption of the sample population.

Insert Table 6 about here

When analyzing the data for companies that succeeded in terms of sales, similar results were seen to those of the probit analysis including all companies. The results revealed a significant relationship between government investment and sales in companies specializing in conventional power plant-based new technology. However, in firms specializing in renewable technologies, no correlation was found between government R&D investment and sales. In addition, no significant relationship was observed between sales of beneficiary companies and any other independent variable included in the analysis. So, what is the political implication of the results from the regression analysis from government R&D point of view? Using current methods of assessment of government-supported R&D programs, we must conclude that future government R&D investment should be focused on conventional power plant-based new technology judging by the investment effects. In other words, government R&D investment in renewable energy technologies should be reduced in those firms showing poor performance, and funding for conventional power plant-based new technologies should be increased. However, there are many unresolved problems resulting from deciding the direction of future R&D investment based on past performance.

3.2. LCOE foresight model

The LCOE foresight model is now utilized to determine increases in technology performance and cost reduction according to government R&D investment. These factors determine the values for market penetration and the CAPEX and OPEX, ultimately also affecting the LCOE. Technologies subjected to analysis in 2015 are ranked by LCOE as follows: fuel cell, solar PV, wind power, new gas CCGT, new coal, and nuclear energy (Figure 3). The LCOE is relatively low for conventional power plant-based new technology, the standard against which others compete. By contrast, the LCOE is relatively high for renewable technology, varying according to region.

Insert Figure 3 about here

3.2.1. Learning effect

For many products and services, unit costs decrease with the accumulation of experience. This kind of technological progress is referred to as a learning curve [59,60]. The learning rate is now increasingly being applied in research models to evaluate the long-term effects of energy technology [10,12].

The equation for the single-factor learning curve is as follows [61,62] :

$$\mathrm{UC}_t = UC_o\left(\frac{CUM_t}{CUM_0}\right)^{\alpha}$$

where UC_t represents the cost per unit at time t, CUM_t means cumulative production or installed capacity, and α is the learning index (LI).

The so-called progress ratio (PR) and the learning rate (LR) are defined as follows:

$$\text{Progress Ratio(PR)} = \frac{UC_t}{UC_0} = \left(\frac{2CUM_0}{CUM_0}\right)^{\alpha} = 2^{\alpha},\ \text{Learning rate(LR)} = 1 - \text{PR}$$

where UC_t represents the unit cost, CUM_t means cumulative production or installed capacity, and α is the learning index (LI). Progress ratio (PR) and learning rate (LR) are variables commonly used to explain the learning effect instead of LI for a more intuitive understanding. Learning rate (LR) is defined as cost reduction per doubling of cumulative production.

The learning curve in the current policy scenario is shown in Figure 4. The technology with the highest learning rate from 2015 to 2035 is solar PV, followed by wind power. It is expected that the LCOE of the fuel cell technology will be reduced to 41% in 2035 compared to 2015, as it shows ongoing development in the stages of R&D and demonstration. However, additional market penetration during the period of analysis would be difficult due to the lack of price competitiveness when compared to other power-generating technologies. Thus, estimation of the learning rate is impossible. New coal, new gas CCGT, and nuclear power, unlike the renewable energy technologies, showed a learning rate close to 0% during the forecasting periods (Table 7). This means that it is unrealistic to expect a further price reduction in conventional power plant-based new technology at current levels of government investment in R&D.

Insert Figure 4 about here

Insert Table 7 about here

In the enhanced R&D scenario, the LCOE values for the technologies generally decrease compared to the current policy scenario. Increases in the learning rate of the renewable technologies and supply expansion data are presented in Figure 5. As in the current policy scenario, values determined by the LCOE foresight model are rapidly reduced, and the highest learning rate is observed for solar PV from 2015 to 2035 (Table 8). Greater support for the fuel cell energy option, which failed to enter into markets in the current policy scenario, is expected as of 2020 in the enhanced R&D scenario. In addition, the learning rate is expected to increase from 49% to 57%, which is second only to solar power. Wind power showed a considerable change in learning rate from 1.6% to 7.9% per year when compared to the current policy scenario. Interestingly, in 2035, the LCOE values of the renewable technologies in the current policy scenario can be ranked in the following order: fuel cell, solar PV, and wind power, but in the enhanced R&D scenario, the order is as follows: wind power, fuel cell, and solar PV. This indicates that the ranking of technologies may vary depending on the extent of government investment in R&D. Results were also different for conventional power plant-based new technology compared to the current policy scenario. In the case of new coal, in which a learning rate increase of 2.9 to 6.2% is evident between 2015 and 2025 in the current policy scenario, a lower increase in learning rate of 2.3 to 4.2% is observed in the enhanced R&D scenario. This can be explained in two ways. First, in response to the development of the new gas CCGT technology, the supply of new coal was relatively diminished. Second, the percentage of the renewable energy in the electricity market increased as renewable energy technology began to be disseminated throughout the market. The overall learning rate of the conventional power plant-based new technology was expected to maintain its very low level compared to the renewable energy, despite the fact that the learning rate of the new gas CCGT is very high. The learning rate of the nuclear power was expected to remain close to 0% regardless of the scenario. New coal and new gas

CCGT were associated with learning rates of less than 4.2% and 9.3%, respectively, during the analysis period.

Insert Figure 5 about here

Insert Table 8 about here

3.2.2. Technology dynamics

If technologies develop according to the extent of government support to enter into the market, the market share of each technology should reflect the interaction within the market. Assuming that the total amount of power produced by the new technologies included in this analysis is 100%, we defined this position as the percentage of total power output of each new technology. The results for the current policy scenario show a reduction in market share for new coal, an increase for nuclear power, and a U-shaped form for new gas CCGT (Figure 6). In terms of technology development, the growth of new coal included a phase from saturation to senescence, and for nuclear power, a phase from pervasive to saturation was observed. However, all renewable technologies together (solar PV, wind power, and fuel cell technology) occupied less than 3% of the market during the phase from innovation to niche market.

Insert Figure 6 about here

In the enhanced R&D scenario, changes in market share differed compared to the current policy scenario (Figure 7). In the case of new coal, as in the current policy scenario, it was expected to go through the stages from saturation to senescence. However, the market share for new coal would be reduced to 42% when analyzed in terms of total electricity production in 2035, and the reduction in market share proceeds more rapidly after 2030. Nuclear power progresses from pervasive to saturation in the current policy scenario, but in the enhanced R&D scenario, it shows signs of entering into the senescence beyond the saturation stage. Renewable technologies, which failed to expand their market shares in the current policy scenario, were expected to succeed in entering into the market in the following order after 2030: wind power, solar PV, and fuel cell technology. Expanding of the market share for renewable technologies represents the transition to the pervasive diffusion stage in 2035 beyond the niche market stage in 2030. The power generated by renewable technologies was expected to increase by 16% compared with total power.

Insert Figure 7 about here

The expected learning rate and technology dynamics as a result of increased government investment in R&D in the enhanced R&D scenario are presented in Table 9. When government investment in R&D increases, an increase in learning rate of more than 12% for renewable technologies was observed, which affected market penetration, expansion, and cost reduction. As for the market share, the model predicted that the current market share of 3% for all renewable technologies would expand to 16% by 2035, and that fuel cell technology will have progressed to the stage of the niche market, and that solar PV and wind technology will have progressed to the stage of pervasive diffusion. On the other hand, a lower learning rate of less than 3% is observed for conventional power plant-based new technology during the same period despite an increase in government investment in R&D (except for new gas CCGT). At this point, new coal and nuclear energy, currently at the saturation stage, would progress to the stage of senescence. New gas CCGT would progress from the senescence stage to the pervasive diffusion stage. These unusual results can be explained in two ways. First, an increase in new gas CCGT occurs to cope with volatility due to expansion of renewable energy. The intermittent problem of renewable energy causes a time discrepancy between energy demand and supply. For this reason, the reserve margin becomes higher when renewable energy is diffuse. Gas CCGT will diffuse once again with flexible backup facilities after 2030, when the diffuse of renewable energy will continue. Second, the amount of gas CCGT power generation will increase in order to offset the decline in base load power generation due to new coal and nuclear power reduction. Gas CCGT will be re-diffused as the most economical power source to replace existing base load power generation during the analysis period due to improved efficiency in power generation and operating rates.

Insert Table 9 about here

4. Conclusions and Policy Implications

Implications with regard to future government R&D investment decision-making from the comparison of the regression analysis and the LCOE foresight analysis are as follows.

First, in decision-making regarding investing in energy-generating technologies, governments should take into account the effects of long-term R&D investment in addition to short-term performance assessment. Energy-generating technologies require large-scale, long-term investment, and the return on that investment takes a long time to be realized. Some new technologies, such as fuel cell technology, require infrastructure changes as well as R&D investment for successful dissemination. In addition, energy-generating technologies have a long life span; for example, the lifespan of wind power is 20~25 years, that of solar PV is 30 years, that of fuel cell technology is 10~15 years, that of thermal power is 20~30 years, and that of nuclear power is 60 years. Changing the direction of investment midstream is difficult once government funds have been committed. Analyses of past investment performance cannot reflect these characteristics of energy-generating technologies. The results of the regression analysis in this paper demonstrate low performance for renewable energy technologies in terms of commercialization and return on investment in the short run; however, these technologies will undoubtedly replace existing energy-generating technologies in the long run as we can see through the LCOE analysis.

Second, by analyzing the learning effect of R&D investment by technology, the government can choose investment priority, investment timing, and investment duration. To begin with, based on the reduction ratio on investment in the LCOE analysis, the technology with the highest learning rate should be the investment priority. In general, for technologies at development stages between initial innovation and niche level, the learning rates are generally higher, while for technologies at the pervasive diffusion level or later, the learning rates are lower. However, there is a difference in the change in learning rate according to government R&D investment even among technologies at the same development stage such as fuel cell, solar power, and wind power. Thus, estimating the learning rate by technology based on R&D investment can be a standard for enhancing the efficiency of government R&D investment.

The learning rate also provides information on how long the R&D investment should last at a certain juncture. For example, considering the change in the learning rate of solar PV due to R&D investment, the cost savings will be significant in the short term as a result of early investment from 2015, and the continuing period of investment will be 15 years in the future. In addition, the LCOE foresight model identifies key drivers of changes in the learning rate, which have not been considered in previous research. Using this model, it is possible to identify the key factors influencing the learning rate and the influence level of each factor, which cannot be done using the methods employed in previous research on the learning curve.

Third, the improvement of the learning rate through R&D investment does not always guarantee successful technology diffusion. Concerning the degree of improvement in the learning rate, the technology development stage is significant, but even for technologies that are beyond the saturation stage, performance improvement continues. For example, technologies such as PV and fuel cell, in which the learning rate rises sharply according to R&D investment, will take longer than 15 years to replace existing mature technologies.

Governments should consider the learning rate at the initial technology development stage as well as continuous improvement during the maturing process in the mid to long term. Next, in the case of co-evolving technologies, diffusion proceeds independently from a potential government R&D investment. For instance, the learning rate of gas CCGT improves by an average of 5.3% in the government R&D investment scenario as compared to the base scenario in 2015–2035, but the market share tends to decrease. Concerning gas CCGT, which diffuses with other technologies such as PV and wind in the early stage, it may be desirable to induce diffusion through market mechanisms rather than government-led R&D investment. Finally, technologies in which the product and the complement form a single unit together cannot diffuse early on with only R&D investment in the power generation system. As for fuel cell, the diffusion of technology must be accompanied by reductions in the cost of power generation systems as well as the construction of complementary components such as hydrogen production facilities, supply chains, and storage facilities. In the case of such technologies, investment in the power generation system and infrastructure should be entailed together.

Government R&D investment is essentially an act of referring to the value of the future and investing in the present. However, many countries in which governments have engaged in R&D investment are determining their future investment directions based on the assessment of current R&D programs. The future value of energy-generating technologies can be estimated by analyzing the learning effect and technology dynamics. Although the foresight model, which analyzes performance, cost, and interaction effects in the development of future technologies, inherently entails greater uncertainty, it can be minimized using a systematic approach such as that suggested in this paper. To sum up, the LCOE foresight model should be utilized in future government R&D decision-making because it brings to light important information, including the technology development stage, market position, and learning rate, all of which are unaddressed in analyses of past performance.

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Table 1. Research on government-supported R&D program assessment

Topic	Research Question	References
R&D logic models	· How should we define R&D processes? · What are the characteristics of each R&D stage? · Which performance index best represents the purposes of R&D programs?	[63–65]
Analytical methodology	· Which methodology should be applied to evaluate the efficiency of government investment? · What is the most robust model for analyzing the macroscopic/microscopic ripple effects of R&D?	[64,66–72]
Empirical analysis	· What are the results of performance analyses of national R&D programs involving real data? What are the points for improvement?	[73–81]

Table 2. Stages of technological development and typical characteristics

Stage	Mechanism	Cost	Market share	Learning rate
Invention	Trial and error	High	0%	N/A
Innovation	R&D projects	High	0%	>50%
Niche market	Identification of special niche commercialization applications; learning by doing	High, but declining	0~5%	20~40%
Pervasive diffusion	Standardization and mass production; economies of scale	Rapidly declining	Rapidly rising (5~50%)	10~30%
Saturation	Exhaustion of improvement potentials and scale economies	Low	Maximum (up to 100%)	Near 0%
Senescence	Inability to compete because of exhausted improvement potentials	Low	Declining	Near 0%

Table 3. Technologies and definitions included in our analysis

Technology	Subcategory
Fuel cell	Molten carbonate fuel cell (MCFC), solid oxide fuel cell (SOFC)
Solar PV	Utility scale PV system w/o ESS
Wind	Onshore, offshore (MW-class) w/o ESS
New coal	Ultra-super critical power plant (USC, maximum temperature≥600℃) Hyper-super critical power plant (HSC, maximum temperature ≥700℃)
New gas CCGT	F-class gas turbine (1300℃ class) G-class gas turbine (1400℃ class) H-class gas turbine (1500℃ class)
Nuclear energy	Advanced power reactor plus (APR+)

Table 4. Definitions of variables included in the regression analysis

Variables	Definition
Government R&D investment	Subsidy of R&D activities by the government
R&D investment of beneficiary company	R&D investment by a beneficiary company
Consortia number	The number of companies participating in a given R&D project
Technology performance level	Relative level of technology compared to the highest performing company
Technology readiness level	Maturity of critical technology-related elements of a program during the acquisition process [82]
Additional investment after R&D	Investment from beneficiary companies after completion of R&D (customized R&D, investment in facilities, etc.)
Company sales	Sales of beneficiary company resulting from technology developed through R&D project

Table 5. Results of probit analysis

Variables	Renewable power (solar PV, wind, fuel cell)	Conventional power plant-based new technology (new coal, new gas CCGT, nuclear energy)
Government R&D investment	0.003 (0.006)	0.008* (0.005)
R&D budgeting in beneficiary companies	-0.014* (0.007)	-0.010 (0.009)
Number of consortia	0.058 (0.042)	0.027 (0.055)
Project period	0.148 (0.113)	0.016 (0.117)
Initial technology level	-0.000 (0.004)	0.012* (0.006)
Initial TRL	0.390*** (0.133)	0.395*** (0.146)
Additional investment after R&D	0.084*** (0.030)	0.924** (0.378)
Constant	-3.879*** (0.878)	-4.337*** (1.027)
Observations	207	177

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6. Results of the OLS analysis

Variables	Renewable power (solar PV, wind, fuel cell)	Conventional power plant-based new technology (new coal, new gas CCGT, nuclear energy)
ln(government R&D investment)	0.523 (0.543)	0.310* (0.158)
ln(R&D investment from beneficiary company)	-0.097 (0.330)	0.428** (0.158)
Number of consortia	0.105 (0.147)	-0.096 (0.117)
Project period	-0.330 (0.366)	0.330 (0.225)
Initial technology level	0.013 (0.012)	-0.008 (0.011)
Initial TRL	0.431 (0.433)	0.154 (0.255)
ln(additional investment after R&D)	0.056 (0.103)	0.274*** (0.073)
Constant	0.262 (3.986)	0.691 (1.961)
Observations	58	36
R^2	0.278	0.606

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7. Learning rate in the current policy scenario

Technology	Learning Rate				
	2013–2015	2015–2020	2020–2025	2025–2030	2030–2035
Fuel cell	-	-	-	-	-
Solar PV	4.3%	17.3%	76.6%	18.9%	0.3%
Wind power	40.2%	11.7%	18.5%	29.5%	4.7%
New coal	0.0%	6.2%	2.9%	0.0%	0.0%
New gas CCGT	0.0%	0.0%	0.0%	0.0%	0.0%
Nuclear energy	-	0.0%	0.0%	0.5%	0.3%

Table 8. Learning rate in enhanced R&D scenario

Technology	Learning Rate				
	2013–2015	2015–2020	2020–2025	2025–2030	2030–2035
Fuel cell	-	-	49.1%	57.1%	0.9%
Solar PV	9.7%	43.1%	77.6%	84.6%	2.2%
Wind power	7.7%	13.3%	22.8%	37.4%	2.2%
New coal	0.0%	4.2%	2.3%	0.0%	0.0%
New gas CCGT	1.9%	9.3%	4.3%	5.6%	1.8%
Nuclear energy	-	0.0%	0.0%	0.4%	0.2%

Table 9. Technology development according to R&D investment (2015→2035)

Technology	Learning Rate	Market Share	Technology development stage
Fuel cell	12.2%	0% → 2.2%	Innovation→Niche market
Solar PV	18.4%	0.6% → 5.7%	Innovation→Niche market→Pervasive diffusion
Wind power	16.2%	2.8% → 8.1%	Niche market→Pervasive diffusion
New coal	2.4%	66.6% → 42.7%	Saturation→ Senescence
New gas CCGT	9.9%	21% → 12.8%	Senescence→ Pervasive diffusion
Nuclear energy	0.1%	9.0% → 28.5%	Saturation→ Senescence

Figure 1. Research process

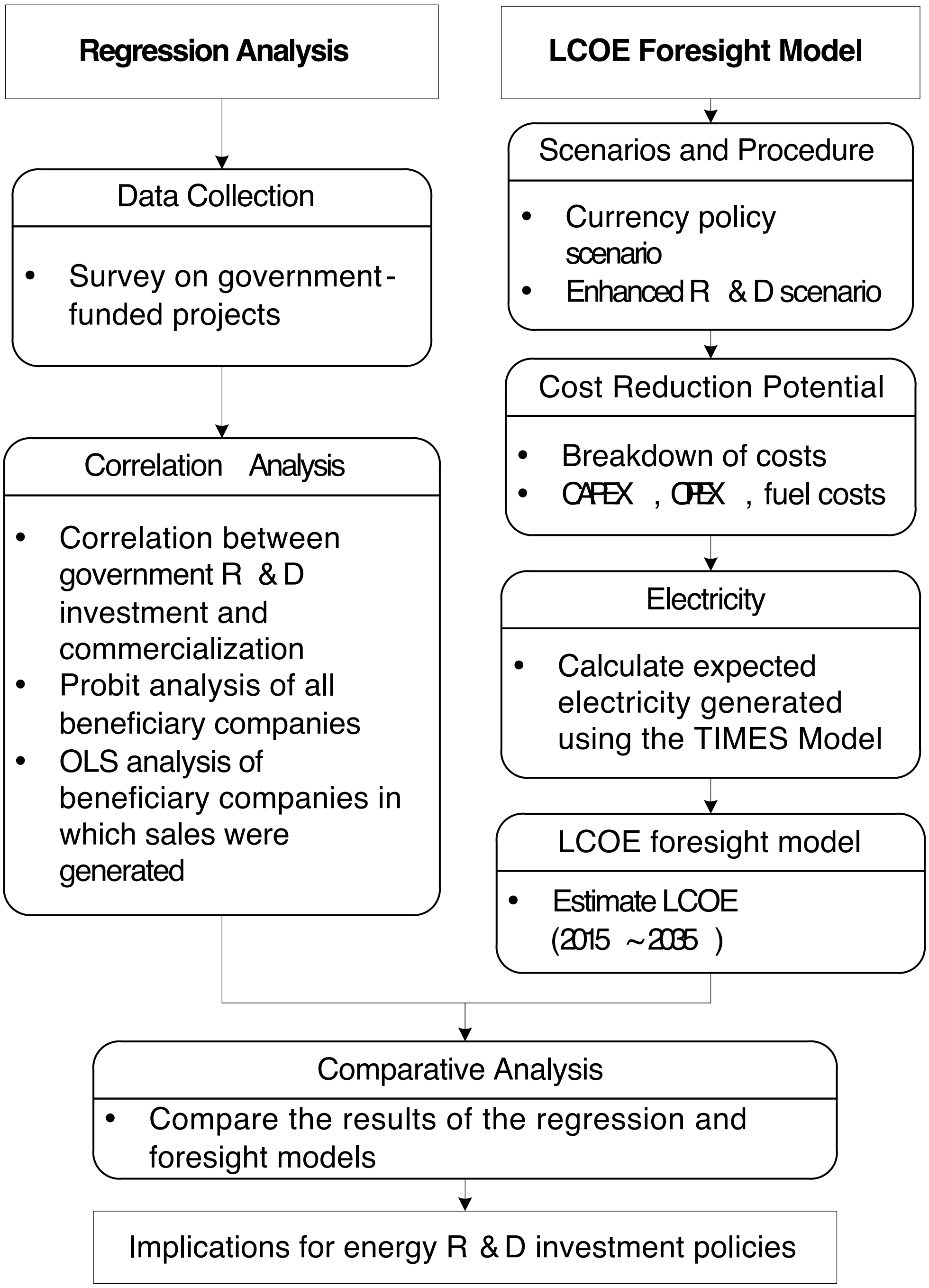
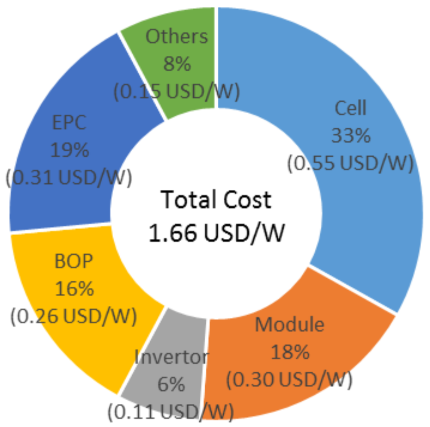


Figure 2. Cost reduction potential as derived from cost structure (solar PV)

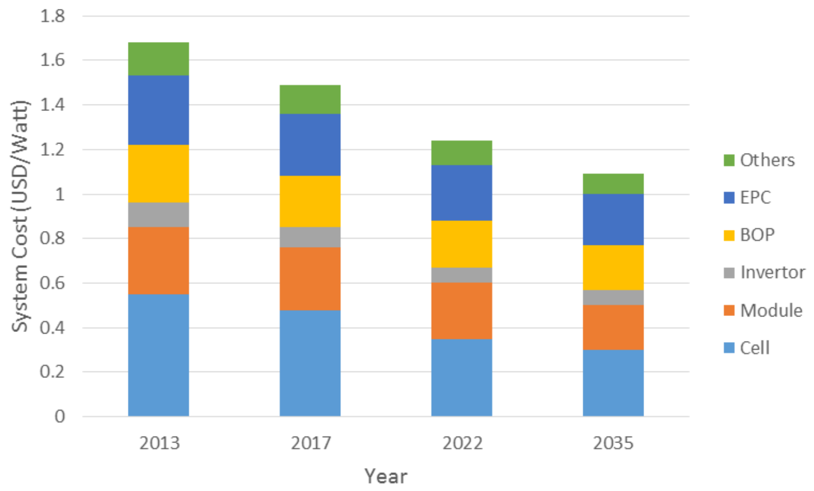
(1) Current cost structure of solar PV (utility scale)



(2) Key parameters for cost reduction

Parameter	Effect on costs
Wire saw	Kerf-loss reduction
Wafer	Increase in minority carrier lifetime (MCLT)
Passivation equipment	Diffuse suppressed by forming a protective film on the cell
PCS	Increase in conversion efficiency and durability
Metal paste	More efficient movement of electrons
Ribbon	Improved adhesion between cells
Black sheet	Protected from foreign substances

(3) Outlook for cost reduction (2013~2035)



1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
System Cost (USD/Watt)
2013
2017
2022
2035
Year
Others
EPC
BOP
Invertor
Module
Cell

Figure 3. LCOE of power-generating technology in 2015

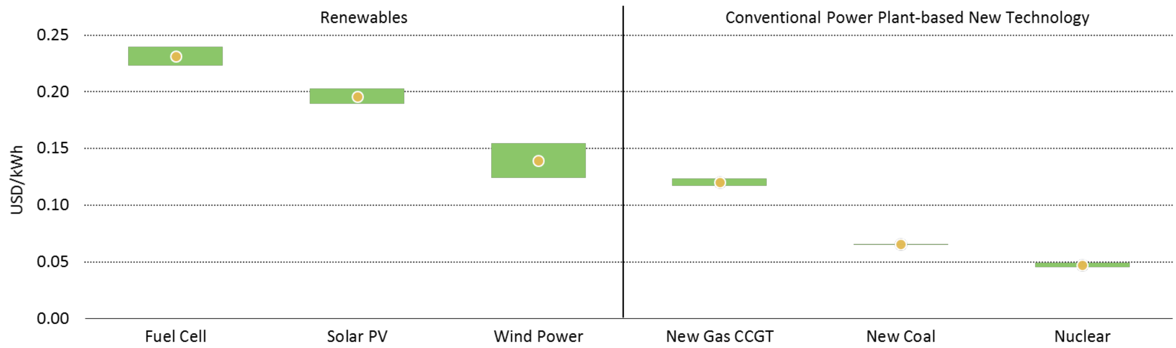


Figure 4. Learning curve in the current policy scenario

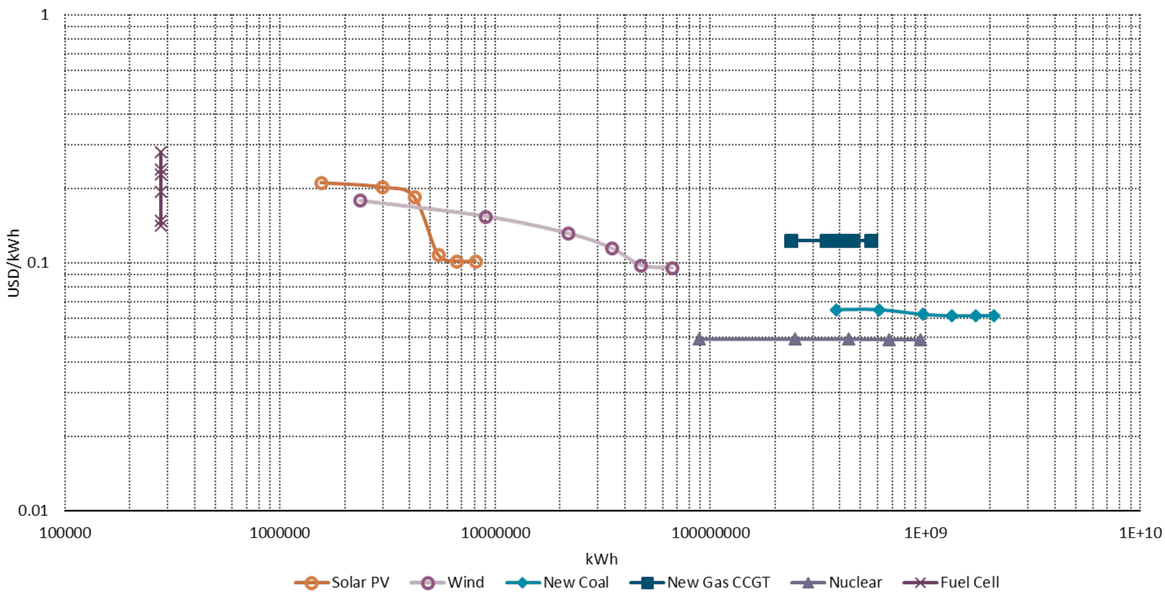


Figure 5. Learning curve in enhanced R&D scenario

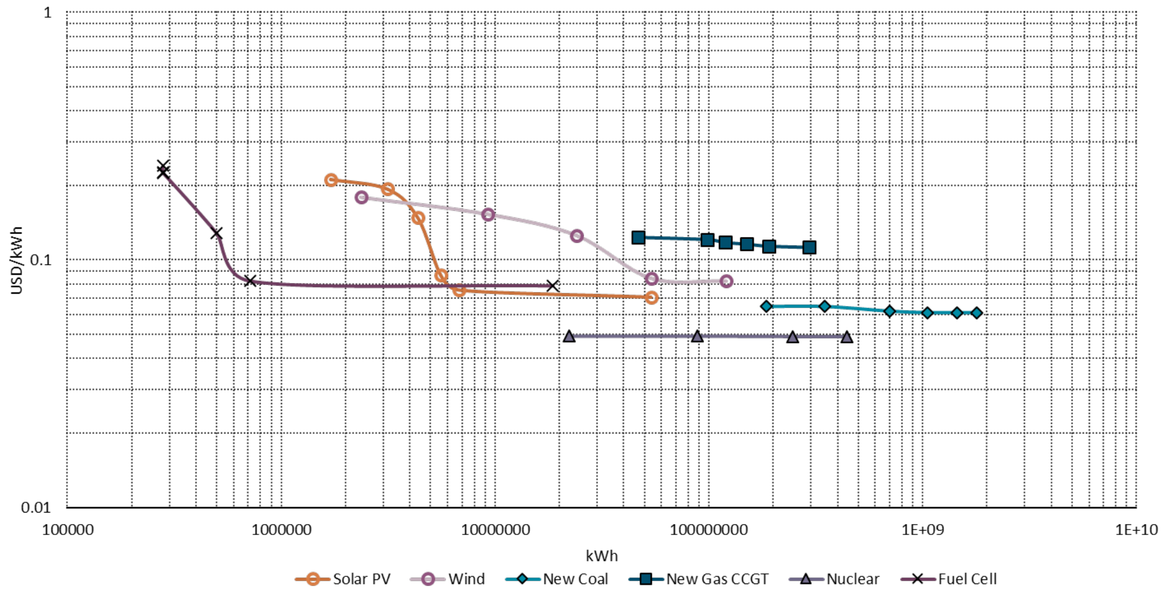


Figure 6. Market share of electricity-generating technologies in the current policy scenario

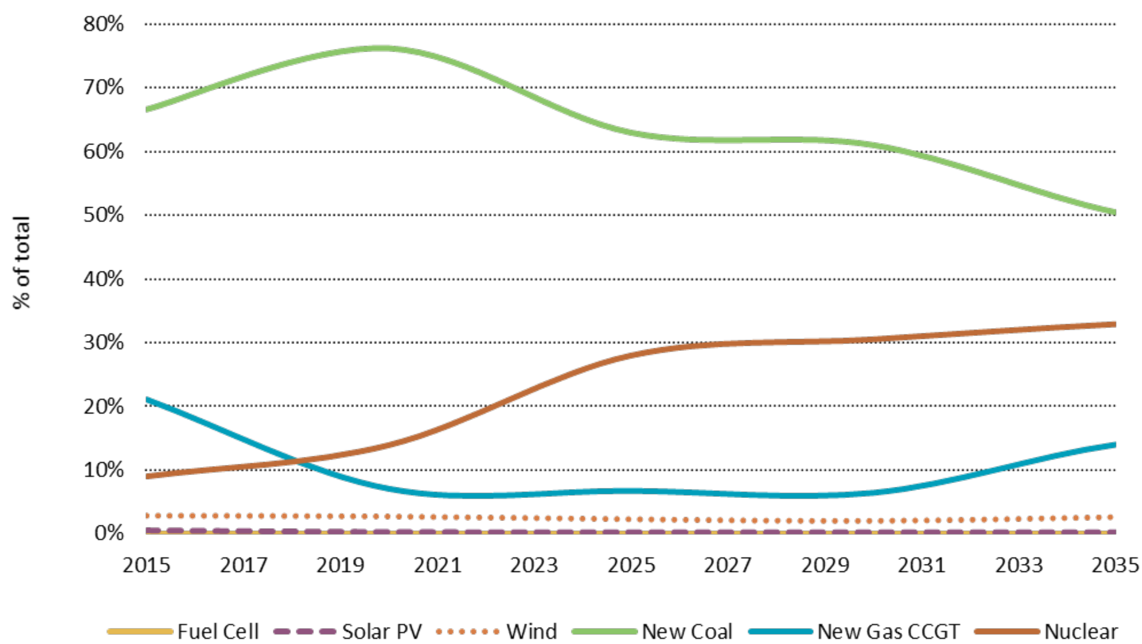


Figure 7. Market share of electricity-generating in the enhanced R&D scenario