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Methodology of Optimal Power Generation Mix Considering Volatility and Reliability Risk

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Optimal Power Generation Mix
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이 논문을 경제학박사학위 논문으로 제출함

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Abstract

Methodology of optimal power generation mix considering volatility and reliability risk

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Long-term power planning has been focused primarily on cost minimization, which was the same in other countries as in Korea. Since 2000, several studies applied Markowitz's portfolio theory to the portfolio of power generation sources. However, many of the earlier studies only concentrated on finding the efficient frontier of the portfolio, and there has not been a study on the trade-off ratio value between the cost and its volatility. Therefore, in earlier studies, the optimal portfolios from the efficiency frontier were found through scenario analysis, and not the real value of the policymaker's trade-off ratio.

The primary aim of this paper is to estimate reasonably the exchange ratio between costs and their volatility in the analysis of the optimal power mix using the

mean-variance model. This study started from the microeconomic foundation, which the policy makers used to establish the power plan to maximize their social welfare, estimate the marginal rate of substitution (MRS) between these elements using the time series of the power structure in Korea, and derive the optimal power portfolio from this. The secondary aim of this paper is to include in the analysis model the reliability risks that must be considered in the optimal power generation mix. Several studies describe power generation assets in the same way as securities traded in the capital market, but it is very important to maintain power supply reliability as well as minimize cost, and avoid volatility in real-world power plant investment. In this study, the reliability risk was defined as the loss of load probability, and the mean-variance portfolio model was expanded by including it as an element of the social welfare function of policy-makers in establishing a power plan.

The findings of the study are as follows: First, from the perspective of cost and volatility, the ratio of substitution between the two factors gradually changed from 1992 to 2014 to take more volatility risk. This was a major reason for the expansion of combined cycle gas turbine, which was eco-friendly and continuously improved in thermal efficiency since the 1990s, whereas diversifying power sources with nuclear power and coal after the oil shock in the 1970s.

Second, the actual power generation portfolio was gradually approaching the optimal portfolio during the analysis period, but the share of LNG combined cycle power generation has increased significantly compared to the optimum level since 2011 when a large-scale power outage occurred in Korea. This can be attributed to the fact that in the early 2010s, the approval for the construction of LNG combined cycle power plants increased significantly to cope with the electricity crisis because of a short construction time.

Third, when considering power reliability, the ratio of the optimal power generation portfolio was found to increase in proportion to peak-load generator, especially LNG, as compared to the volatility-risk-only model. This is because the combined power generation technology is composed of several gas turbines and a steam turbine, and the unit capacity per generator is small, which has a considerable diversification effect even in the event of generator failure.

Based on these results, it is expected that the proportion of LNG in the power generation portfolio will have to be increased in the future. This is because policy makers are gradually changing the viewpoint of allowing volatility risk in their utility, and LNG CC is superior to other power sources in terms of reliability. In particular, the expansion of renewable power sources, which will increase the risk of reliability, is expected to require more LNG facilities in the future.

Keywords: Portfolio Theory, Optimal Power Generation Mix, Volatility, Reliability, National Power Planning, Loss of Load Probability

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Chapter 1. Introduction

1.1 Research Background

Economic growth and electricity consumption affect each other bi-directionally (Yoo, 2005). In Korea, the primary goal of the electricity sector during the high growth period from 1970s to 1990s was to supply low-cost stable electricity to support the stable growth of other industries (Han, Yoo, & Kwak, 2004). Such an objective was not confined to Korea alone(Afful-Dadzie, Afful-Dadzie, Awudu, & Banuro, 2017). In the majority of developed countries, the main goal of electricity planning was cost minimization, but did not include cost volatility(Huang & Wu, 2008).

Electric power generation cost consists of fuel, capital, operation, and maintenance (O&M) costs. All these electricity cost generation components are exposed to volatility. Investment and O&M costs have varied continuously with uncertain technological changes, and fossil fuel prices have fluctuated wildly over time. Such cost volatilities have threatened energy security and hindered national economic development. Consequently, diversifying power sources to maintain national energy security has become an important decision-making criterion (Huang & Wu, 2008). Subsequent to the two oil crises in 1973 and 1979 which resulted in a significant increase in price volatility, South Korea gradually increased the portion of low-cost-volatility sources to avoid supply cost fluctuations, mostly coal and nuclear power generation, and the energy portfolio to strengthen energy security was diversified (Masih, Peters, & De Mello, 2011).

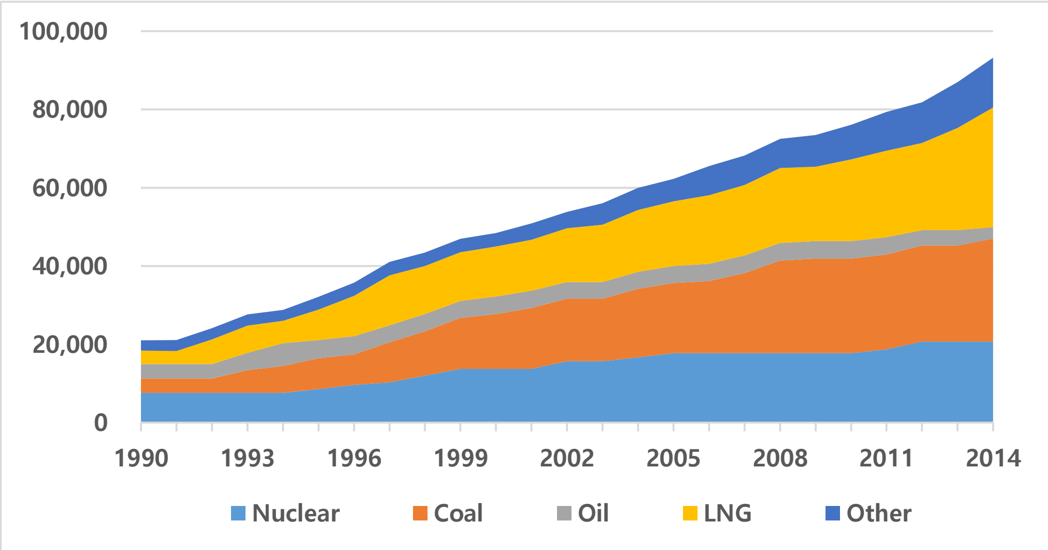


Figure 1. Power generation capacity expansion in South Korea, 1990-2014

The power generation expansion planning has entered a new phase from the perspective of minimizing the costs, as the problem of climate change caused by greenhouse gases has emerged. The reason is that the renewable energy source, an alternative power source to reduce greenhouse gas in the power field, has a much higher generation cost than traditional energy sources, so there is little room to be included in the power plan. However, renewable power sources do not require variable costs, and if they are included in the power portfolio, policymakers can alleviate cost volatility, which is one of the negative characteristics of existing fossil fuels. Awerbuch was the first researcher to pay attention to this area and to show that renewable power generation sources are well worth considering in the national energy portfolio by incorporating volatility as another decision criterion (Awerbuch, 1993, 1995).

Awerbuch (Awerbuch, 2000) applied Markowitz's theory (Markowitz, 1952) of mean-variance portfolios, commonly known as the theory of asset allocation in finance, into the field of electric power generation. Portfolio theory states that the proper combination of two assets whose prices move in opposite directions can lower risk (volatility of rate of return) while maintaining the mean of the rate of return. The more diverse types of assets in the portfolio are considered, the more effective is the reduction of volatility at the same rate of return. This means that we can achieve an asset portfolio that minimizes risk while maintaining the same rate of return or maximizes the rate of return at the same level of risk.

The pioneering work of Awerbuch (Awerbuch, 2000) by using portfolio theory played a significant role in addressing the need for volatility risk in the power sector. However, power assets are somewhat like securities in the financial market where portfolio theory is working well, but they are also quite different from other points of view. First, there are no risk-free assets in power generation assets. Because there are no variable costs in renewable power generation sources, renewable power generation sources look like a risk-free asset, but the total supply cost of renewable power generation also changes due to the time-varying construction cost. Construction investment costs fluctuate and the discount rate, which we call weighted average cost of capital (WACC) can alter fixed costs. Since it is difficult to derive the market portfolio in general, capital asset pricing model (CAPM) theory in the power generation field is necessary to find the trade-off ratio between cost and volatility from the decision maker's social welfare function when finding the optimal portfolio.

In addition, power generation facilities are real assets that have more restrictions than normal financial assets. In the case of power facilities, low cost and moderate volatility are important, but reliability is just as important. This is because, in the event of a power outage, it damages not only industrial facilities but also household consumers. If we do not consider the constraints of reliability and apply the portfolio theory of financial assets directly, we may not be able to obtain an optimum solution for the study.

1.2 Research Objectives

The research objective of this study is to develop a methodology to derive the optimal power generation portfolio in the environment closest to the power industry and compare the results with practical reality. As mentioned above, previous studies that applied portfolio theory to power generation mix would derive only a market portfolio through the use of risk-free assets, as if they were like the financial assets, without deriving an appropriate exchange rate between cost and volatility. However, risk-free assets do not exist in the electricity sector, and since a strict regulatory authority determines optimal power mix, the social planner’s preference for volatility risk becomes an important decision criterion.

The primary objective of this paper is to estimate the MRS reasonably between the mean of the cost and its volatility when analyzing the optimal power mix using the mean-variance model. This study assumes that the social welfare function of policy makers is to establish the long-term power expansion plan and derives the optimal power portfolio equation from the FOC of this social welfare maximization. The empirical MRS is estimated from this equation using the time series of the power generation capacity and cost data in Korea.

The secondary objective of this study is to add to the analysis model the reliability risks that should be important in the power industry when considering the optimal power generation configuration. To this end, this study defined the risk of reliability as the loss of load probability (LOLP), and extended the mean-variance portfolio model by including it as the third factor of the Social Welfare function of policy makers in establishing a power plan. The microeconomic foundation of the model is the same as that of the volatility-risk-only model, and it was calculated using Monte Carlo simulation to derive the LOLP function in Korea.

1.3 Research Outline

This dissertation consists of five chapters, as follows: Chapter 2 covers previous studies through a literature review related to its main topics: portfolio theory, capital asset pricing model, application to the power generation field, and econometric method of estimating MRS. Finally, Chapter 2 addresses the limitations of previous studies and the contribution of this dissertation. Chapter 3 illustrates the methodologies and two model types: the 1-risk model with the expectation of cost and its variance, and a 2-risk model that adds reliability risk to the 1-risk model. In the 2-risk model, this study regards the LOLP function as a reliability risk and proposes a calculation method through Monte Carlo simulation. Chapter 4 conducts the empirical studies of the proposed models through the Korean cost and capacity data from 1992 to 2014. At the end of chapter 4, the estimation results obtained from the two models are compared with the actual power generation portfolio, and the implications and policy implications are reviewed. Chapter 5 summarizes the implications and limitations of this study and suggests future research direction.

Chapter 2. Literature Review

This chapter outlines previous studies in relation to subject of this dissertation: portfolio theory, capital asset pricing model, application to the power generation field and econometric method to estimate MRS. Moreover limitations of previous studies and contribution of this dissertation are addressed

2.1 Portfolio Theory

Reasonable investors who invest in financial instruments should choose assets with high returns, regardless of future risk, unless the future is uncertain. In many cases, however, investors are faced with uncertainty in the future, so they prepare for a combination of financial assets. Portfolio theory is a methodology that starts with the premise that a reasonable investor maximizes the expected rate of return under uncertain circumstances in the future. This is because not only the future rate of return, but also the frequency of risk is important as an asset selection criterion for investors. In other words, diversifying investment in multiple assets rather than intensively investing in one asset can significantly reduce the risk of investment loss due to uncertain circumstances.

2.1.1 Markowitz's Concept

When an investor makes an investment in an asset, it is reasonable to choose a high-yield asset when there is no uncertainty, but if there is uncertainty, it is rational to try to reduce uncertainty through a combination of assets. Portfolio theory is one of the simpler models used in finance to analyze investor behavior to maximize expected returns under these uncertain situations or to minimize uncertainty under constant expected returns. This financial model, proposed by Markowitz, provided an important clue as to how to allocate and manage a portfolio of assets in both financial and real product transactions(Markowitz, 1952).

The return on the portfolio of the invested assets is the weighted average of the return on the individual assets by the holding ratio.

$$Expected\ \ Return\ of\ \ Porfolio = \sum_{i=1}^{n} w_i E(r_i) \qquad \text{Eq. (2.1)}$$

In this case, w_i represents the holding ratio of individual asset i in the portfolio and $E(r_i)$ is the expected value of the return. Based on this, the variance of the investment portfolio return is as follows.

$$Risk\ of\ Porfolio = \sigma_p^2 = \begin{bmatrix} w_1 & w_2 & \cdots & w_n \end{bmatrix} \begin{bmatrix} \sigma_{11}^2 & \sigma_{12}^2 & \cdots & \sigma_{1n}^2 \\ \sigma_{21}^2 & \sigma_{22}^2 & \cdots & \sigma_{2n}^2 \\ \vdots & \vdots & \cdots & \vdots \\ \sigma_{n1}^2 & \sigma_{n1}^2 & \cdots & \sigma_{nn}^2 \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix} \quad \text{Eq. (2.2)}$$

In this case, σ_{ij} is the covariance between the returns of individual assets *i* and *j*, and is sometimes expressed as a standard deviation to keep the same scale as the mean. When a specific portfolio share allocation vector $w = (w_1, w_2, w_3, \cdots w_n)$ is given based on these two equations (Eq. 2.1 and Eq. 2.2), the set of means and standard deviations obtained by solving the following optimization is referred to as an efficient portfolio set, that is, an 'efficiency frontier'.

$$\begin{aligned} &Min \quad w' \sum w \\ &\quad s.t. \qquad \sum_{i=1}^{n} w_i E(r_i) = E(\mathrm{c}_p) \\ &\qquad\qquad\quad \sum_{i=1}^{n} w_i = 1 \quad (0 \le w_i \le 1) \end{aligned} \quad \text{Eq. (2.3)}$$

In Eq. 2.3, you find the point that is the minimum cost while changing $E(\mathrm{c}_p)$, the expected cost value of the first constraint little by little, as shown in Figure 2 below. Each point corresponding to the boundary is the minimum return within the same risk or the minimum risk at the same return

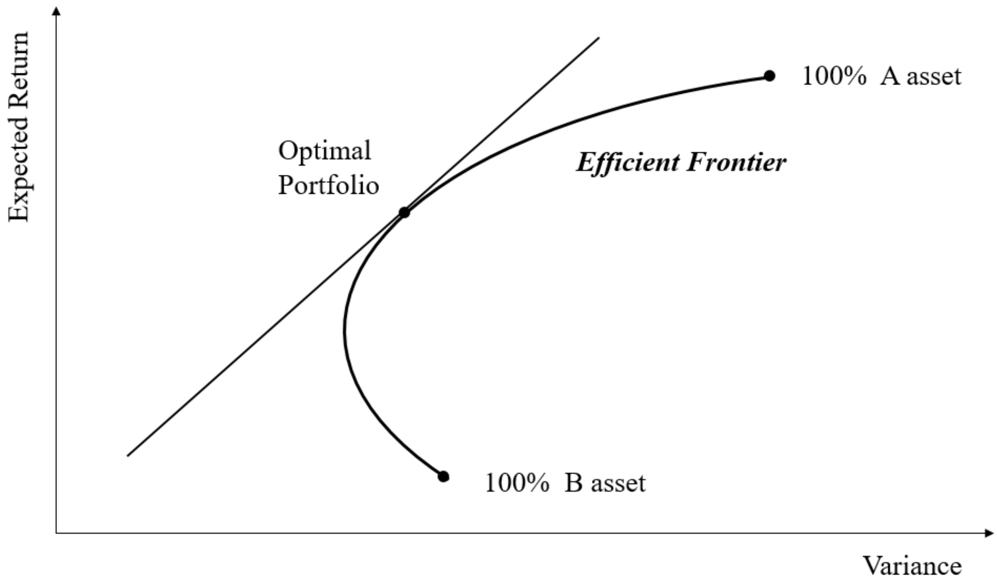


Figure 2. Efficient frontier of mean-variance asset portfolio

2.1.2 Capital Asset Pricing Model

The Capital Asset Pricing Model (CAPM) is a general model that derives the equilibrium rate of return of a risky asset on the equilibrium of the capital market. Based on Markovitz's portfolio theory, it was developed by Sharpe, Lintner and Black, including assumptions of risk-free assets(William F. Sharpe, 1964)(Lintner, 1965)(Fischer Black, 1972). In a broad sense, the concept includes the capital market line and the stock market line, but usually CAPM means the stock market line.

The CAPM describes how capital assets are priced under market equilibrium. Here capital assets mean securities such as stocks and bonds, which are assets that investors have the right to earn in the future, and the equilibrium of the market means that the demand and supply of all securities traded in the market are in agreement. In general, the demand and supply of securities are determined by the expected return and risk level of the securities. Therefore, when the appropriate expected return of the securities is determined according to the risk level of the securities, it can be said that the market is balanced. At that time, the price of each security is called the equilibrium price.

Markowitz's portfolio theory is a normative model that explains how investors should invest in a portfolio of risk securities only to maximize their utility. Whereas CAPM is a theory that explains the mechanism of pricing to determine whether the price of a capital asset is determined while the capital market is balanced when investors act according to Markowitz's theory. CAPM theory adds two elements to the assumptions established by Markowitz in his portfolio theory. CAPM's assumptions are as follow.

First, all investors choose securities according to Markowitz' mean-variance criteria. Reasonable investors prefer securities with the highest expected return among securities with the same risk and securities with the lowest risk among securities with the same expected return. Therefore, when investing in risky securities, investors choose the optimal portfolio on Markowitz's efficient frontier.

Second, All investors prefer homogeneous expectation of capital assets. All investors make the same predictions about the expected return and variance of securities before investing in them.

Third, there are risk-free assets, and investors can borrow or lend any amount of investment at a risk-free rate. Risk-free assets are those of reliably predicting future cash flows from an investment, and the expected rate of return from these assets are the risk-free capital rate.

Forth, the stock market is a perfect market. A perfect market is a market in which all investors become price-takers, and no single individual investor can affect the market price of securities due to a single transaction. In addition, there are no frictional factors such as transaction costs, taxes, and market restrictions that restrict free trading in the complete market and all investors can immediately obtain the information of interest at no cost and can make a split investment.

Fifth, the securities market is in an equilibrium condition. The price of each security is determined at a level where the demand and supply of all securities traded in the stock market match.

$$CML:\ E(R_p) = R_f + \frac{E(R_M) - R_f}{\sigma_M} \cdot \sigma_p \qquad \text{Eq. (2.4)}$$

Based on these premises, a Capital Market Line (CML) is derived, which is shown in Eq. (2.4). The Capital Market Line means an efficient investment line that minimizes the unsystematic risk, which means diversifiable risk in the market, when risk-free assets exist. It means that we can create a new portfolio by including risk-free assets in an efficient frontier derived from Markowitz's portfolio theory. This new portfolio set is called as the Capital Allocation Line (CAL), and the special CAL that satisfies the dominant principle is called as the Capital Market Line.

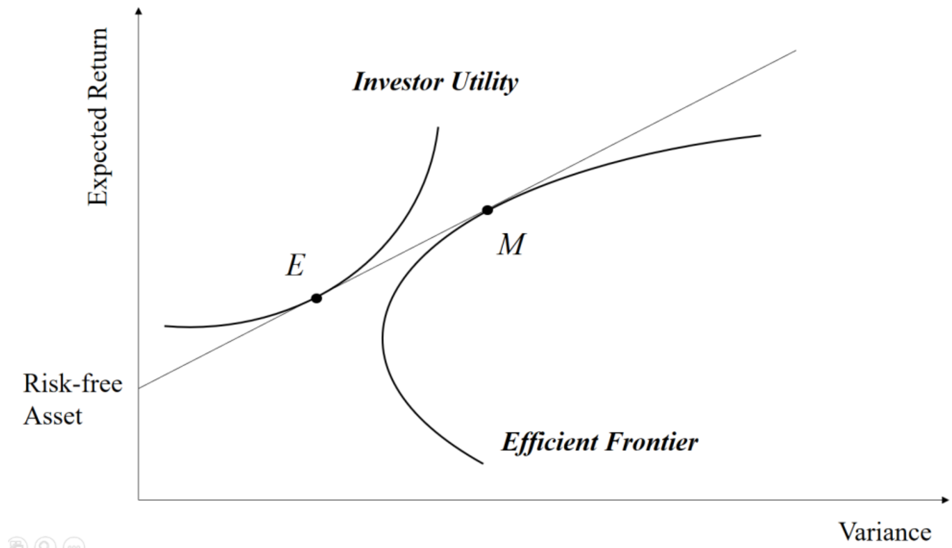


Figure 3. Selection of portfolio that achieved utility maximization in CAPM

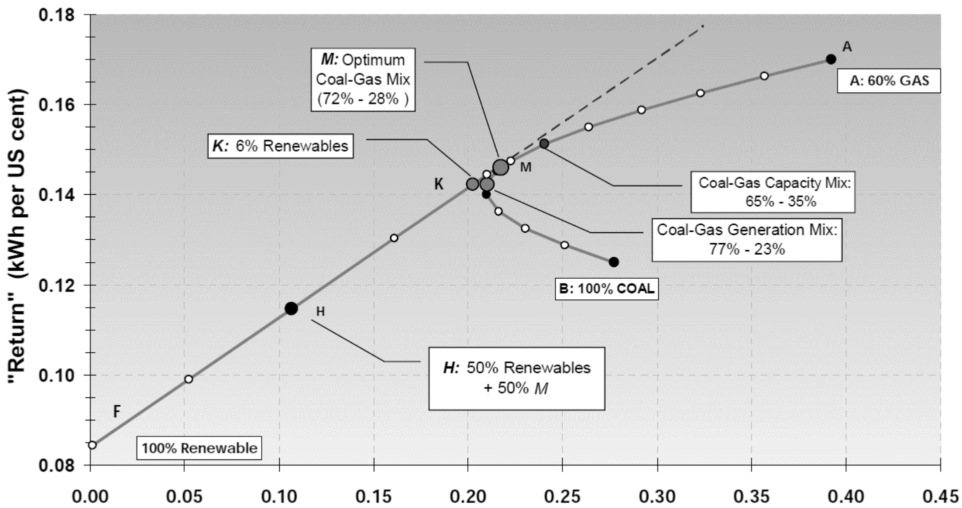
Finally, the most superior portfolio that hedged the market's unsystematic risk under the CAPM model is the tangent point between Capital Market Line and Markowitz's efficiency frontier. We call this point the market portfolio, which is the point of M in Figure 3. In the CAPM model, the optimal portfolio is determined by the point E in which the derived capital market line and the social welfare function of the investor, that is the exchange ratio between return and risk, are tangent.

2.2 Application to Power Generation Mix

The first study to introduce a portfolio theory perspective into the power industry is Bar-Lev & Katz(Dan Bar-Lev and Steven Katz, 1976). When electric power utilities experienced an oil shock and sudden fluctuations in oil prices, they applied portfolio theory to find the optimal point of procurement in the power industry sector. The power sources used in this study were oil, coal, and gas, and they evaluated how close the fossil fuel portfolios of utilities in each region of the United States are to the efficiency frontier. However, since the 1980s, as the global low-growth phase, the price of primary energy sources has been kept low for a long period, interest in volatility has decreased, and no further studies have been conducted.

2.2.1 Application to Global Case

However, as the global interest in climate change was concentrated in the late 1990s, the role and meaning of renewable energy in the portfolio composition in the energy conversion sector emerged, and portfolio theory was re-examined. Awerbuch suggested that the volatility of generation costs should be considered in the decision-making process of the national energy portfolio(Awerbuch, 1993). Awerbuch also suggested that renewable sources are worth considering in the national energy portfolio to resolve price volatility of power generation, even though its generation cost is relatively more expensive than other comparative technologies(Awerbuch, 1995). Awerbuch highlighted the importance of the generation portfolio with the perspective that the relative value of generation technology should be determined not by alternative resources, but by alternative resource portfolios, which encounter the value of supply cost risks(Awerbuch, 2006).



Source : S. Awerbuch, "Getting it Right: The Real Cost Impacts of a Renewables Portfolio Standard" ,Public Utilities Fortnightly, February 15, 2000

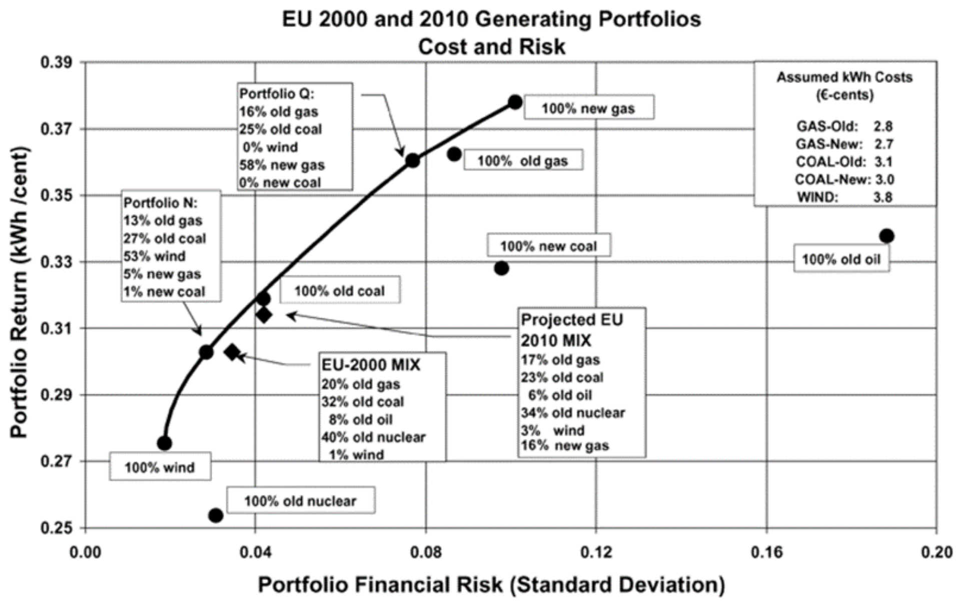
Figure 4. Application of portfolio theory to power generation sector

Awerbuch first applied the mean-variance portfolio theory (CAPM) that had been suggested by Markowitz (1952) in financial research, in the power-planning field (Awerbuch 2000). The superiority of the mean-variance model lies in considering both asset prices and risks together. The overall objective of the mean-variance portfolio theory is the maximization of the risk-weighted present value of profit, or minimization of the risk-weighted present value of the cost. In Markowitz's theory, a combination of multiple alternatives of investment can reduce the variance of return, while retaining its level.

Awerbuch (Awerbuch, 2000) adopted the mean-variance portfolio with the perspective of cost and its variance, and suggested that appropriately mixing gas and coal in electricity generation can reduce volatility while maintaining the fuel cost level, but the study did not consider capital and O&M costs, and considered only fuel costs. Here, Awerbuch used the reciprocal of the cost while applying the mean-variance portfolio theory to convert the cost into the profit maximization concept of the portfolio theory). In addition, Awerbuch suggested the possibility that adding renewables such as wind turbines and solar generation in the power generation mix may reduce the risk of the price, while maintaining the same cost level as before.

Awerbuch and Berger applied the correlation coefficient between portfolio components with volatility risks with all kinds of costs including fuel price, O&M

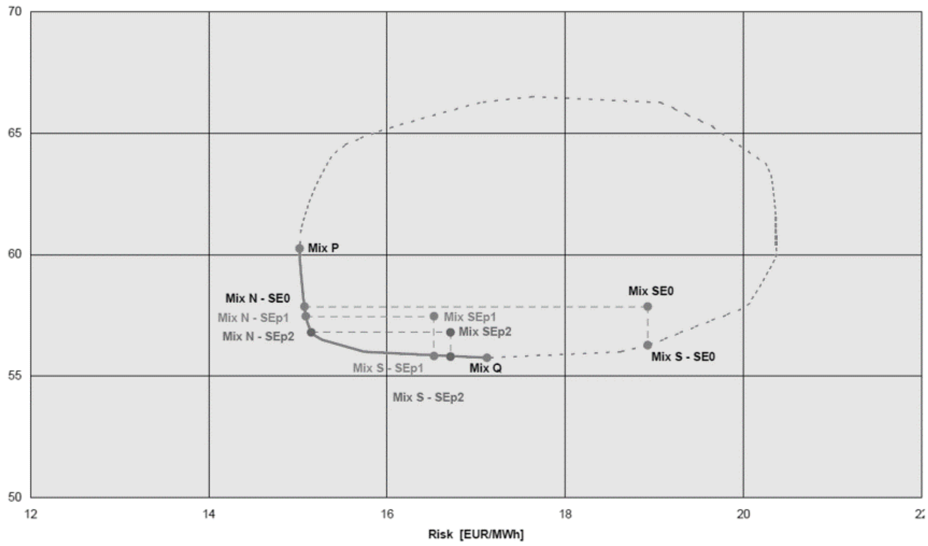
costs, and investment costs(Awerbuch & Berger, 2003). In addition, Awerbuch and Berger suggested a more realistic portfolio that was closer to the real world by utilizing actual EU data that added power sources such as nuclear and oil power generation. Awerbuch(Awerbuch, 2006) identified a comprehensive cost-risk change by regarding conventional power sources (nuclear, coal, gas, and oil) and renewable power sources (solar, hydro, and wind). These works concluded that the levelized cost of electricity (LCOE) of the optimal portfolio increased slightly, but the effect of reducing cost volatility was offsetting the increase in LCOE caused by renewable power sources.



Source : S. Awerbuch and M. Berger, *"Applying Portfolio Theory to EU Electricity Planning and Policy-Making*" IEA, 2003

Figure 5. Optimal power generation portfolio of EU power sector

Jansen, Beurskens, and Tilburg pointed out that cost and its variance in power generation are different from return and variance concepts in the financial asset portfolio, because both cost and its variance have undesirable properties(Jansen, Beurskens, & Van Tilburg, 2006). As a result, Jansen et al. estimated the optimal portfolio by using energy-based portfolios



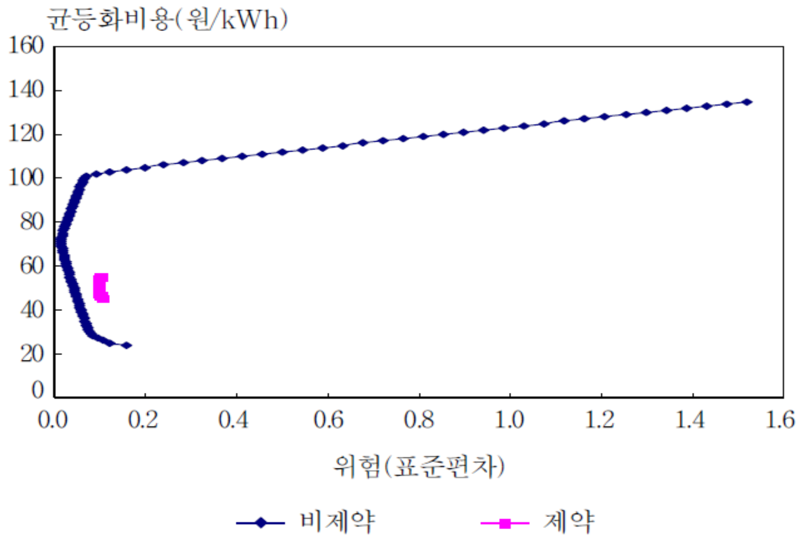
Source : Jansen et. al., " *Application of portfolio analysis to the Dutch generating mix Reference case and two renewables cases: year 2030-SE and GE scenario Acknowledgement*" Energy research centre of the Netherlands, 2006

Figure 6. Application of portfolio theory to power sector in the Netherlands

Delarue el. (2011) separate the concepts of the generation capacity (MW) and the generation (MWh) and apply the mean-variance portfolio theory considering the technical limitations of power generation to model it closer to reality(Delarue, De Jonghe, Belmans, & D'haeseleer, 2011). Fixed and variable terms among each cost factor were classified to derive a variance matrix. In addition, in order to reflect the output fluctuation of the wind turbine generator, the volatility was measured by subtracting the power of the wind turbine generator from the total power demand load. Based on this premise, they analyzed the effect of real-time wind power generation on the decision change in the optimal portfolio by comparing the results using a standard mean-variance model.

2.2.2 Application to Korean Case

As a Korean case study, Yun studied the asset portfolio of a power generation company in Korean by applying the Markowitz theory(Yun, 2009). From the company's point of view, he judged whether it would be economically feasible to invest in coal power generation and gas-combined power generation in the future.



Source : Yun, W. Ch. *"Selection of new power facilities using portfolio techniques (in Korean)"*. Korean Energy Economic Review, 2009

Figure 7. Efficient frontier of a generation company in Korea

First, based on the existing portfolio, Yun (2009) constructed an efficiency frontier using the mean and standard deviation of the cost of equalizing power generation. Then, by changing the exchange ratio between cost and risk from 1 : 9 to 9 : 1, the comparative advantage of coal and gas combination was selected when selecting a new power source, and sensitivity was analyzed when additional cost factors such as greenhouse gas were included. However, this is limited to a specific company's portfolio, and there is a limit not to analyzing the volatility of the overall cost, limiting the main causes of volatility to only fuel costs.

Lee (2012) applied the portfolio theory from the perspective of the whole country energy mix in the same way(Y. Lee, 2012). It is a new step forward from Yun (2009) in that it targets the entire country's power mix, not a specific company. However, there is the limitation that it use the transaction price of each power generation source from Korean Power Exchange instead of the levelized power generation cost to measure costs. The levelized generation cost directly considers the life-cycle cost of the generation, whereas the settlement price for each power source in the power exchange is calculated through observation of the spot market, which causes measurement error. This is because the exchange settlement price is based on the transaction amount, and thus includes not only the net cost but also the profit margin.

Jung & Min (2012) evaluated the national power expansion plan’s portfolio based on the uncertainty of electricity demand(Chung & Min, 2012). The characteristic of this study was to analyze the change in power generation cost caused by the volatility of demand by measuring the risk using the VaR technique rather than variance. The analysis method was optimized as a single objective function presented by Van Zon and Fuss (2005), unlike the general mean-variance model. As shown in Eq. (2.5), this study expressed the coefficient that converts risk to cost in lambda(Zon & Fuss, 2006). In the empirical analysis, this number was assumed 0.01 to derive optimal portfolio. Here, K represents *VaR* (Value at Risk), which means the worst 5% of the total generator probability distribution. The distribution was derived through Monte Carlo simulation with each component constituting power generation portfolio as a random vector.

$$Min \ \sum_{i}^{I} E(x_i) + \lambda \cdot K$$
$$s.t. \quad \sum_{i=1}^{n} y_{i,t} \geq D_t \ , \ z \geq \sum_{i}^{I} x_i - \eta \ , \qquad \text{Eq. (2.5)}$$
$$K = \eta + (1-\alpha)^{-1} \sum_{i}^{I} y_{i,t}$$

Ahn, Woo, and Lee (2014) incorporated renewable energy in the mean-variance portfolio theory of electricity planning in the light of carbon emission values(Ahn, Woo, & Lee, 2015). They assumed that total cost consists of investment cost, fuel cost, and O & M cost as shown in Eq. (2.6). The applicable cost is the leveled cost of generating electricity expressed by converting the total cost required for power generation during the standard operation period of each power generation into a present value. As shown in Eq. (2.7), in order to measure volatility risk, they classified the cost into three factors and derived the correlation coefficient of each cost element. Some of the correlation coefficients for each cost are from Korea, but some of the US research data were used as a limitation of data acquisition. From the empirical studies, they addressed that the least-cost power allocation is sub-optimal from the cost-risk perspective and hinders the adoption of renewables. Additionally, they implied that Korean electricity generation is far from the efficient frontier (optimal portfolio) in both cost and risk perspectives.

$$Total\ Cost = \sum_{t}^{N_t}\sum_{e}^{N_e}\frac{1}{(1+d)^t}\left\{\begin{matrix}\left(C_{e,t}\big/C_{e,0}\right)^{\alpha_{e,t}} \times X_{e,t} \times Invest\_c_e \\ + C_{e,t}\left(OM\_c_e + \tau_e \times Fuel\_c_{e,t}\right)\end{matrix}\right\} \qquad \text{Eq. (2.6)}$$

$d : discount\ rate$
$X_{e,t} : Installed\ capacity\ of\ energy\ source\ e\ in\ time\ t$
$C_{e,t} : Cummulative\ capacity\ of\ energy\ source\ e\ in\ time\ t$
$Invest\_c_e : unit\ cost\ of\ investment$
$Fuel\_c_{e,t} :\ fuel\ cost\ of\ energy\ source\ e\ in\ time\ t$
$OM\_c_e : O\&M\ cost\ of\ energy\ source\ e$
$\tau_e : Capacity\ factor$
$N_t : Number\ of\ time$
$N_e : Number\ of\ sources$
$\alpha_{e,t} : Learning\ effect\ of\ investment$

$$P\_Risk_t = \sigma_t = \sqrt{\sum_{i=1}^{N_i}\sum_{h=1}^{N_h} X_i \cdot X_h \cdot \rho_{ih} \cdot \sigma_i \cdot \sigma_h} \qquad \text{Eq. (2.7)}$$

$$\rho_{ih} = \frac{\sum_{k=1}^{N_k}\sum_{l=1}^{N_l}\rho_{kl,hi}\cdot\sigma_{i,k}\cdot\sigma_{h,l}}{\sigma_i \cdot \sigma_h} \quad for\ all\ k,l\ which\ mean\ factors\ of\ total\ cost$$

$$X_e = \frac{C_e}{\sum_{e}^{N_e} C_e}, \quad \sum_{e}^{N_e} X_{e,t} = 1, \quad 0 < X_{e,t} < 1$$

2.3 Estimation of the Trade-off Ratio

Huang and Wu (2007) used the trade-off relationship between generation costs and their volatility risks to develop Taiwan's optimal power generation portfolio. They assumed a fixed exchange rate that converts volatility risks to monetary values, and constructed an optimal portfolio that minimizes the risk-reflected cost function that was created by adding the value of this converted risk to the generation cost. Their analysis showed that renewables are included in the generation portfolio within 15% as they mitigate volatility risks despite their expensive generation costs. However, this study, too, failed to derive a statistical estimate of the exchange rate between cost and risk, only considering the change in the portfolio through scenario analysis to vary the value of the exchange rate from 0.001 to 0.0075.

Wolak and Kolstad(1991) empirically estimated the MRS between risk and cost in a homogeneous input demand under price uncertainty, which is not present in the electricity planning field(Wolak & Kolstad, 1991). They assumed that a firm with homogeneous input demand decides its optimal input supply allocation for maximizing its social welfare function considering the trade-off between the expected input cost and its volatility (risk of the cost). Wolak and Kolstad (1991) derived the first-order condition (FOC) of the social welfare function, and estimated the MRS, ϕ, between the risk and cost from historical data as shown in Eq. (2.8). The model estimated the MRS and risk premium of the inputs in the Japanese steam-coal import market.

$$\underset{q_t}{Max} \quad U\ [F - E(\mathbf{p_t} \cdot \mathbf{q_t} \mid I_t),\ \ Var(\mathbf{p_t} \cdot \mathbf{q_t} \mid I_t)]$$

$$s.t. \quad \mathbf{i}'\mathbf{q_t} = Q_t, \quad \mathbf{q_t} \geq 0$$

Eq. (2.8)

$$\mathrm{w}_t^{\ *} = \frac{\mathrm{q}_t^{\ *}}{Q_t} = \left[\frac{1 + \phi\ (\iota'\Sigma_t^{-1}\mu_t)}{\iota'\ \Sigma_t^{-1}\ \iota} (\Sigma_t^{-1}\ \iota) - \phi\ (\Sigma_t^{-1}\mu_t) \right]$$

2.4 Limitations of Previous Research and Research Motivation

The approach for electric power capacity planning mostly focused on optimization methods such as least-cost method. Moreover, until now, numerous research adopted CAPM on the electricity fields to derive just efficient frontier of power generation portfolio. However, no research suggested that the interrelation between components on CAPM in the generation mix portfolio.

The methodology adopted in this study considered both CAPM of power generation portfolio and the MRS of its components, namely supply costs and its variance, which is different from previous studies. Based on the above literature review, this study derived decision-makers' social welfare function of supply cost and its variance while decision-maker decided the national generation fuel portfolio. Then, this study derived MRS by first-order-condition and empirically estimated the MRS between the risk and cost based on the planner's social welfare function in a reasonable way before applying the CAPM of the optimal allocation. In order to estimate the empirical MRS, we assumed that: (1) a policymaker's social welfare is a function of two inputs, namely, expected total supply cost of generation and its variance, and (2) the realized generation mix vector was the result of social welfare maximization, even though there may be optimization errors. In this way, we obtained a statistically significant estimate of MRS.

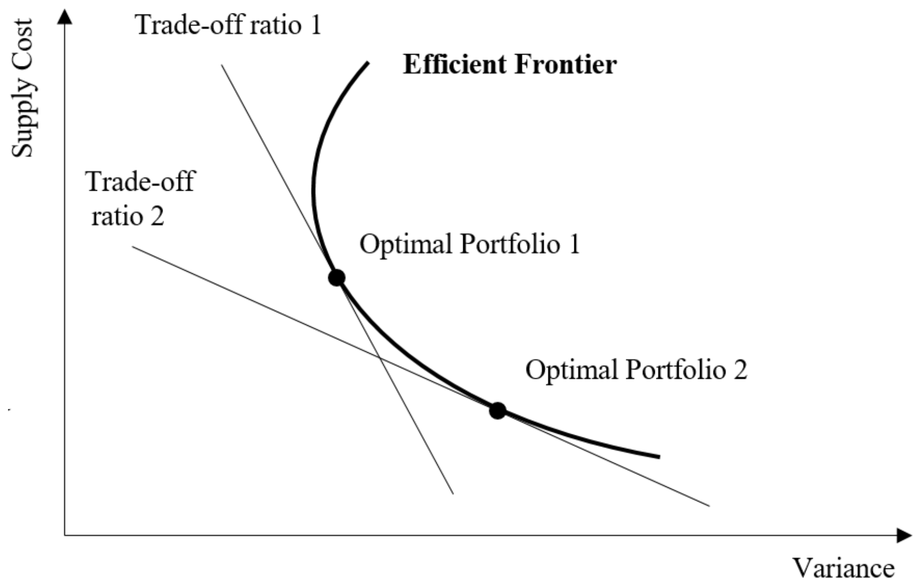


Figure 8. How the change of trade-off ratio can alter the optimal portfolio

This study used the historical data of the Korea electricity generation market to measure the MRS between the generation costs and cost variances, assuming that the MRS is time-invariant and only one decision-maker exists in electricity planning. In the Korean case, for a decade, the planner has conducted electricity supply planning in a consistent way, because the KEPCO (Korea Electric Power Corporation) is the only dominant player in the Korean electricity market that has been the national enterprise of electricity supply, and has consistently operated with a coherent plan.

After estimating the MRS from historical data, this study found the optimal portfolio on the efficient frontier by tangent line (the MRS) on efficient frontier and concluded that the Korean national generation portfolio has become closer to the optimal portfolio, which implies that the social welfare maximization scheme of Korean government has worked well.

Second, the contribution of this study is to take into account the risk of reliability of the power system in the traditional portfolio theory. The result of the optimal power generation portfolio using the mean-variance model was generally to suggest a much supply of renewables that is unacceptable in reality. The reason is that in the energy field, not only cost minimization and volatility minimization, but also supply stability, that is, reliability is an important value, because the reliability risk is overlooked. In particular, in the case of renewable power sources, unlike traditional thermal power sources, there is a disadvantage that the generation output cannot be controlled by itself.

Therefore, in order to apply the risk to the portfolio of the energy sector, it is necessary to construct a portfolio that consider two risk factors, not only price volatility, but also supply and demand risk, that is, reliability risk. This study will show how the optimal share of power supply composition is changed by considering another risk of reliability risk in addition to the average-variance model based on Awerbuch and Berger (2003).

Chapter 3. Methodology

This chapter proposes the microeconomic foundation of the MRS between cost and its volatility and econometric method to estate it. In the first section, the methodology of volatility risk only model, which is applied to traditional mean-variance portfolio model. In the second section, Chapter 3.2 shows the methodology that we should add reliability risk to make up for the 1-risk model. At the front of each chapter, the microeconomic foundation is presented and next, the econometric method for estimation was represented. In addition, Chapter 3.2.1 section describes a methodological framework for computing LOLP.

3.1 Volatility Risk Only Model (1-risk model)

This section proposes the methodological framework of the derivation of MRS of variance to supply cost. In the first section, the microeconomic foundation that can borrow the rationale from the consumer's choice behavior under constraint is presented. Next, the process to derive the optimal share equation and a way to estimate it efficiently is described.

3.1.1 Microeconomic Foundation

Consider a government that systematically designs power allocation. A policymaking authority has a social welfare function of two components, the mean and variance of the cost. The authority wants to configure a generation portfolio that maximizes its social welfare under given budget constraints Eq. (3.3). At this time, the authority considers the average unit cost and the variance of the cost, including investment costs, O&M costs, and fuel costs of each power source as a whole. If the authority has a risk-averse tendency, it will want to reduce the portion of the generation sources that have significant volatility, and diversify to the other sources by easing its variance in order to increase its social welfare.

We begin by defining the notations. Let the number of power sources be n. We use the following notations through the dissertation:

Cost_t : Annual sum of investment, O&M, and fuel cost in period t (per kW)

$\mathbf{c}_t$: n-dimensional vector of unit capacity investment cost in period t, which is annualized through discount rate (per kW)

$\mathbf{o}_t$: n-dimensional vector of unit O&M cost in period t (per kW)

$\mathbf{f}_t$: n-dimensional vector of fuel price in period t (per kWh)

$\mathbf{s}_t$: n-dimensional vector of unit gross supply price in period t

$\mathbf{q}_t$: n-dimensional vector of facility capacity in period t

Q_t : Total sum of facility capacity in period t (scalar)

I_t : Information set available in period t, set of price information until period t-1

$\boldsymbol{\mu}_n$: Conditional expectation of s_t in period t conditioned on I_t, i.e. $E(S_t \mid I_t)$

Σ_t : Conditional variance of s_t in period t conditioned on I_t,

i.e. $E\left((\mathbf{S}_t - \boldsymbol{\mu}_t)(\mathbf{S}_t - \boldsymbol{\mu}_t)' \mid \mathbf{I}_t\right)$

All the cost components (i.e., investment cost, O&M cost, and fuel cost) are random variables. In many previous studies, investment and O&M costs have been regarded as non-stochastic terms. However, it is more rational to consider all the three cost components as stochastic variables because the investment and O&M costs have also historically fluctuated due to technology development. Here, capacity $\mathbf{q}_t$ is considered a non-stochastic vector. Expectation and variance of costs are shown in Eq. (3.1) and Eq. (3.2)

$$E(Cost_t) = E[(\mathrm{c}_t + \mathrm{o}_t + \mathrm{f}_t)' \cdot \mathrm{q}_t \mid I_t] = E[\mathrm{s}_t' \cdot \mathrm{q}_t \mid I_t] = \mu_t' \cdot \mathrm{q}_t \qquad \text{Eq. (3.1)}$$

$$Var(Cost_t \mid I_t) = \Sigma_t \qquad \text{Eq. (3.2)}$$

The authority's social welfare is a function of expected cost and its variance (Eq. 3.3). The authority decides the optimal power mix by solving the maximization problem of its social welfare under capacity constraint $Q_t = \iota' \times q_t$ to meet the electricity demand in period t. The difference between this optimization problem and the conventional firm's profit maximization problem is that the authority does not directly decide Q_t which maximizes its profit under the production function constraints. This is because the main purpose of the government is not to maximize profits, but to satisfy national demands; hence, Q_t is given. The policy maker's social welfare maximization condition is shown in Eq. (3.4), and the Lagrangian of social welfare maximization is shown in Eq. (3.5).

$$U = U\ [E(Cost_t \mid I_t),\ \ Var(Cost_t \mid I_t)] \qquad \text{Eq. (3.3)}$$

$$\begin{aligned} \underset{q_t}{Max} \quad & U\ [E(Cost_t \mid I_t),\ \ Var(Cost_t \mid I_t)] \\ s.t. \quad & i' q_t = Q_t, \quad q_t \geq 0 \end{aligned} \qquad \text{Eq. (3.4)}$$

$$L = U(\ \mu_t{}' \cdot q_t\ ,\ \ q_t{}' \cdot \Sigma_t \cdot q_t\ )\ \ +\ \ \lambda(Q_t - \iota' \cdot q_t) \qquad \text{Eq. (3.5)}$$

The FOC of this social welfare maximization is shown in Eq. (3.7). Multiplying with $\Sigma_t^{-1} \cdot \iota$ on both sides of Eq. (3.3), solving for the scalar λ, substituting it to Eq. (3.3), and then solving it to q derives Eq. (3.7).

$$\frac{\partial L}{\partial \mathrm{q}_t} = U_1 \cdot \mu_t{}' + 2U_1 \cdot \mathrm{q}_t{}' \cdot \Sigma_t - \lambda \cdot \iota' = 0 \qquad \text{Eq. (3.6)}$$

$$\mathrm{q}_t{}^* = \frac{Q_t \cdot \Sigma_t^{-1} \iota}{\iota' \Sigma_t^{-1} \iota} + \frac{1}{2}\left(-\frac{U_1}{U_2}\right)\left(\Sigma_t^{-1} - \frac{\Sigma_t^{-1} \iota \iota' \Sigma_t^{-1}}{\iota' \Sigma_t^{-1} \iota}\right)\mu_t \qquad \text{Eq. (3.7)}$$

From the planner's perspective, the main interest is the share of each facility, not the capacity level of each facility. Therefore, we are also interested in the share of the generation portfolio. Dividing Eq. (3.7) by Q_t, and substituting $\gamma_t = -U_1/U_2$, the optimal portfolio share equation can be derived as Eq. (3.8).

$$\mathrm{w}_t{}^* = \frac{\mathrm{q}_t{}^*}{Q_t} = \frac{\Sigma_t^{-1} \iota}{\iota' \Sigma_t^{-1} \iota} + \frac{1}{2} \cdot \frac{\gamma_t}{Q_t}\left(\Sigma_t^{-1} - \frac{\Sigma_t^{-1} \iota \iota' \Sigma_t^{-1}}{\iota' \Sigma_t^{-1} \iota}\right)\mu_t \qquad \text{Eq. (3.8)}$$

Here, γ_t refers to the MRS of the expected cost for its variance at time t. There are some specifications for γ_t in order to simplify the notation. One is that γ_t is time-invariant (i.e., $\gamma_t = \gamma$), and another is that γ_t / Q_t is time-invariant, which means the MRS is constant regardless of whether the total capacity Q_t changes. The second specification for γ_t is very useful because the optimal share of the generation portfolios remains constant, independent of the magnitude of Q_t. In reality, the main interest of the authority is the portfolio ratio of each power source, rather than the capacity of each source. Therefore, we assumed that the MRS γ_t of the expected cost for variance is time-variant, but independent of the total capacity Q_t. The marginal substitute rate γ equals to γ_t / Q_t, and the final portfolio ratio equation with possible error term is shown in Eq. (3.9).

$$\begin{aligned} \mathrm{w}_t &= \mathrm{w}_t^* + \varepsilon_t = f(\Sigma_t, \mu_t ; \gamma) + \varepsilon_t \\ &= \mathrm{x}_{0t} + \gamma \cdot \mathrm{x}_{1t} + \varepsilon_t \end{aligned} \qquad \text{Eq. (3.9)}$$

$$\textit{where} \quad \mathrm{x}_{0t} = \frac{\Sigma_t^{-1} \iota}{\iota' \Sigma_t^{-1} \iota}, \quad \mathrm{x}_{1t} = \frac{1}{2} \left(\Sigma_t^{-1} - \frac{\Sigma_t^{-1} \iota \iota' \Sigma_t^{-1}}{\iota' \Sigma_t^{-1} \iota} \right) \mu_t$$

Eq. (3.9) shows that γ is econometrically estimable by using the historical cost (calculate $\boldsymbol{\mu}_t$ and $\boldsymbol{\Sigma}_t$) and $\mathbf{q}_t$. Eq. (3.9) is a simultaneous equation in which error terms are correlated, because the increment of one share causes a decrease in other shares. Therefore, we estimate Eq. (3.9) with a non-linear seemingly unrelated regression. Each μ_t and Σ_t is the mean and variance of $\mathbf{s}_t$, and estimation method will be explained in the next section.

3.1.2 Econometric Method

Supply costs of power generation data to be used in this study are time series data, not cross section data. In the case of time series, the value between adjacent times cannot be said to be completely independent of each other, because the present is dependent on the past. Particularly, in the case of fuel cost date, they feature to fluctuate up and down with a random trend. This characteristic is called a random walk process, and when the time series having this characteristic is analyzed with a general regression model, the result becomes unreliable.

In the case of this random walk time series, they should be altered into a stable form through the first-order difference. Since the mean value applied in the general portfolio theory is already a return, it is stable time series data. However, since the cost of power generation does not have the stability of time series, the concept of Holding Period Return should be utilized. In the normal case, HPR should be subtracted from the current period from the previous period and then divided by the previous period. However, statistically, the natural logarithm of the current period and the previous period is subtracted, which approximates the HPR. Therefore, this study chooses the latter method for the convenience of analysis as shown in Eq.

(3.10).

$$HPR = \frac{Price_t - Price_{t-t}}{Price_{t-t}} \approx \ln(Price_t) - \ln(Price_{t-1}) \qquad \text{Eq. (3.10)}$$

This study derives a variance-covariance matrix of power generation costs using a VAR model through the HPR data. In general, the time series cost data converted to HPR does not have a dependent relationship between adjacent periods, but may have a systematic relationship with other power generation sources. In particular, coal and gas, and gas and oil have a substitution relationship with each other, so there is a possibility of showing a systematic relationship. In this respect, it is reasonable to replace the time series with a vector to create a system of equations in the form of simultaneous equations and to create a variance matrix from the error terms. It means that we should use Vector Autoregressive Model.

The VAR is a model that extends the univariate autoregressive model to the multivariate autoregressive model, and is frequently used in relation to prediction and analysis of effects of changes in endogenous variables. The structural equation model based on the traditional regression uses the causal relationship between variables to define the dependent variable Y as several explanatory variables X_1, X_2, … X_n. However, the traditional regression model has an assumption that the influence of the explanatory variable is always constant even when the time t is changed. Therefore, there is a weakness that the structural change is rapid and the influence of the explanatory variable cannot be properly reflected. In addition, the structure model has a disadvantage in that it builds a model based on economic theory, so that variable selection and selection of internal exogenous variables in the model are determined by the model designer's subjectivity.

Therefore, the method to overcome these rigidity and subjectivity can be said to be the ARIMA model of Box and Jenkins(George E. P. Box, 1976). The ARIMA model attempted to predict the future, assuming that the current observation Z_t is reproduced by some regularity in the past, and that this regularity is maintained in the future. However, it ignores the interactions between variables although this model is easy to set up, and faces the limit of univariate analysis. A model that complements the limitations of this univariate regression is the VAR model of Sims (Sims, 1980).

$$\Delta \log \mathbf{s_t} = \boldsymbol{\rho} + \boldsymbol{\delta}_1' \cdot \Delta \log \mathbf{s_{t-1}} + \boldsymbol{\delta}_2' \cdot \Delta \log \mathbf{s_{t-2}} + D_{crisis} + \boldsymbol{\nu}_\mathbf{t} \qquad \text{Eq. (3.11)}$$

$$\nu_t \sim iid$$

This study used a VAR model with natural logarithms to estimate $\boldsymbol{\Sigma}_t$, the variance of cost as shown in Eq. (3.11). In the model, the cost variables of each power generation are explained as the first and second lagged past variables, and in addition to these endogenous relationships, they are influenced by exogenous variable D_{crisis}, which means the economic crisis. This is because, during the global financial crisis in 2008, the international prices of coal and oil are largely fluctuating, which can distort the estimation of variance. As in equation 11, the economic crisis was treated as a dummy variable.

As mentioned at the end of section 3.2.1, the optimal share equation from the FOC of the social welfare maximization is estimated with the Seemingly Unrelated Regression (SUR) model, which was first proposed by Zeller (Zellner, 1962). This model is used when all the error terms of system equations seems in correlation with each other. Apparently, there is no difference from the ordinary linear regression model and it looks like no correlation of each dependent variable, so it was named the SUR model.

In general, when multiple equations need to be estimated at the same time, the SUR model is widely utilized in order that it guarantees more efficient results than estimating each equation independently like OLS. The structure of the SUR model can be said to be a system equation in which the general regression model is given by Eq. (3.12).

$$\mathbf{y} = \mathbf{X} \cdot \boldsymbol{\beta} + \boldsymbol{\varepsilon} = \begin{pmatrix} X_1 & 0 & \cdots & 0 \\ 0 & X_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & X_m \end{pmatrix} \cdot \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_1 \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_m \end{pmatrix}$$

$$\boldsymbol{\varepsilon} \sim N(\mathbf{0}, \boldsymbol{\Omega} \otimes \mathbf{I}) \qquad \text{Eq. (3.12)}$$

At this time, estimating the regression coefficients of each equation by the OLS (ordinary least square) method, it is assumed that each error term is not correlated with each other. However, if the error term ε_k is correlated with other error terms in the system equation, it violates the prerequisite of the regression model that the error terms are mutually independent. Therefore, in this case, the coefficients of the equations should be estimated through the alternative estimation process.

The SUR model estimates the regression coefficient of the same independent variable included in the *m* regression equations using the GLS (general least squares) method. If the correlation coefficient between error terms is zero, the result estimated using the SUR model is the same as the result obtained by estimating each regression model individually.

The share equations derived in section 3.1.1 of this study has exactly these properties. The optimal share of each power source is explained by the mean and the variance of their cost. However, if a certain power generation share increases, then the proportions of other power sources become smaller, which means that all the kinds of power source' shares interfere with each other. This means that the error terms of the share equations of each power source are linked to each other. In addition, the regression coefficients of each equation are also the same as γ , and this situation is the same as the conditions assumed by the SUR model. As shown in Eq. (3.9), the optimal shares are composed of nonlinear functions of $\boldsymbol{\mu}_t$ and $\boldsymbol{\Sigma}_t$, so a nonlinear sur model is used.

3.2 Reliability Risk Added Model (2-risk model)

3.2.1 Measure of Reliability risk

The power system's reserve power is closely related to its reliability. In order to maintain a stable power supply in the operation of the power system, which means that power system reliability is good, supply capacity exceeding the maximum demand, that is, reserve power is required. It is because that a period of preventive maintenance on a regular basis to keep the generators operating is need and the supply capacity decreases due to the failure of the generators. In addition, electricity demand may increase more than expected. Therefore, the more reserve power, the higher the supply reliability.

The indexes used for the determination of reserve power in the long-term power planning are largely deterministic reliability index and probabilistic reliability index.

A representative deterministic reliability index is a reserve ratio that expresses the relative size of the total equipment capacity and the expected maximum load as a ratio. Probabilistic reliability indices include Loss of Load Probability, Loss of Energy Probability, and Frequency and Duration(Prada, 1999).

In this study, LOLP was used as a stochastic index to analyze. The reason is that the ratio of the optimal power portfolio to be drawn in this study is based on the power plant capacity, not the amount of energy for each power source. LOLP is the result of calculating the probability of supply disruption from the load perspective, while LOEP is the result of calculating the probability of supply disruption from the energy perspective. The method of mathematically modeling the LOLP followed Prada (Prada, 1999).

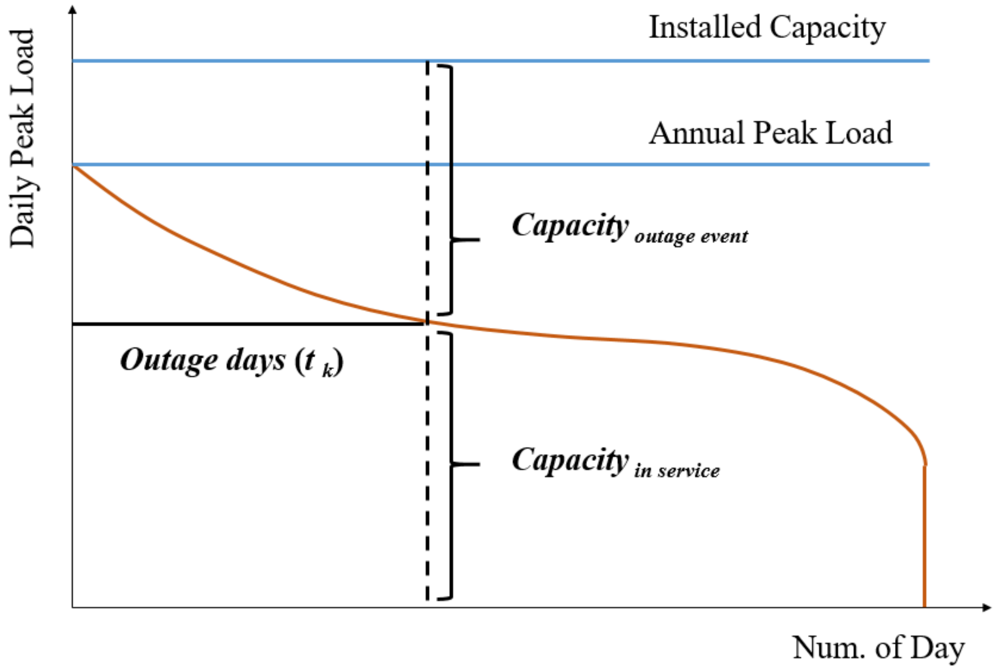
(1) LOLP

In case that total system load exceeds the total available capacity, a loss of load appears. The total sum of probability in one year that a system load is greater than system capacity is Loss of Load Probability (LOLP). The mathematical formulation of LOLP is shown as Eq. (3.13) for an expected total system load, available total generation capacity, and the realized system capacity in a specific event j of event set K.

$$LOLP = \sum_{j \in K} P(Capacity_A = Capacity_j) \cdot P(Load > Capacity_j)$$

Eq. (3.13)

For convenience of calculation, consider the load curve that accumulates the system load from the maximum to the minimum of the year. This cumulative load curve is called the Load Duration Curve (LDC), where the largest load per year is located in the y-intercept and the smallest load per year is located at the right end.



Note. This conceptual figures is rearranged from the chapter 2 in Prada (1999)

Figure 9. Concept of Loss of Load Probability

Figure 9 shows the LDC curve and supply disruption situation. Assume that the total size of the supply interruption when the k event occurs in the set K of total events that can cause a generator failure is called Outage $_k$, and the probability at that time is p_k. At this time, the total system capacity in service is the capacity obtained by subtracting the Outage $_k$ from the total installed capacity. Then, a load having the same size as the total system capacity of this service state is found in the LDC curve. As a result, all daily peak loads larger than that load will cause the loss of load events, so the number of applicable days, t_k, is the number of days of annual power outage.

Therefore, in the equation Eq. (3.13), the first term means the probability of a specific event k being realized among the total failure events, p_k, and the second term is the total number of days per year (365 days) when the k event occurs, t_k. Therefore, Eq. (3.13) can be converted to Eq. (3.14.)

$$LOLP = \sum_k p_k \cdot t_k \qquad \text{Eq. (3.14)}$$

In the end, LOLP measured the generator failure event as a probability and took an expectation for the annual supply disruption probability that is the number of loss of load event days divided by 365 days. This is the so-called LOLE (Loss of

Load Expectation). In general, most countries are designed to meet certain standards of LOLE when making long-term power generation plans. In Korea, it was 0.7day/year until 1992, 0.5day/year until 2013, and recently it was changed to 0.3day/year. Both revisions are due to the electricity supply crisis.

(2) Loss of Energy Probability

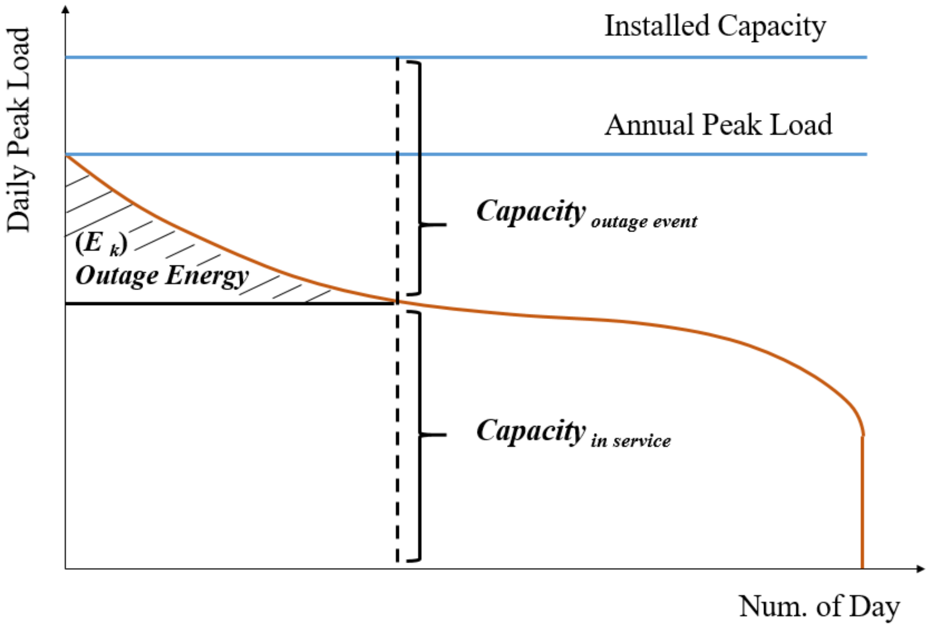
The Loss of Energy Probability is the energy version of the Loss of Load Probability. In LOEP's formula, we only need to change t_k to the total amount of outage energy occurring by the supply disruption, not the supply interruption time. Figure 10 shows the concept of LOEP. In the figure, the hatched area is the amount of outage energy that appears in the system when the k event occurs. Therefore, LOEP is the expected value of the hatched area as the probability measure of the generators' failure. If this is expressed as an equation, it becomes Eq. (3.15).

$$LOEP = \sum_{k \in K} \frac{E_k \cdot p_k}{E} \qquad \text{Eq. (3.15)}$$

Here, the shaded area E_k is the sum of the demands exceeding the capacity in service when the k event occurs, so it can be expressed as an integral such as Eq. (3.16).

$$E_k = \int_0^{t_k} (Load - Capacity_k)\, dt \quad and \quad E = \int_0^{8760} Load\ dt$$

Eq. (3.16)



Note. This conceptual figures is rearranged from the chapter 2 in Prada (1999)

Figure 10. Concept of Loss of Energy Probability

3.2.2 Microeconomic Foundation

The LOEP is mainly used to evaluate the total value of the energy generated by the supply disturbance. Representing the reliability risk of the power supply as frequency is the LOLP index. Therefore, in this study, Reliability risk will be modeled as LOLP

LOLP is the expected value of a specific function that uses the probability distribution of available generators as a probability measure. Here, the specific function refers to the Load Duration Curve function in which power demands are arranged in order of size, as shown in Figure 11. When this LDC function is converted to an inverse function, as shown in Figure 12, it means a function that is mapping the number (or frequency) of power load greater than that load during the year.

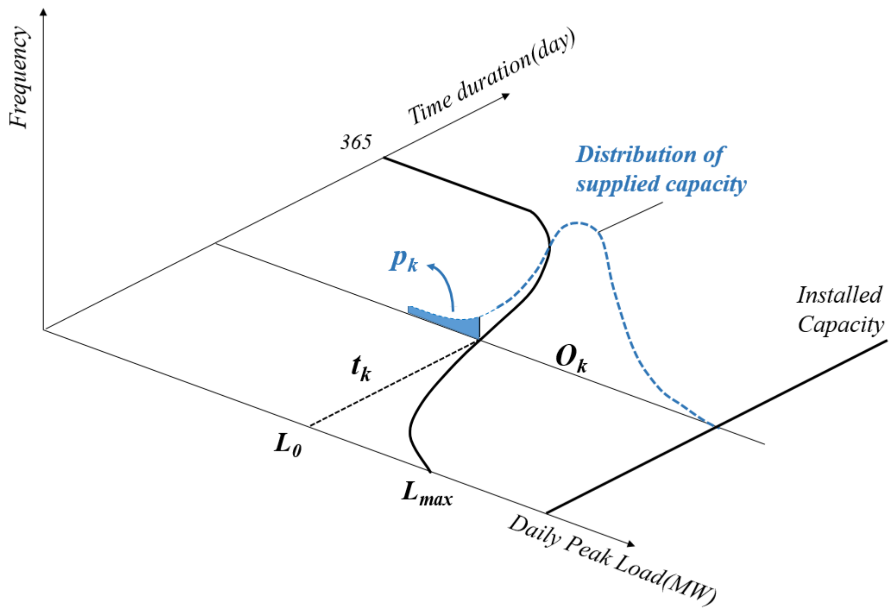


Figure 11. Concept and measurement of Loss of Load Probability

To derive this integral function, we first assume the available probability distribution of generators as follow. **x** is a probability vector representing the operation status of each power source and g(**x**) is the joint probability distribution, **q'x** can be expressed as the total amount of power generation capacity that can be supplied.

$$\mathbf{x} \equiv (x_1,\ x_2,\ x_3,\ \cdots x_n)\ \sim g(\mathbf{x}) \qquad \text{Eq. (3.19)}$$

When a failure event occurs, the generator produces zero output. Therefore, the probability distribution $g(\mathbf{x})$ of the probability vector $\mathbf{x}$ becomes a combined binomial distribution. The parameters of this distribution are the total number of power generation units and the probability of annual failure by power generation sources

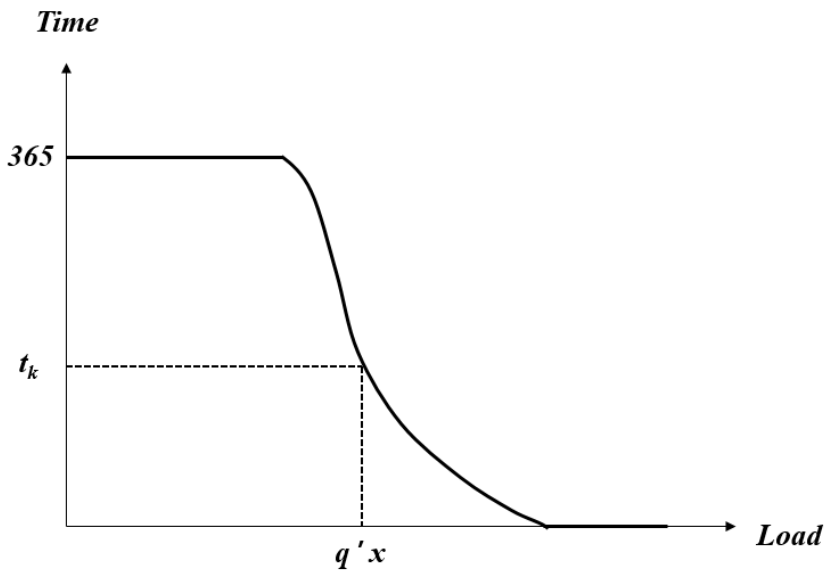


Figure 12. Meaning of the inverse load duration curve

If the inverse function of the load duration curve is defined as $D(\mathbf{q}'\mathbf{x})$, the value of this function means t_k that is the total number of the days that the supply disruption occurred. Therefore, when LOLP is defined in a continuous function, it can be expressed as follows Eq. (3.20).

$$LOLP = \sum_k p_k \cdot t_k = \int D(\mathbf{q'x}) \cdot g(\mathbf{x}) dx \equiv R(\mathbf{q})$$

Eq. (3.20)

In the Lagrangian formulation of the two-risk model, the 3rd term of the first order condition, r(**q**), means the first derivative of LOLP for **q**. Therefore, the first order condition of the utiltiy maximization problem that includes the reliability risk in the social welfare function is as shown in Eq. (3.21).

$$\frac{\partial L}{\partial \mathbf{q}_t} = U_1 \cdot \boldsymbol{\mu}_t{}' + 2U_1 \cdot \mathbf{q}_t{}' \cdot \boldsymbol{\Sigma}_t + U_3 \cdot r(\mathbf{q}_t) - \lambda \cdot \iota' = 0$$

Eq. (3.21)

$$where \quad r(\mathbf{q}) = \frac{\partial R(\mathbf{q})}{\partial \mathbf{q}} = \frac{\partial LOLP(\mathbf{q})}{\partial \mathbf{q}} = \frac{\partial}{\partial \mathbf{q}} \int D(\mathbf{q'x}) \cdot g(\mathbf{x}) dx$$

This study approximates the inverse demand function, $D(\mathbf{q'x})$, as the sum of the linear functions for convenience of calculation. This can be done by using the indicator function to divide by many intervals, which is well shown in Equation (3.22).

$$\begin{aligned} D(\mathbf{q_t'x}) &= \sum_{i=0}^{n-1} D_i(\mathbf{q_t'x}) \cdot I_i \qquad I_i \sim indicator\ \ function\ of\ \ i\,th\ interval \\ &= \sum_{i=0}^{n-1} \left\{ b_i(\mathbf{q_t'x}) + c_i \right\} \cdot I_i \{ z_i \le \mathbf{q_t'x} \le z_{i+1} \} \end{aligned}$$

Eq. (3.22)

The approximated invers LDC function is substituted to the LOLP function and then, it is arranged as follows Eq. (3.23). Here, Monte Carlo integration method was used to derive the integral value of the inverse load duration curve separated by intervals.

$$
\begin{aligned}
R(\mathbf{q_t}) &= \int \left[\sum_{i=0}^{n-1} D_i(\mathbf{q}_\mathbf{t}'\mathbf{x}) \cdot I_i \right] \cdot g(\mathbf{x})\, d\mathbf{x} \\
&= \int_{A_i} \sum_{i=0}^{n-1} D_i(\mathbf{q}_\mathbf{t}'\mathbf{x}) \cdot g(\mathbf{x})\, d\mathbf{x} \qquad \text{Eq. (3.23)} \\
&= \sum_{i=0}^{n-1} \int_{A_i} \left\{ b_i(\mathbf{q}_\mathbf{t}'\mathbf{x}) + c_i \right\} \cdot g(\mathbf{x})\, d\mathbf{x}
\end{aligned}
$$

$$
where \quad A_i = \left\{ \mathbf{x} | z_i \le \mathbf{q'}_\mathbf{t}\mathbf{x} \le z_{i+1} \right\}
$$

LOLP is a function of **q, x** vectors. r(**q**) is a function, which differentiates LOLP function to **q,** which is integrated into **x**. It is extension of the rule known as 'Leibniz Rule' into vector space to develop the equation(Sims, 1980). (Refer to the appendix for related equation development.) Finally, the first order derivative of the LOLP function as a **q** vector is derived as in Equation (3.24). This means the weighted average of the expected value of the random vector **x** at a specific weight in every demand load interval. At this time, the weights are *b*, which are the slopes when the inverse LDC function is approximated with a linear function.

$$
\begin{aligned}
r(\mathbf{q_t}, \mathbf{x}) \;=\; \frac{\partial R(\mathbf{q_t}, \mathbf{x})}{\partial \mathbf{q_t}} \;&=\; \frac{\partial}{\partial \mathbf{q_t}} \sum_{i=1}^{n} \int_{A_i} \left\{ b_i(\mathbf{q_t'x}) + c_i \right\} \cdot g(\mathbf{x})\, d\mathbf{x} \\
&=\; \sum_{i=1}^{n} \frac{\partial}{\partial \mathbf{q_t}} \int_{A_i} \left\{ b_i(\mathbf{q_t'x}) + c_i \right\} \cdot g(\mathbf{x})\, d\mathbf{x} \\
&=\; \sum_{i=1}^{n} b_i \int_{A_i} \mathbf{x} \cdot g(\mathbf{x})\; d\mathbf{x} \\
&=\; \sum_{i=1}^{n} b_i \cdot E_i(\mathbf{x}) \;\equiv\; \boldsymbol{\beta}_{\mathbf{t}}'
\end{aligned}
\qquad \text{Eq. (3.24)}
$$

Finally, the following is a rearrangement of 2-risk model optimization FOC by replacing r(q) with β as shown in Eq. (3.25).

$$
\frac{\partial L}{\partial \mathbf{q}_t} = U_1 \cdot \boldsymbol{\mu}_t' \;+\; 2U_1 \cdot \mathbf{q}_t' \cdot \boldsymbol{\Sigma}_t \;+\; U_3 \cdot \boldsymbol{\beta}_t - \lambda \cdot \iota' = 0 \qquad \text{Eq. (3.25)}
$$

Multiplying with $\Sigma_t^{-1} \cdot \iota$ on both sides of FOC equation, solving for the scalar λ, substituting it to the FOC, and then solving it to q derives optimal capacity for each power source with consideration for reliability, we can derive the optimal q vecter equation as shown in Eq. (3.26).

$$\mathbf{q_t}^* = \frac{Q_t \cdot \Sigma_t^{-1}\,\iota}{\iota'\,\Sigma_t^{-1}\,\iota} + \frac{1}{2}\left(-\frac{U_1}{U_2}\right)\left(\Sigma_t^{-1} - \frac{\Sigma_t^{-1}\,\iota\,\iota'\Sigma_t^{-1}}{\iota'\,\Sigma_t^{-1}\,\iota}\right)\boldsymbol{\mu}_\mathbf{t} + \frac{1}{2}\left(-\frac{U_3}{U_2}\right)\left(\Sigma_t^{-1} - \frac{\Sigma_t^{-1}\,\iota\,\iota'\Sigma_t^{-1}}{\iota'\,\Sigma_t^{-1}\,\iota}\right)\boldsymbol{\beta}_\mathbf{t} \qquad \text{Eq. (3.26)}$$

From the planner's perspective, the main interest is the share of each facility, not the capacity level of each facility. Dividing optimal power capacity equation as above by Q_t, and substituting $\gamma_t = -U_1/U_2$, $\tau_t = -U_3/U_1$, the optimal portfolio share equation can be derived as follow in Eq. (3.27)

$$\mathbf{w_t}^* = \frac{\Sigma_t^{-1}\,\iota}{\iota'\,\Sigma_t^{-1}\,\iota} + \frac{1}{2}\left(\frac{\gamma_t}{Q_t}\right)\left(\Sigma_t^{-1} - \frac{\Sigma_t^{-1}\,\iota\,\iota'\Sigma_t^{-1}}{\iota'\,\Sigma_t^{-1}\,\iota}\right)\boldsymbol{\mu}_\mathbf{t} + \frac{1}{2}\left(-\tau_t \cdot \frac{\gamma_t}{Q_t}\right)\left(\Sigma_t^{-1} - \frac{\Sigma_t^{-1}\,\iota\,\iota'\Sigma_t^{-1}}{\iota'\,\Sigma_t^{-1}\,\iota}\right)\boldsymbol{\beta}_\mathbf{t} \qquad \text{Eq. (3.27)}$$

Like 1-risk model, this study represent that γ_t / Q_t is time-invariant value γ, which means the MRS is constant regardless of whether the total capacity Q_t changes. Whereas the trade-off ratio between cost and reliability risk, τ_t, is assumed to be time-invariant value, τ, by itself as shown in Eq. (3.28).

$$\mathbf{w_t}^* = \frac{\Sigma_t^{-1}\,\iota}{\iota'\,\Sigma_t^{-1}\,\iota} + \gamma \cdot \frac{1}{2}\left(\Sigma_t^{-1} - \frac{\Sigma_t^{-1}\,\iota\,\iota'\Sigma_t^{-1}}{\iota'\,\Sigma_t^{-1}\,\iota}\right)\boldsymbol{\mu}_\mathbf{t} - \gamma \cdot \tau \cdot \frac{1}{2}\left(\Sigma_t^{-1} - \frac{\Sigma_t^{-1}\,\iota\,\iota'\Sigma_t^{-1}}{\iota'\,\Sigma_t^{-1}\,\iota}\right)\boldsymbol{\beta}_\mathbf{t} \qquad \text{Eq. (3.28)}$$

As the 1-risk model, this study estimate it with seemingly unrelated regression (SUR model) and nonlinearity was considered in the estimation.

$$\mathrm{w}_t = \mathrm{w}_t^* + \varepsilon_t = \mathrm{x}_{0t} + \gamma \cdot \mathrm{x}_{1t} + \tau \cdot \gamma \cdot \mathrm{x}_{2t} + \varepsilon_t \qquad \text{Eq. (3.28)}$$

$$\textit{where} \quad \mathrm{x}_{2t} = \frac{1}{2}\left(\frac{\Sigma_t^{-1}\,\iota\,\iota'\Sigma_t^{-1}}{\iota'\,\Sigma_t^{-1}\,\iota} - \Sigma_t^{-1} \right)\boldsymbol{\beta}_\mathbf{t}$$

This study compared the portfolios of the 1-risk model and the 2-risk model by changing 2-risk model to 1-risk model. It is possible by converting reliability into economic costs using MRS between reliability risk and supply cost. Eq. (3.29) is the equation given by converting the 2-risk model to the 1-risk model. As can be seen, $-\tilde{\tau} \cdot \boldsymbol{\beta}_\mathbf{t}$ is added to the supply cost as a penalty factor and it becomes a key element that changes the share of the optimal power supply. The optimal portfolio change resulting from this penalty is shown in Figure 13.

$$\text{1-risk Model : } \hat{\mathrm{w}}_t^* = \mathrm{x}_{0t} + \hat{\gamma} \cdot \frac{1}{2}\left(\Sigma_t^{-1} - \frac{\Sigma_{2t}^{-1}\,\iota\,\iota'\Sigma_t^{-1}}{\iota'\,\Sigma_t^{-1}\,\iota} \right)\boldsymbol{\mu}_\mathbf{t}$$

$$\text{2-risk Model : } \tilde{\mathrm{w}}_t^* = \mathrm{x}_{0t} + \tilde{\gamma} \cdot \frac{1}{2}\left(\Sigma_t^{-1} - \frac{\Sigma_t^{-1}\,\iota\,\iota'\Sigma_t^{-1}}{\iota'\,\Sigma_t^{-1}\,\iota} \right)(\boldsymbol{\mu}_\mathbf{t} - \tilde{\tau} \cdot \boldsymbol{\beta}_\mathbf{t}) \qquad \text{Eq. (3.29)}$$

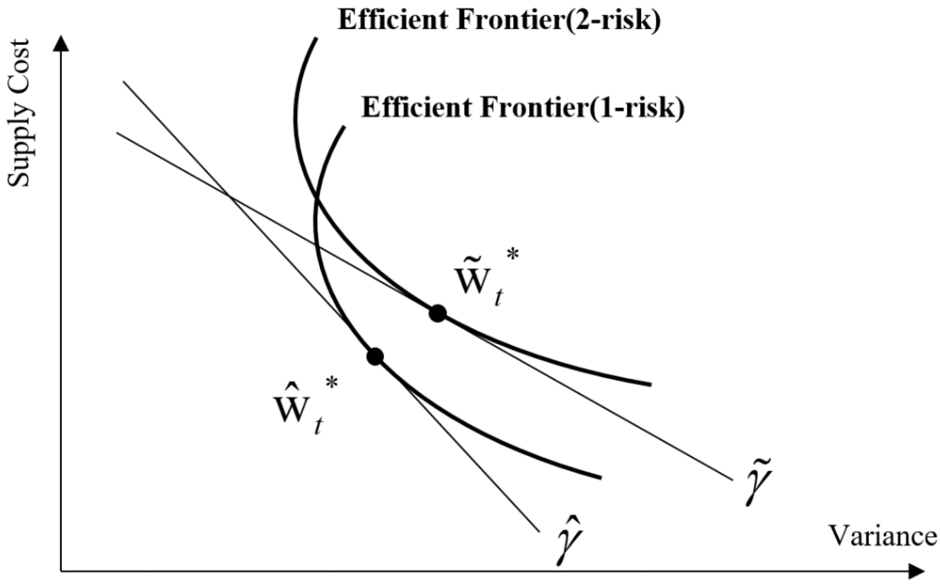


Figure 13. Optimal point change between 1-risk and 2-risk model

Chapter 4. Empirical Studies

4.1 Data Specification

This section reports the data specification and its reference sources. The original meta-data set cannot be provided in public because of data security, but the refined cost data collected by each power source is provided in Appendix 1.

This study assumed that there are four options that make up a portfolio for power generation facilities: nuclear, bituminous coal (coal), combined cycle gas turbine, and other fossil power plants (i.e., n=4). Other fossil power plants mostly consist of oil steam turbines and include a few gas steam and single-cycle combustion turbines. In Korea, some hydro and pumped storage power plants play a role in electricity supply. However, the installation of these plants is mainly decided by non-economic decisions such as water supply for agriculture and consumption. The total supply cost of each power generation facility is composed of construction cost, O&M cost, and fuel cost. To calculate the LCOE of each year, which is the annual supply cost; the construction cost is annualized by the cost recovery factor.

4.1.1 Investment Cost

The construction investment cost is based on past construction data from the

Korea Power Exchange(KPX, 2019). The actual construction cost of each type of plant was applied from 1990 to 2014. If a number of facilities with different construction costs were built each year, they were weighted by capacity. In certain cases of years, some kinds of the power plants did not have a construction, so we cannot obtain the accurate construction cost in those years. In this case, the construction data were generated by interpolation. The overnight capital cost (thousand Won/kW) of power generation is shown in Figure 14.

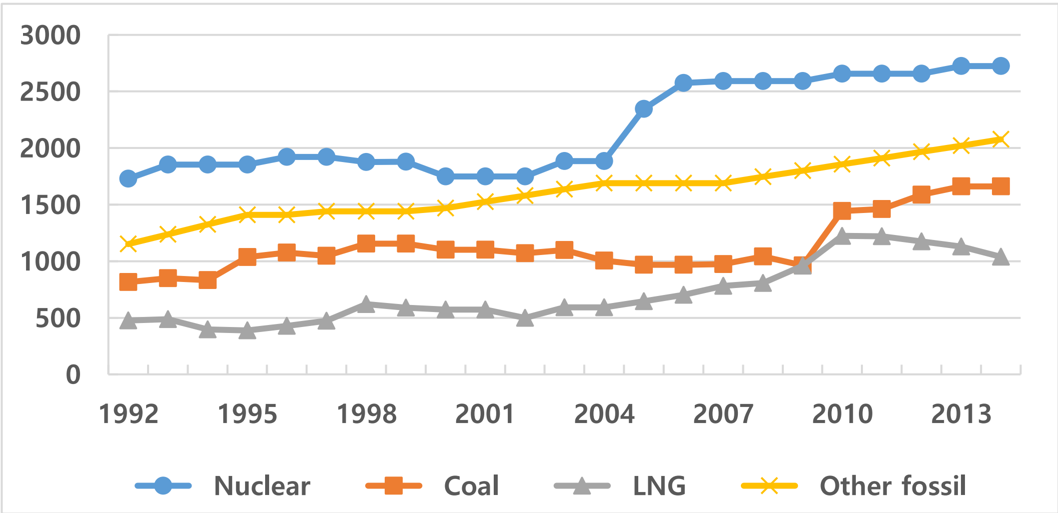


Figure 14. Overnight capital costs by generation sources, 1992-2014

To calculate the annual total power supply cost, the overnight construction cost was converted to the annualized cost for which we use capital recovery factor (CRF) in Eq. (4.1). The CRF consists of a discount rate(i) and the number of years to be able to operate plants(N), so the annual total power supply cost can vary by these parameters significantly. In this study, 40 years of discounting period for nuclear and 30 years of discounting period for the other power generators such as coal, LNG, and oil were applied in according to the statutory standards. The discount rate was decided based on the corporate bond rate and capital cost by weighted average cost of capital (WACC).

$$CRF = \frac{i \times (1+i)^N}{(1+i)^N - 1} \qquad \begin{array}{l} i \ : discount\ rate \\ N : durable\ years\ of\ a\ generator \end{array} \qquad \text{Eq. (4.1)}$$

The WACC data for annualized investment cost are applied as the discount rate in the government's long-term expansion plan, 'Basic Plan for Electricity Supply and Demand'(Ministry of Trade, 2017). However, data set prior to the 2000s were not available and other alternatives had to be sought. With analyzing the data since the 2000s, where the data could be collected, the WACC of the national expansion planning showed average spread of about 2%p against AA-class corporate bond interest rate. Therefore, this study was derived by adding the spread to the AA corporate bond interest rate, which obtained from the Bank of Korea statistical system for the 1990s WACC data. AA corporate bond interest rates are shown in the Figure 15.

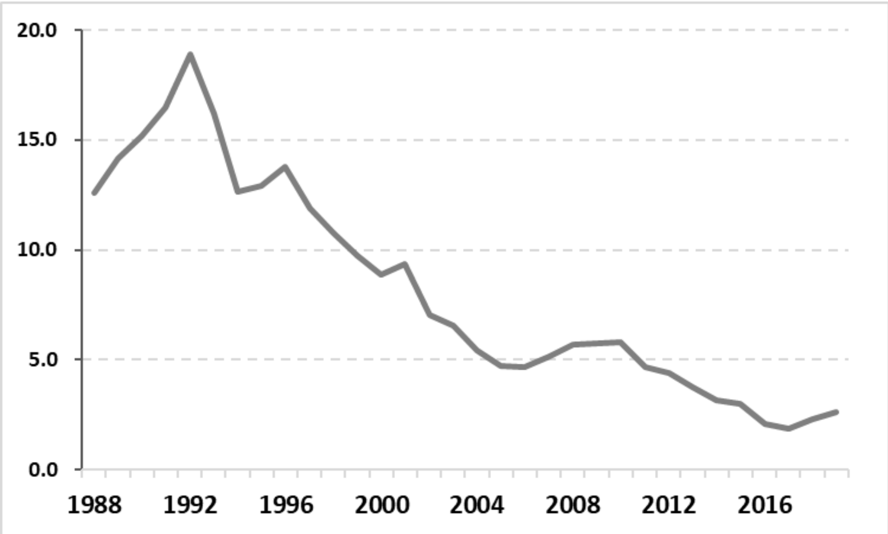


Figure 15. Trend of the interest rate of AA corporate bond, 1988-2018

4.1.2 O&M and Fuel cost

O&M costs were based on the historical cost accounting data from KEPCO. O&M costs include fixed and semi-fixed costs such as labor, repair, and miscellaneous costs. Costs were converted on an annual basis and calculated in thousand KRW/kW.

The biggest problem in collecting O & M cost data was too much noise in the data. Looking at the historical data of KEPCO, the cost is divided for each generator. In some generators, O & M costs sometimes fluctuate greatly due to changes in the aggregation method or cost divergence. These data were excluded when reconciling the data by unifying the aggregation criteria or when counting outliers that were too large. The time series of O&M costs (thousand Won/kW) by power generation sources from 1992 to 2014 are shown in Figure 16.

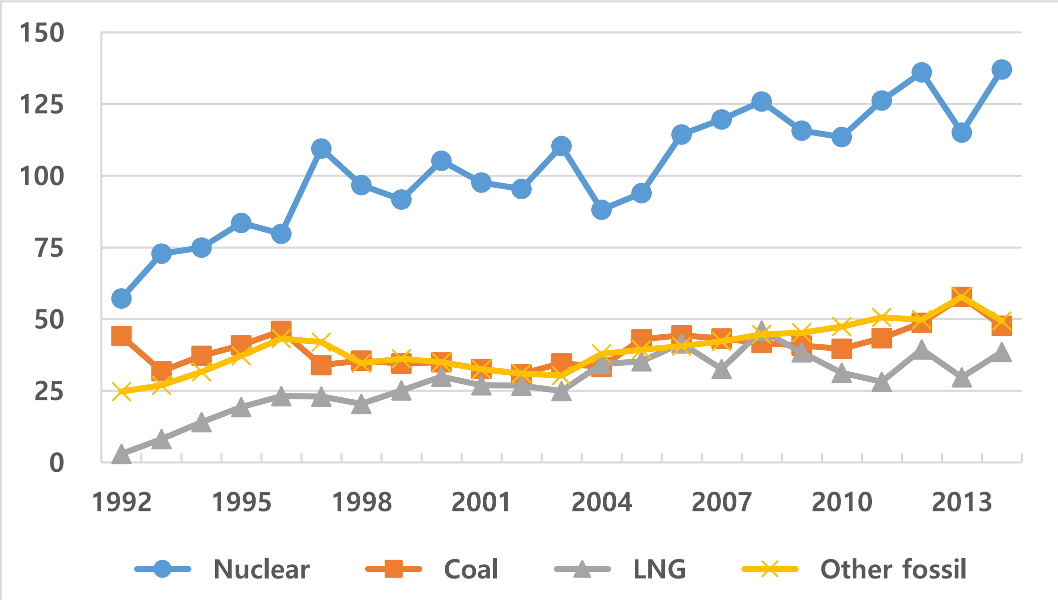


Figure 16. O&M costs by generation sources, 1992-2014

We used the fuel costs from KEPCO and its subsidiary power producers. The calculation of fuel cost per unit capacity depends on the capacity factor. When calculating the annual fuel cost per kW for each power source, the actual capacity factor may be used. However, in this case, the lower the capacity factor is, the cheaper the fuel seems to be. This can provide a bias in estimating the cost of supply per power unit per kW. The reason is that in order to evaluate the economic efficiency of the power source based on the generator's capacity, it should be based on a common capacity factor. In this study, we adopted the capacity factor as 85%, which is used in the LCOE calculation(IEA, 2015). Time series of fuel costs by power generation sources from 1992 to 2014 are shown in Figure 17

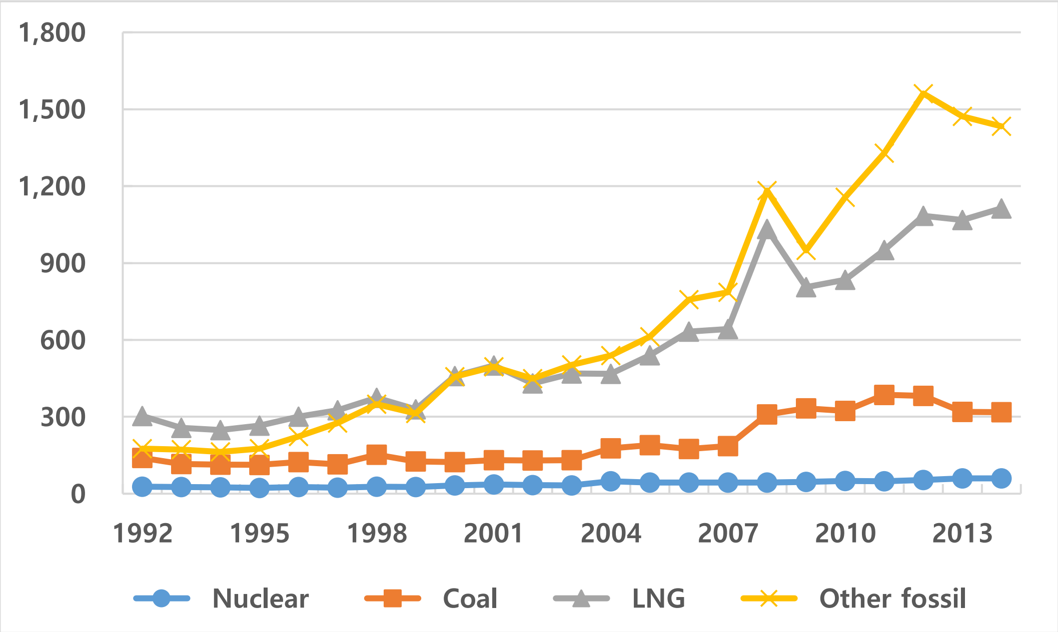


Figure 17. Fuel costs by generation sources (85% capacity factor), 1992-2014

4.1.3 Total Supply Cost

As a result, the total supply cost of the power plant combined with the yearly cost factors was calculated based on the above methods as shown in Figure 18.

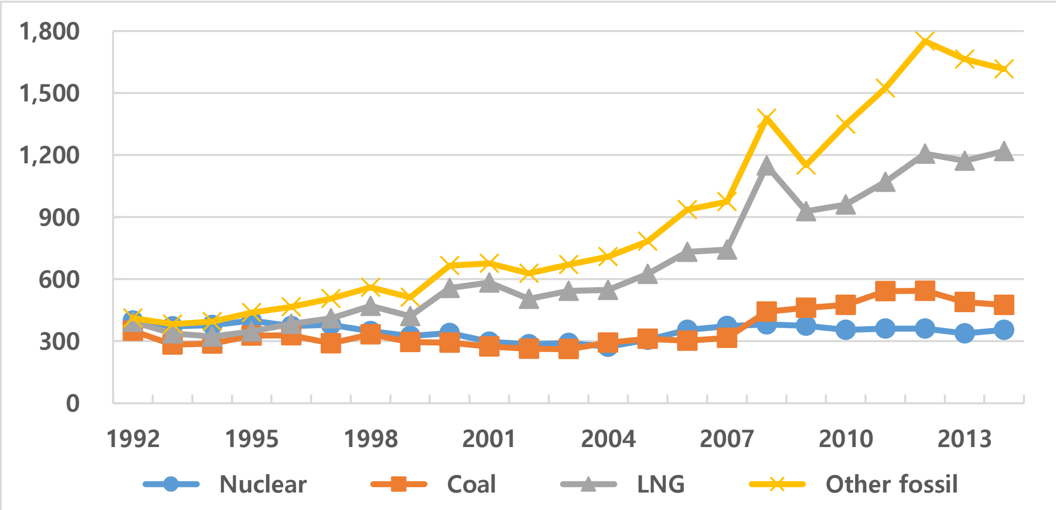


Figure 18. Total supply costs by generation sources, 1992-2014

Despite the change in time, the supply cost of nuclear power and coal power did not change significantly from 400,000KRW/kW, since the portion of the fixed costs in supply costs is higher than variable costs such as fuel costs in nuclear and coal power generation. The construction costs, which account for the majority of the fixed cost, gradually increased over time, and did not fluctuate in the period; however, the interest rate decreased significantly during the same period, which means that the annualized value of fixed costs remained almost constant. The construction cost increased about 1.8 times during the period, while the interest rate of federal bonds decreased from 15% (the 1990s) to 5% (late 2000s). However, due to the rapid increase in fuel costs, generation supply costs of coal increased after 2007. Other fossil power plants, such as LNG and oil, have a relatively low proportion of fixed costs and high proportion of fuel costs, which tends to shift the total supply costs as fuel costs change. Therefore, the supply cost showed almost similar movement to oil prices.

4.2 Estimation of 1-risk Model

This section reports the results of estimating the MRS between cost and volatility when the model consider only volatility risk and finds the implications. First, the stability of the time series is statistically tested on the unit root of the total supply cost time series, and then the HPR is derived from the time series of the cost. From these data, the VAR model estimates the variance matrix, from which the share equation is estimated using the SUR model.

4.2.1 Estimation of Covariance Matrix

The supply cost of each of the four power generation sources showed a form of unstable time-series that increases or decreases with time (Figure 18). Unit root tests were conducted for a more precise statistical confirmation. The Augmented Dickey Fuller (ADF) test was used for the unit root test method, which is a representative unit root test method to determine stationarity of a time series(Fuller, 1976). The null hypothesis used in the test is that the unit root exists in the time series, and the alternative hypothesis is that the time series satisfies normality. Before performing an ADF test, we should find the appropriate number of lags and decide whether to include time trends and constant terms. In this study, the two lags were found to be proper, and the time trend was not included, but the constant term was included.

As a result of the test, the unit-roots were found in the level variables, but not observed in first-order differential variables in all the four fuel types as shown in Table 1.

Table 1. ADF test results of supply costs on the four power generation sources

Source	Level (s_t)		First difference ($\triangle s_t$)	
	Statistics	P-value	Statistics	P-value
Nuclear	-2.241	0.1917	-7.232	0.0000
Coal	-0.686	0.8503	-4.299	0.0004
LNGCC	-0.179	0.9410	-6.820	0.0000
Other	0.159	0.9699	-6.312	0.0000

Note: P-value is the MacKinnon approximate p-value for *Z(t)*

Therefore, we needed to derive the variance-covariance matrix from the differential variable, rather than the level variables. This study derived the variance-covariance matrix using holding period rate of return, differential variables of costs, as used in the previous researches that applied CAPM to the electricity sector.

A vector autoregressive regression (VAR) was used to estimate the variance-covariance matrix of the total supply costs. In this study, the logarithm of each time series was taken so that the differential time series represented the holding period rate return. This is shown in Eq. (4.1). The model's lag was analyzed in two, and the 2008 dummy variable was added as an exogenous variable to reflect the peculiarity of international energy prices fluctuating due to the 2008 global financial crisis. In particular, LNG and oil prices were very high in the summer of 2008, just before the crisis

$$\Delta \log \mathrm{s}_t = \rho + \delta_1' \cdot \Delta \log \mathrm{s}_{t-1} + \delta_2' \cdot \Delta \log \mathrm{s}_{t-2} + \Phi \cdot \mathrm{crisis}_t + \mathrm{v}_t \qquad \text{Eq. (4.1)}$$

$crisis_t$: a dummy variable indicating the 2008 energy price fluctuation

As expected, the log-likelihood showed a higher value, and coefficients (δ_k) were statistically significant when the crisis dummy was included, as shown in Tables 2 and 3. Nuclear costs were not statistically significant for the economic crisis, but coal, gas, and oil were all statistically significant for the financial crisis dummy. The reason is that nuclear power has a small share of fuel cost, but fossil fuel has a high share of total fuel cost.

Table 2. Estimation results of VAR model without exogenous variables

	Nuclear		Coal		LNG		Other	
	coefficient	Std.	coefficient	Std.	coefficient	Std.	coefficient	Std.
ρ	0.032	0.037	0.066	0.047	0.106*	0.061	0.106**	0.047
δ_{11}	0.203	0.239	0.609**	0.300	0.737*	0.392	0.689**	0.304
δ_{12}	0.210	0.271	0.681**	0.341	0.388	0.445	0.227	0.346
δ_{21}	0.126	0.176	0.125	0.222	-0.279	0.289	-0.121	0.225
δ_{22}	0.046	0.160	-0.274	0.201	0.062	0.262	0.182	0.204
δ_{31}	-0.004	0.400	-0.783	0.503	-0.825	0.656	-0.757	0.510
δ_{32}	-0.179	0.370	0.155	0.466	-0.695	0.608	-0.564	0.473
δ_{41}	-0.360	0.566	0.426	0.712	0.281	0.930	0.173	0.723
δ_{42}	-0.011	0.466	-0.326	0.586	0.583	0.765	0.468	0.595
R^2	0.1703		0.4503		0.4464		0.5474	

Table 3. Estimation results of VAR model with exogenous variables

	Nuclear		Coal		LNG		Other	
	coefficient	Std.	coefficient	Std.	coefficient	Std.	coefficient	Std.
ρ	0.035	0.038	0.033	0.037	0.051	0.039	0.066**	0.032
δ_{11}	0.225	0.251	0.325	0.246	0.273	0.256	0.344	0.212
δ_{12}	0.259	0.322	0.064	0.315	-0.616*	0.328	-0.521**	0.271
δ_{21}	0.127	0.176	0.115	0.172	-0.295	0.179	-0.133	0.148
δ_{22}	0.029	0.171	-0.056	0.167	0.418**	0.174	0.447***	0.144
δ_{31}	-0.017	0.401	-0.627	0.393	-0.572	0.409	-0.569*	0.339
δ_{32}	-0.187	0.371	0.259	0.363	-0.525	0.378	-0.437	0.313
δ_{41}	-0.365	0.566	0.492	0.554	0.388	0.576	0.253	0.477
δ_{42}	0.001	0.467	-0.481	0.458	0.330	0.476	0.280	0.394
crisis	-0.024	0.087	0.308***	0.085	0.502***	0.089	0.373***	0.073
R^2	0.1735		0.6681		0.7873		0.8030	

. In the total supply cost of coal, LNG, and oil power generation, fuel costs accounted for 50.3%, 75.4%, and 65.1% respectively on average, which means that the global financial crisis directly affected supply costs of those power generations. On the contrary, the fuel cost of nuclear power generation only accounted for 10.2% of the supply cost. Therefore, crisis coefficients showed statistical significance in coal, LNG, and other fossil fuels, but not in nuclear power

In addition, the LR test showed that the model including the crisis dummy is significantly different from the model not including the crisis dummy, as shown in Table 4.

Table 4. LR test result of the VAR model with exogenous variables

`	VAR with Crisis	VAR without Crisis
Log-Likelihood	116.452	101.387
LR chi square(4)	28.14	
Prob. > chi2	0.000	

Table 5 shows the result of the estimated variance matrix from Eq. (3.11). The sizes of the covariance between the power source costs was smaller than those of the individual variance of each power source. The covarinaces between nuclear power and fossil power generators were very small, especially close to zero in case of coal. It is because the investment cost and fixed O&M cost of nuclear power are much higher than those of fossil power generators, which is relatively less volatile than other thermal power plants. In the case of coal, the covariances with LNG or other thermal power (most of oil) were also very small, compared to the size of the own variance of coal. It is also because the proportion of fixed costs is relatively higher than that of LNG and oil power generators although not comparable to nuclear power. What is different is that it has a weak negative relationship with LNG, while it has a weak positive relationship with oil thermal power

In contrast, LNG and oil thermal power plants show a relatively strong positive correlation, unlike other power sources. This is because the LNG import contracts in Korea has been linked to oil price index, so their volatility are similar to each other.

Table 5. Estimated covariance matrix of 4 generation sources ($\hat{\Sigma}\times 10^3$)

	Nuclear	Coal	LNG	Other
Nuclear	3.870			
Coal	0.070	3.710		
LNG	0.168	-0.340	4.020	
Other fossil	0.121	0.320	2.720	2.750

4.2.2 Estimation of Share Equation

The MRS of expected cost for its variance (γ) described in Eq. (3.9) was estimated by using the mean supply cost vector (μ_t) and the variance-covariance matrix (Σ_t) derived from the previous section. Eq. (3.11) is a system of the nonlinear equations where each equation share the coefficient MRS (γ) in common. Therefore, we estimated the MRS by using the non-linear system equation model with Seemingly Unrelated Regression Model as mentioned in section 3.1. The estimation results and performance of the model are shown in Table 6, and Table 7.

Table 6. Estimation result of marginal rate of substitute in 1-risk model

	Coefficient	Standard Error	z
$\gamma \times 10^6$	-0.646***	0.19	-10.6

Note: *** means significance at the 1% level

The estimated value of MRS was - 0.646×10^{-6}, and statistically significant at the 1% level as shown in Table 6. The estimated value of the MRS was considered a reasonable result since the relation between supply costs and their variance was substitutional, which means that it was a negative value.

Table 7. Performance of share equation estimation result in 1-risk model

Equation	Obs.	RMSE	R^2
Nuclear	23	0.052023	0.9694
Coal	23	0.103427	0.8902
LNC	23	0.102619	0.8498
Other	23	0.058738	0.8401

The estimation performance of each share equation was good. The R square of the nuclear power share equation was the highest at 0.9694, and the R square of the remaining thermal power sources was from 0.84 to 0.89.

4.2.3 Empirical Results and Discussion

In the CAPM model, the horizontal axis is the variance and the vertical axis is the average price, which means that the MRS of the expected cost for its variances in the CAPM model is an inverse of the estimated value ($1/\gamma$), estimated at about 1,547,748. The reason for which gamma has a large value is that the time series of the cost is a level variable, while the variance is measured as a differential time series value, holding a period rate of return.

To overcome the difference in scale between the level value and differential value, and express it intuitively, the estimated MRS was transformed into the elasticity between cost and its variance, as shown in Eq. (4.2).

$$elasticity: \ \eta = -\frac{\Delta\mu/\mu}{\Delta\sigma^2/\sigma^2} = -\frac{\Delta\mu}{\Delta\sigma^2}\cdot\frac{\sigma^2}{\mu} = -\frac{1}{\gamma}\cdot\frac{\sigma^2}{\mu} \qquad \text{Eq. (4.2)}$$

As a result of estimating the elasticity for each year, the elasticity gradually decreased from 6 in 1992 to 3 in 2014. In the 1990s, about a 6% increment of supply cost was allowed to decrease 1% of cost volatility. However, in the 2010s, only 3% increment of supply cost was allowed to decrease 1% of cost volatility. It means that the relative value of cost volatility gradually decreased twice as much.

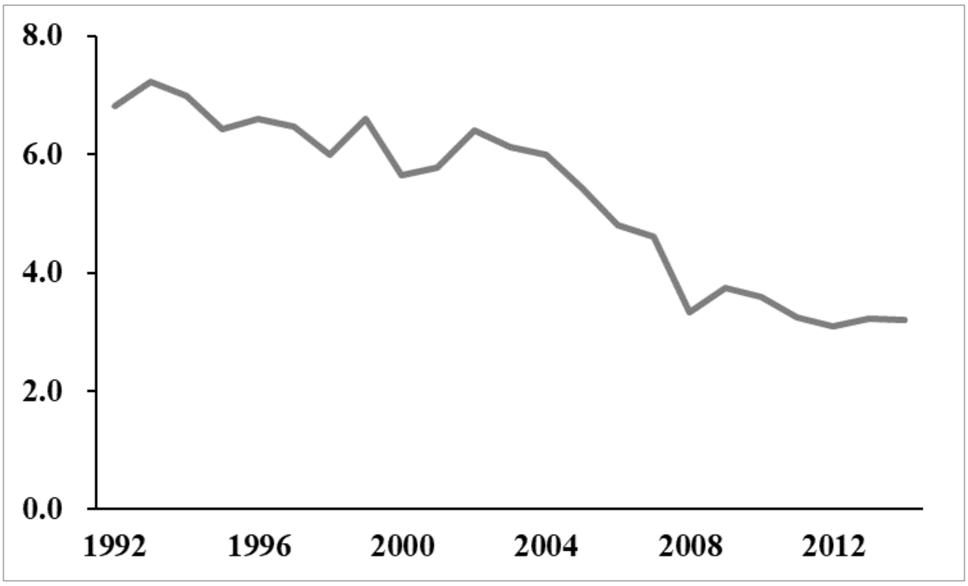


Figure 19. Estimated elasticity trend, 1992-2014

In 1992, the share of nuclear power generation was about 35.9%, and that of coal and LNG was about 17.4% and 17.5% respectively. In 2014, nuclear power was lowered to 25.7%, and coal and LNG increased to 32.6% and 37.5%, respectively. This suggests that the attitude toward volatility risk shifted from risk-averse to risk-taking.

The estimated MRS of expected cost for its variance (γ) can be used to derive the optimal power portfolio and compare it with the actual portfolio to assess the effectiveness and efficiency of the portfolio. The optimal portfolio can be interpreted as the tangent point of contact of the slope of the inverse of the estimated MRS with the efficient frontier. The optimal portfolio for 2014 consisted of 30.5% of nuclear, 43.6% of coal, 20.9% of LNG, and 5.0% of other fossil fuels, while the actual portfolio is in the same year: 25.7% of nuclear, 32.6% of coal, 37.5% of LNG, and 4.1% of other fossil fuels. The actual portfolio was 11.0%p less in coal than optimal portfolio; LNG resulted in 17.2%p more. This is because private LNG generators have increased significantly in the metropolitan area around Seoul in order to solve the shortage of reserve power capacity that have occurred since 2009. This is because LNG can be urgently connected to power grid in the event of an electricity crisis due to the short construction period. Such cases also occurred in the early 1990s when the Korean government under-forecasted electricity demand due to policy failure. These historical experiences prove that it is difficult to show the reality properly considering only the price volatility risk, and that it reflects the reality properly when considering the reliability risk together.

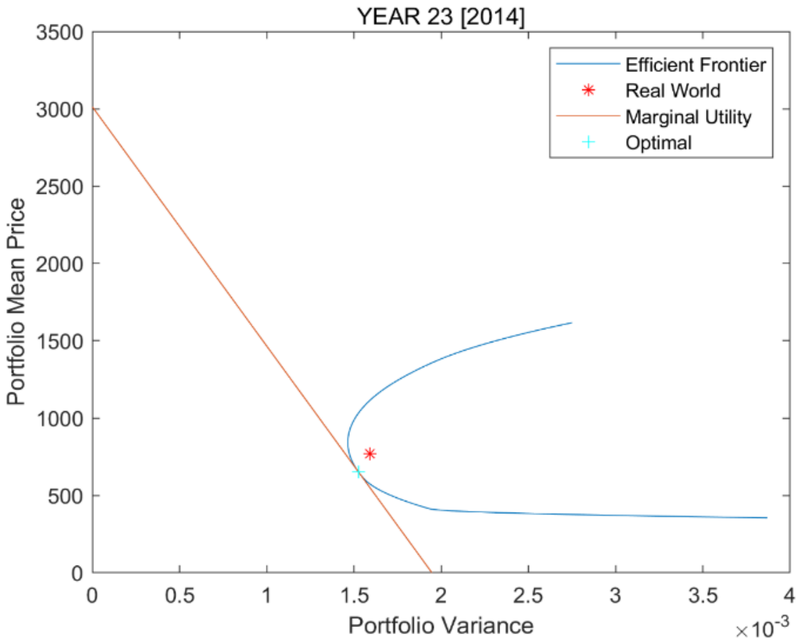


Figure 20. Efficiency frontier and optimal portfolio in 2014

However, the proportion of nuclear and coal power generation in the optimal portfolio was slightly higher than the actual and that of LNG power plants was lower in the opposite direction. This difference is because until 2014, the Korean government did not fully reflect the environmental cost from air pollution damage and the cost of greenhouse gas emissions in fossil fuel power plants. The cost of damage caused by air pollution was replaced by the excise tax of power generation fuel. It is because Korea's fuel excise tax comes from the estimates of air pollution costs to internalize external costs. The estimates are partially reflected in tax rates. Fuel consumption tax reflects the unit cost of coal and LNG for power generation through three revisions in 2017, 2018, and 2019.

Table 8. Excise tax of power generation fuel in Korea (2019)

		Nuclear	Coal	LNG	Oil
Excise tax	(Won/kg)	-	46	36.2	17
	(Won/kWh)	-	16.73	4.54	4.61

Note: The LNG fuel excise tax was lowered from 60 won/kg to 12 won/kg in 2019, and 36.2 won includes import charges of 24.2 won/kg.

In addition, since Japan's nuclear accident in 2011, the accident risk cost of nuclear power plants has been considered as another external cost of nuclear power plants. Considering these costs, the optimal portfolio can be expected to change somewhat.

Table 9. Additional environmental cost by power generation source

	Nuclear	Coal	LNG	Oil
Environmental Cost	29.9	46.4	17.5	30.1

Note: We considered the expected cost of accident risks for nuclear power generation and the cost of air pollution and GHG emissions for thermal power generation as external costs

Table 8 shows the environmental costs of nuclear, coal, LNG, and other fossil fuel power plants. We took the data reported by KEPCO[1] as the accident risk cost of nuclear power plants(KEPCO, 2018), and Parry et al.(2014)'s data, which was adjusted by taking into consideration the inflation and growth rate of real GDP per capita, as the air pollution damage cost of thermal power generation(Parry, Heine, Lis, & Li, 2014). The price of carbon credits was used as 34,500 won/ton(KEPCO, 2018). In this case, the optimal portfolio was 28.0% of nuclear, 41.5% of coal, 22.4% of gas, and 8.1% of other fossil fuel power. As a result, considering environmental costs, the optimal portfolio and the actual portfolio were slightly more similar. Although it has a value close to reality, it still has a higher proportion of coal and a lower proportion of LNG than reality. This is because reliability risks and other limitations in reality have not been fully reflected.

Finally, in order to evaluate the closeness of the historical portfolios to the estimated optimal portfolio, this study measured the distance between the actual portfolio and the estimated optimal portfolio during the sample period by applying the L2-norm as shown in Eq. (4.3).

---

[1] Nuclear accident risk costs consist of compensation for damages, decontamination and decommission costs. We referred to the methodology of JCER and re-estimated the costs according to Korean conditions.

$$L2Norm_t = \sqrt{\sum_i \frac{\left(w_{optimal,it} - w_{real,it}\right)^2}{w_{optimal,it}}}$$

$w_{optimal,it}$: *optimal portion of fuel i at time t* Eq. (4.3)

$w_{real,it}$: *real portion of fuel i at time t*

The calculated value of L2-norm from Eq. (4.3), which is the measure of the distance between the actual and the estimated optimal portfolio, fell until the late 2000s, and then increased since the early 2010s. It is because authority decide to increase LNG generator due to easing generation capacity shortage after 2011 power crisis. Since the 1990s, the Korean government has developed large-scale coal-fired power plant complexes to cope with the rapid increase in electricity demands due to economic growth, and the oil-oriented peaking power plants have been replaced with high-efficiency combined cycle gas turbines. The transition of the power mix showed that the Korean government has effectively transitioned to the optimal configuration of power during the observed period.

Table 10. Comparison between the real generation mix and the optimal mix

	Optimal Portfolio				Real Portfolio				L2norm
	Nuclear	Coal	LNGCC	Other	Nuclear	Coal	LNGCC	Other	
1992	23.6%	38.1%	11.9%	26.4%	35.9%	17.4%	17.5%	29.3%	14.3%
1993	23.4%	38.5%	12.8%	25.3%	30.8%	23.3%	20.9%	25.1%	10.5%
1994	23.3%	38.7%	13.6%	24.4%	29.3%	26.2%	20.5%	23.9%	8.6%
1995	23.4%	38.7%	14.1%	23.8%	29.9%	27.1%	21.4%	21.5%	8.4%
1996	23.9%	38.7%	13.5%	23.9%	29.7%	24.2%	26.9%	19.2%	10.9%
1997	23.9%	39.2%	14.2%	22.6%	27.4%	27.1%	29.9%	15.6%	10.3%
1998	24.7%	39.0%	13.6%	22.8%	30.0%	28.3%	27.0%	14.7%	9.5%
1999	24.5%	39.0%	13.8%	22.8%	31.5%	29.9%	25.1%	13.5%	9.0%
2000	25.3%	39.8%	14.3%	20.6%	30.5%	31.2%	25.0%	13.4%	8.0%
2001	25.7%	39.7%	13.7%	20.9%	29.4%	33.2%	24.5%	12.9%	7.0%
2002	25.4%	39.7%	14.5%	20.4%	31.7%	32.1%	24.5%	11.7%	7.9%
2003	25.6%	39.9%	14.6%	19.9%	31.1%	31.5%	25.9%	11.5%	8.3%
2004	25.9%	40.0%	15.4%	18.8%	30.8%	32.1%	26.3%	10.8%	7.8%
2005	26.2%	40.2%	15.3%	18.3%	31.3%	31.8%	26.6%	10.3%	8.2%
2006	26.5%	41.2%	16.8%	15.5%	30.5%	31.8%	27.5%	10.2%	8.0%
2007	26.5%	41.4%	17.5%	14.6%	29.2%	33.7%	27.2%	9.9%	6.8%
2008	29.4%	42.3%	16.8%	11.5%	27.3%	36.5%	27.0%	9.3%	5.8%
2009	28.0%	41.2%	16.6%	14.2%	27.1%	37.0%	27.7%	8.2%	5.7%
2010	28.8%	42.5%	21.1%	7.6%	26.4%	36.0%	29.7%	8.0%	6.0%
2011	29.8%	43.0%	22.3%	5.0%	27.0%	34.9%	30.5%	7.7%	6.8%
2012	30.9%	44.2%	24.3%	0.6%	29.0%	34.4%	29.8%	6.8%	7.2%
2013	30.8%	44.1%	23.3%	1.8%	27.5%	32.6%	33.5%	6.4%	9.3%
2014	30.5%	43.6%	20.9%	5.0%	25.7%	32.6%	37.5%	4.1%	10.8%

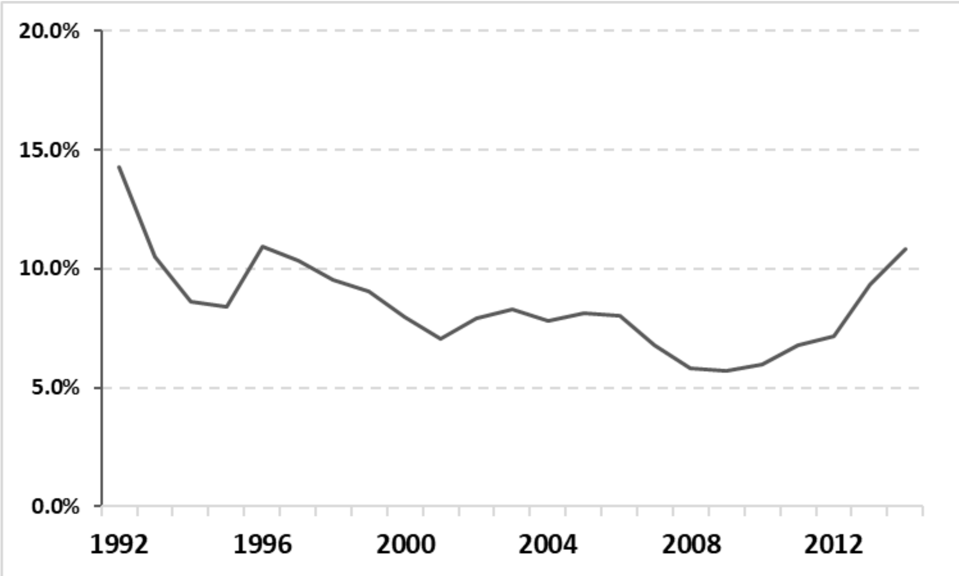


Figure 21. Trend of L2 norm between optimal and actual portfolios, 1992-2014

4.3 Estimation of 2-risk Model

In this section, we consider a two-risk model that cover the reliability risk of the power system in addition to the volatility risk. From this model, this section report the results of estimating MRSs between cost and volatility risks, cost and reliability risks, and find their implications.

The process of estimation is as follows. First, the LOLP function, which is a definition of reliability risk in this dissertation, is derived through numerical integration with Monte Carlo simulation, and the results are shown from 1992 to 2014. Next, the share equation is then estimated using the cost and variance matrix estimated in Section 4.2 and the first-order derivative of LOLP estimated in this section. Compare the estimated value of each MRS with the 1-risk model and find the implications.

4.3.1 Calculation of LOLP

To obtain the numerical integral value for deriving the LOLP in this study, we remind the definition of LOLP again, as shown in Eq. (4.4). The inverse Load Duration Curve, $D(\mathbf{q}'\mathbf{x})$, included in the LOLP function has several linear values for computational convenience. It is expressed as the sum of the functions as stated in Section 3.2. The $\mathbf{x}$, which is a probability vector representing the state of the generator, follows joint probability distribution function $g(\mathbf{x})$.

$$
\begin{aligned}
LOLP \equiv R(\mathbf{q_t}) &= \sum_k p_k \cdot t_k = \int D(\mathbf{q}'\mathbf{x}) \cdot g(\mathbf{x}) dx \\
&= \sum_{i=1}^{n} \int_{A_i} \{ b_i (\mathbf{q}_t'\mathbf{x}) + c_i \} \cdot g(\mathbf{x})\, d\mathbf{x} \\
&= \sum_{i=1}^{n} b_i \cdot \int_{A_i} (\mathbf{q}_t'\mathbf{x}) \cdot g(\mathbf{x})\, d\mathbf{x} + \sum_{i=1}^{n} c_i \cdot \int_{A_i} g(\mathbf{x})\, d\mathbf{x}
\end{aligned}
\qquad \text{Eq. (4.4)}
$$

Unlike renewable power generation, traditional generators can be operated at any point in time just by starting the generator. However, when a failure event occurs, the generator produces zero output. Therefore, the probability distribution $g(\mathbf{x})$ of the probability vector $\mathbf{x}$ becomes a combined binomial distribution. The parameters of this distribution are the total number of power generation units and the probability of annual failure by power generation sources. If they are represented by *n* and *1-p* respectively, g(x) can be expressed as Eq. (4.5).

$$
g(\mathbf{x}) = \prod_{k=1}^{4} \binom{n_k}{j_k} \cdot (1-p)^j \cdot p^{n-j}
$$

$$
where \quad \mathbf{x} = \begin{pmatrix} j_1/n_1 \\ \vdots \\ j_4/n_4 \end{pmatrix} \qquad \text{Eq. (4.5)}
$$

The failure probability of the generator was the average value for each power source applied in the government's power expansion plans, and the number of units by the power generation source was the Korea Electric Power Statistics(KEPCO, 2020), as shown in Table 11.

Table 11. Total capacity and number of generators by power sources, 1992-2014

	Generation Capcity(MW)				Number of Generators			
	Nuclear	Coal	LNGCC	Other	Nuclear	Coal	LNGCC	Other
1992	7,616	3,700	3,706	6,212	9	14	7	29
1993	7,616	5,760	5,173	6,212	9	18	10	28
1994	7,616	6,820	5,334	6,212	9	20	10	26
1995	8,616	7,820	6,184	6,212	10	22	12	27
1996	9,616	7,820	8,719	6,202	11	22	18	26
1997	10,316	10,200	11,269	5,878	12	25	24	25
1998	12,016	11,331	10,785	5,878	14	28	25	25
1999	13,716	13,031	10,935	5,878	16	32	25	25
2000	13,716	14,031	11,257	6,028	16	34	26	27
2001	13,716	15,531	11,436	6,028	16	37	26	27
2002	15,716	15,931	12,186	5,818	18	37	28	25
2003	15,716	15,931	13,086	5,818	18	37	30	25
2004	16,716	17,465	14,313	5,846	19	38	33	25
2005	17,716	17,965	15,015	5,846	20	39	35	26
2006	17,716	18,465	16,004	5,926	20	40	37	25
2007	17,716	20,465	16,511	6,026	20	44	39	26
2008	17,716	23,705	17,556	6,026	20	49	40	26
2009	17,716	24,205	18,087	5,366	20	50	41	22
2010	17,716	24,205	19,946	5,366	20	50	45	22
2011	18,716	24,205	21,160	5,366	21	50	47	22
2012	20,716	24,534	21,305	4,838	23	51	48	20
2013	20,716	24,534	25,209	4,838	23	51	57	20
2014	20,716	26,274	30,189	3,338	23	53	65	13

Note: LNG CC included facilities for cogeneration for heat and electricity.

Among the power generation sources, the LNG complex also included facilities for cogeneration. This is because, in recent years, the government's power policy direction has been decided to improve energy efficiency and expand distributed power, while LNG combined cycle power generation is built for cogeneration purposes.

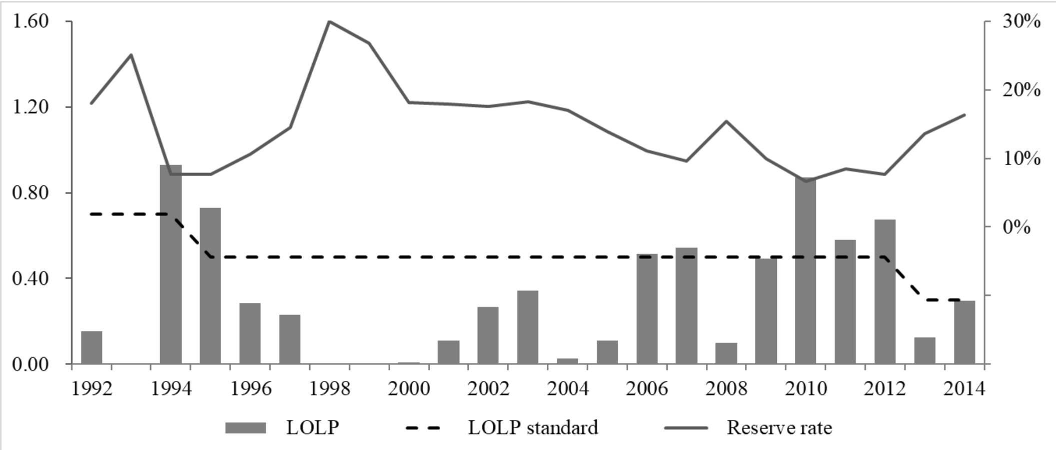


Figure 22. Calculation result of LOLP by Monte Carlo integration, 1992-2014

Figure 22 shows the result of numerically integrating Eq. (4.4) through Monte Carlo simulation. As shown in the Figure 22, LOLP has cycled but meets government regulatory standards on average, for 23 years from 1992 to 2014. The government's regulatory standard of LOLP was 0.7 days/year until 1994, and after the power crisis in 1994, the reliability regulations were tightened to reduce the number of days per year of power outages to 0.5 days. This standard continued until

2012, but after the power shortage in 2011 caused a wide area power outage, the standard was changed to the strengthened standard of 0.3 day / year and it continues to this day.

As shown in Figure 22, LOLP exceeded the legal thresholds in 1994-1995 and 2010-2012, when the reserve rate of power capacity fell below 10%. In the year when the reserve rate was over 20%, LOLP had a value close to 0, and when it was 12 ~ 22%, which is known as the appropriate level, the LOLP range was also stable at 0.1 ~ 0.5.

In this way, the first-order derivative of LOLP in the share equation was also calculated. The first-order derivative of the reliability risk function by the capacity vector q can be expressed as Equation 4.6, as described in Section 3.2 above.

$$
\begin{aligned}
\frac{d\,LOLP}{d\,\mathbf{q_t}} &= \sum_{i=0}^{n-1} \int_{A_i} \frac{d\,G(\mathbf{x},\,\mathbf{q})}{d\,\mathbf{q_t}}\,d\,\mathbf{x} \qquad A_i = \left\{ \mathbf{x} \mid z_i \le \mathbf{q}_t'\mathbf{x} \le z_{i+1} \right\} \\
&= \sum_{i=0}^{n-1} \int_{A_i} \left\{ b_i \mathbf{x} \right\} \cdot g(\mathbf{x})\; d\mathbf{x} \\
&= \sum_{i=0}^{n-1} b_i \int_{A_i} \mathbf{x} \cdot g(\mathbf{x})\; d\mathbf{x} = \sum_{i=1}^{n} b_i \cdot E_i(\mathbf{x}) \\
\textit{where}\;\; E_i(\mathbf{x}) &= \int_{A_i} \mathbf{x} \cdot g(\mathbf{x})\; d\mathbf{x} = \sum_{A_i} \mathbf{x} \cdot \prod_{k=1}^{4} \binom{n_k}{j_k} \cdot (1-p)^j \cdot p^{n-j}
\end{aligned}
\qquad \text{Eq. (4.6)}
$$

The Monte Carlo simulation was performed in the same way as the calculation of LOLP to obtain the conditional expectation $E_i(\mathbf{x})$ according to the combined binomial probability distribution $g(\mathbf{x})$. Figure 23 shows the available probability of total power generators as numbers of points in the interval where the electric power demand is from z_i to z_{i+1}, assuming there are two types of power generation sources

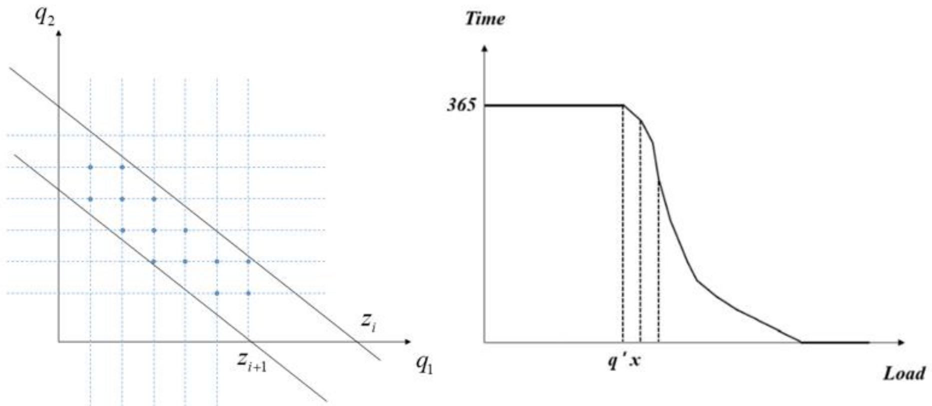


Figure 23. Conceptual graphs of the simulation for calculating $E_i(\mathbf{x})$ in 2-dimesion

4.3.2 Estimation of Share Equation

The MRS$_1$ of expected cost for its variance (γ) and MRS$_2$ of expected cost for its LOLP (τ) in described in Eq. (4.7) was estimated by using three variables. They are the mean supply cost vector ($\boldsymbol{\mu}_\mathbf{t}$) and the variance-covariance matrix ($\boldsymbol{\Sigma}_\mathbf{t}$) derived from VAR model and the first order derivative of LOLP ($\boldsymbol{\beta}_\mathbf{t}$). Eq. (4.7) is a system of the nonlinear equations where each equation share the coefficient MRS_1 (γ) and MRS_2 (τ) in common. Therefore, we estimated the MRSs by using the non-linear system equation model with Seemingly Unrelated Regression Model as mentioned in section 3.2. The estimation results and performance of the model are shown in Table 12, and Table 13.

Table 12. Estimation result of marginal rate of substitute in 2-risk model

	Coefficient	Standard Error	z
$\gamma \times 10^6$	-0.532 ***	0.083	-6.43
τ	-18.981 *	10.56	-1.8

Note: * and *** means significance at the 10%, 1% level respectively

The estimate of MRS_1 between cost and variance, γ , was strongly statistically significant at 1% level as - 0.532×10-6 , which was slightly less than that of 1-risk model, as shown in Table 11. In addition, the MRS_2 estimate between cost and reliability risk, τ, was also statistically significant at the 1% level as -18.891 in Table 12. The estimated value of the MRS_1 was considered a reasonable result since the relation between supply costs and their variance was substitutional, which means that it was a negative value. However, the coefficient estimate of the 2-risk model slightly decreased in terms of absolute values, compared to that of the 1-risk model, which seems to be because the reliability risk was added as a new variable and improve the specification of model. The estimated value of the MRS_2 was also considered a reasonable result since the relation between supply costs and reliability risk was substitutional, which means that it was a negative value.

Table 13. Performance of share equation estimation result in 2-risk model

Equation	Obs.	RMSE	R^2
Nuclear	23	0.04236	0.9788
Coal	23	0.08535	0.9318
LNC	23	0.10496	0.8620
Other	23	0.06614	0.6184

The estimation performance of each share equation was good. The R square of the nuclear power share equation was the highest at 0.9788, and the R square of the remaining thermal power sources was from 0.61 to 0.93. What is noticeable is that the share equations of nuclear, coal and gas generators improves explanatory power when reliability risks are included, while the explanatory power of oil, which is R squared, decreases from 0.84 to 0.61.

4.3.3 Empirical Results and Discussion

In the same way as the 1-risk model, to overcome the difference in scale between the level value and differential value, and express it intuitively, the estimated MRS was transformed into the elasticity between cost and its variance, as shown in Eq. (4.2).

As a result of estimating the elasticity for each year, the elasticity gradually decreased from 9 in 1992 to 4 in 2014, which is from 6 in 1992 to 3 in 2014 in 1-risk model, as shown in Figure 24. It means that about a 9% increment of supply cost was allowed to decrease 1% of cost volatility in the 1990s, but only 4% increment of supply cost was allowed to decrease 1% of cost volatility in the 2010s.

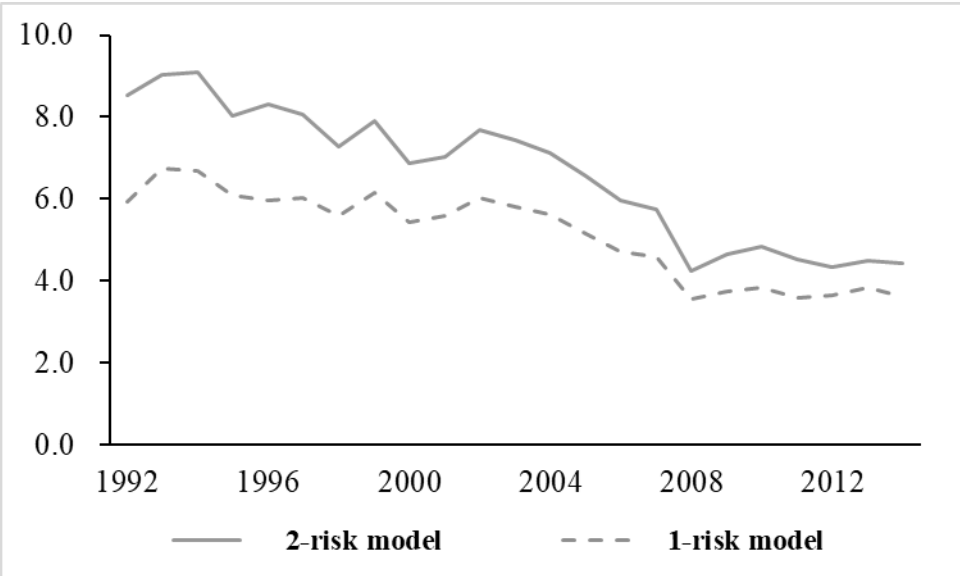


Figure 24. Comparison with trends of elasticity of variance between two models

The estimation results of 2-risk model are not very different from the 1-risk model, but it should be noted that the elasticity of volatility risk to cost in the 2-risk model was somewhat higher than in the 1-risk model. That is why the reliability should be included in this model. Because the optimal power generation share based on ordinary portfolio theory underestimate the risk of volatility if the importance of reliability in the power generation industry is ignored. This implies that the share of power sources that can lower reliability risks even with high volatility, may account for more of the optimal portfolio.

Table 14. Literatures on the estimation of Value of Lost Load (VoLL) by countries

Country	Year	Method	Customer	VOLL($/kW)	Average($/kW)
Italy	2003	WTP, Direct Worth	Commercial	28.5	21.4
			Residental	14.2	
Sweden	2006	WTP	Insdustry	8.7	8.6
			Commercial	24.2	
			Agricultrual	1.1	
			Residental	0.2	
Australia	2008	Direct Worth	Insdustry	34.1	75.0
			Commercial	85.9	
			Agricultrual	105.1	
		WTP	Residental	12.5	12.5
Austria	2009	WTP	Insdustry	23.4	16.4
			Residental	9.4	
		Direct Worth	Insdustry	130.4	246.1
			Residental	361.8	
France	2011	WTP, Direct Worth	Whole Economy	40.1	40.1
UK	2013	WTP	Ind/Com	47.7	24.4
			Residental	1.0	
		WTA	ndustry/Commerci	75.6	44.0
			Residental	12.3	

Tau is the unit cost of the reliability risk, that is, the exchange value of the risk. Tau's estimate indicates that 18.991 is willing to pay an additional cost of about 18.991 thousand won/kW for a 1-unit reduction in reliability risk. This result shows that the estimate does not deviate significantly in spite of the methodological difference between the microscopic estimation studies based on the questionnaire. Compared with the estimates of several past documents shown in Table 14, the results estimated by the WTP and WTA methods were found to seem the same, while those of the Direct Worth method were not.[2]

$$\tilde{w}_t^{*} = x_{0t} + \tilde{\gamma}\cdot\left(\Sigma_t^{-1} - \frac{\Sigma_t^{-1}\,\iota\,\iota'\Sigma_t^{-1}}{\iota'\,\Sigma_t^{-1}\,\iota}\right)\cdot\boldsymbol{\mu}_{\mathbf{t}} + \tilde{\tau}\cdot\tilde{\gamma}\cdot\left(\frac{\Sigma_t^{-1}\,\iota\,\iota'\Sigma_t^{-1}}{\iota'\,\Sigma_t^{-1}\,\iota} - \Sigma_t^{-1}\right)\cdot\boldsymbol{\beta}_{\mathbf{t}}$$
$$= x_{0t} + \tilde{\gamma}\cdot\left(\Sigma_t^{-1} - \frac{\Sigma_t^{-1}\,\iota\,\iota'\Sigma_t^{-1}}{\iota'\,\Sigma_t^{-1}\,\iota}\right)(\boldsymbol{\mu}_{\mathbf{t}} - \tilde{\tau}\cdot\boldsymbol{\beta}_{\mathbf{t}})$$

Eq. (4.7)

Since this study assumed that the social welfare function has three elements, the space for determining the optimal portfolio should also be determined in the three-dimensional space, not the two-dimensional plane. However, since LOLP can derived through numerical integration, it is virtually impossible to calculate all the numbers for each portfolio that can be expressed on a 3-dimensional space. Therefore, this study compared the portfolios of the 1-risk model and the 2-risk model by changing 2-risk model to 1-risk model. It is possible by converting reliability into economic costs using MRS_2 between reliability risk and supply cost, which means VoLL (Value of Lost Load). Eq. (4.7) is the equation given by converting the 2-risk model to the 1-risk model. As can be seen, $-\tilde{\tau}\cdot\boldsymbol{\beta}_{\mathbf{t}}$ is added to the supply cost as a penalty factor and it becomes a key element that changes the

[2] The Direct Worth method is calculated based on a questionnaire that asks the direct cost of damage suffered by customers for a virtual outage. Depending on the environment, culture, and the condition of respondents, there is a possibility of a biased response, and excessive damage costs are often reported, so VoLL estimates tends to be large compared to other survey methods such as WTP.

share of the optimal power supply.

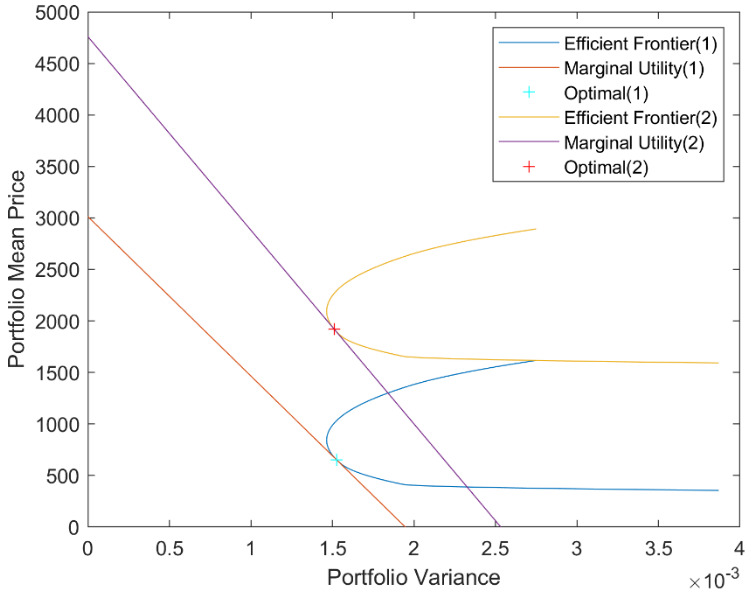


Figure 25. Shift of the optimal portfolio from 1-risk to 2-risk model in 2014

Figure 25 shows the change in the optimal portfolio in a two-dimensional plane of cost and variance in three-dimensional space. Due to the addition of a penalty factor that converts the reliability risk to cost, the efficiency frontier of the 2-risk model has risen above the 1-risk model. In addition, as the γ, which is the MRS estimate of volatility risk, slightly decreased in the 2-risk model, the slope was somewhat modest. Figure 25 shows the optimal portfolio for 2014. When comparing the portfolios between the two models, the base load generator, such as nuclear power and coal, remains almost unchanged, but the gas generator increases by 1%p and the oil generator decreases by 1.3%.

This trend of change in the optimal portfolio appears throughout the analysis period. Compared over the entire period of the analysis sample, nuclear power and coal did not show much difference, but the proportion of the gas generator, the peak facility, increased slightly. The average shares of nuclear power and coal during the entire sample period showed 25.9%, 40.1% respectively in the 1-risk model, and 26.4% and 40.6% in the 2-risk model. However, the gas generator was 15.5% in the 1-risk model, but increased by 3.1%p to 18.6% in the 2-risk model.

It is noteworthy that these results showed a more pronounced difference between high and low reliability conditions. In 1994, when the power reserve rate fell to the level of 8%, the optimal portfolio of gas generation shown by the 1-risk model was 13.2%, but in the case of the 2-risk model with added reliability risk, it was about 31.5%. This was the same in 2011, when the recent power crisis occurred, while it was about 22.3% in the 1-risk model, while it rose to 25.2% in the 2-risk model, as shown in Table 15.

Table 15. Comparison between the real generation mix and the optimal mix

	1 risk Model				2 risk Model				Difference			
	Nuclear	Coal	LNGCC	Other	Nuclear	Coal	LNGCC	Other	Nuclear	Coal	LNGCC	Other
1992	23.6%	38.1%	11.9%	26.4%	24.5%	38.6%	15.8%	21.0%	0.9%	0.5%	4.0%	-5.4%
1993	23.5%	38.4%	12.6%	25.6%	23.5%	38.4%	12.7%	25.4%	0.0%	0.0%	0.1%	-0.2%
1994	23.4%	38.5%	13.2%	24.9%	28.2%	40.0%	31.5%	0.2%	4.8%	1.5%	**18.3%**	**-24.7%**
1995	23.5%	38.5%	13.6%	24.4%	24.6%	39.8%	21.1%	14.5%	1.2%	1.2%	**7.5%**	**-9.9%**
1996	23.8%	38.5%	13.2%	24.5%	25.5%	39.8%	21.2%	13.5%	1.7%	1.3%	**8.0%**	**-11.0%**
1997	23.9%	38.9%	13.6%	23.6%	24.3%	39.5%	16.5%	19.7%	0.4%	0.5%	2.9%	-3.9%
1998	24.5%	38.8%	13.3%	23.4%	24.5%	38.8%	13.3%	23.4%	0.0%	0.0%	0.0%	0.0%
1999	24.3%	38.7%	13.2%	23.7%	24.4%	38.8%	13.4%	23.4%	0.0%	0.1%	0.1%	-0.3%
2000	25.0%	39.4%	13.7%	21.8%	25.1%	39.4%	13.9%	21.7%	0.0%	0.0%	0.1%	-0.1%
2001	25.4%	39.4%	13.3%	21.8%	25.6%	39.6%	14.2%	20.6%	0.1%	0.1%	0.9%	-1.2%
2002	25.1%	39.4%	14.0%	21.6%	25.2%	39.7%	15.5%	19.6%	0.1%	0.3%	1.6%	-2.0%
2003	25.3%	39.6%	14.1%	21.1%	25.4%	39.9%	15.8%	18.9%	0.1%	0.3%	1.7%	-2.2%
2004	25.5%	39.6%	14.6%	20.2%	25.7%	39.7%	15.0%	19.6%	0.1%	0.1%	0.4%	-0.6%
2005	25.7%	39.8%	14.6%	20.0%	26.0%	40.0%	15.8%	18.2%	0.3%	0.3%	1.2%	-1.7%
2006	26.0%	40.6%	15.8%	17.6%	26.0%	40.9%	17.5%	15.6%	0.0%	0.4%	1.7%	-2.0%
2007	26.0%	40.8%	16.5%	16.7%	26.1%	41.3%	19.0%	13.6%	0.1%	0.5%	2.5%	-3.1%
2008	28.4%	41.5%	15.8%	14.3%	28.5%	41.6%	16.6%	13.3%	0.1%	0.1%	0.8%	-1.0%
2009	27.2%	40.5%	15.7%	16.6%	27.4%	41.2%	18.7%	12.7%	0.1%	0.7%	3.1%	-3.9%
2010	27.9%	41.6%	19.3%	11.2%	28.7%	42.9%	25.6%	2.8%	0.8%	1.3%	**6.3%**	**-8.4%**
2011	28.7%	42.1%	20.4%	8.8%	29.6%	43.3%	26.3%	0.9%	0.9%	1.2%	**5.8%**	**-7.9%**
2012	29.6%	43.1%	22.3%	5.0%	30.1%	43.7%	25.2%	1.0%	0.5%	0.6%	**2.9%**	**-4.0%**
2013	29.4%	42.9%	21.4%	6.3%	29.6%	43.2%	22.4%	4.9%	0.2%	0.2%	1.0%	-1.4%
2014	29.3%	42.6%	19.3%	8.8%	29.3%	42.8%	20.4%	7.5%	0.0%	0.2%	1.0%	-1.3%

We previously compared the results of the MRS of the variances in the 1- and 2- risk models, and concluded that a model that does not take into account the reliability risk can result in underestimating volatility risk in the optimal portfolio. After all, the 2-risk model recommends increasing the proportion of gas power plants that are superior in terms of reliability even if their risk of volatility is high

4.4 Implication for Electric Power Industry Policy

In this section, we review the meaning of renewable energy when the existing portfolio theory is applied in the power generation sector, and describe alternative methodologies to find an appropriate level of renewable energy. Section 4.4.1 describes the implications of risk-free assets in the existing CAPM theory and the role of renewable energy in the power generation sector. At the same time, it shows that the area of optimal choice is limited due to the characteristics of power generator as real assets rather than general financial assets. In addition, from the viewpoint of price volatility, renewable energy has an advantage, but it is argued that if only one of those risk factors is considered, there is the possibility of excessively including renewable in the power generation portfolio. Section 4.4.2 shows how the negative utility of renewable energy in the context of the power industry, that is, intermittent power generation patterns, affects the reliability of the entire power system. In addition, we examine the change in LOLP when renewable energy is included in the power system. Section 4.4.3 examines the change in the appropriate portfolio when the proportion of renewable energy in the next 2030 is expanded as a result of this analysis.

4.4.1 Revisit to the CAPM

CAPM model extended Markowitz's portfolio theory as it considers risk-free assets. When a risk-free asset exists in a financial market, the Capital Market Line (CML) becomes an efficient investment portfolio set for all investors in the market. When the capital market line is established, investors can build a portfolio by lending or borrowing according to their preferences. At this time, the risky asset portfolio that is selected by investors becomes the portfolio that the capital market line meets in the efficiency frontier, that is, the market portfolio.

This is different from Markowitz's claim of efficient investment, where investors choose different risk assets according to their own indifference curves. It is because the portfolio to be chosen in CAPM should be determined in the market regardless of the individual's utility, and the investor only needs to maximize his utility through borrowing or lending the market portfolio.

However, the choice of the power generation facilities is different from that of the financial market. The decision-maker who chooses the portfolio of the power generation facility is not an investor who participates in the market, but a power policy official. It is similar to the fact that there is no trading counterparty and only one investor. In addition, unlike financial assets, power generation facilities are unable to borrow and lend the each other. For example, even if policy makers have a utility structure that considers the risk of volatility to be low, renewable energy assets cannot be rented or swapped with thermal power in real world.

Due to these characteristics of real assets, it is the right strategy to make optimal selection of the development portfolio based on the individual utility function according to Markowitz's theory. However, if decision makers can select renewable energy without volatility risk as a portfolio option, it is necessary to find a superior portfolio set by using the information of MRS, the trade-off ratio, obtained from one's utility function.

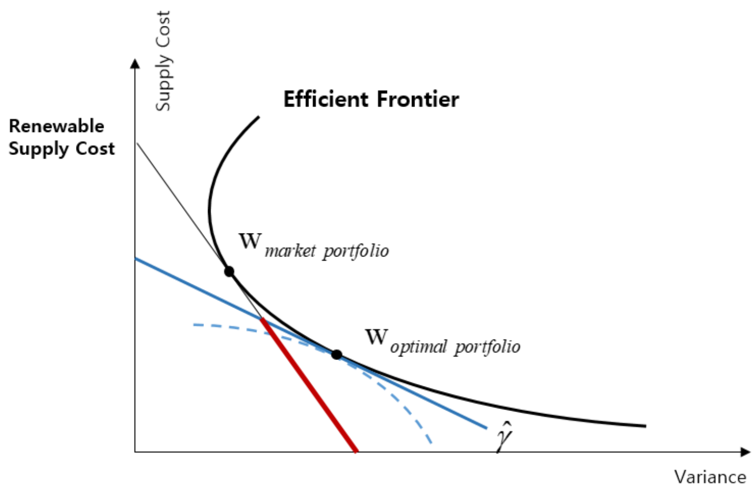


Figure 26. Superior portfolio set when renewable options are available (Case1)

Figures 26 and 27 show the superior choice area when renewable energy can be included in the portfolio of power generation assets. The black straight line, which is the same as the Capital Market Line, starts at the supply cost of renewable energy, a non-risk asset, and touches the efficiency frontier. The blue curve is the indifference curve of the policy maker's social welfare function, and the tangent line is the marginal rate of substitution (MRS). In the case of Fig. 26, the supply cost of renewable energy is very huge, which is higher than the y-intercept of the MRS tangent. In this case, the set that is superior to the optimal portfolio obtained from the social welfare function is a straight red line. That portfolio set means an area in which the proportion of the market portfolio has been more than 100% by borrowing risk-free assets. However, it is not possible in real power generation assets. Therefore, the policy maker cannot help selecting the rest area of the Capital Market Line, but they are inferior to the optimal portfolio, $W_{optimal}$. This means that in case that renewable energy becomes too expensive, including renewables in the power generation portfolio will further reduce social welfare.

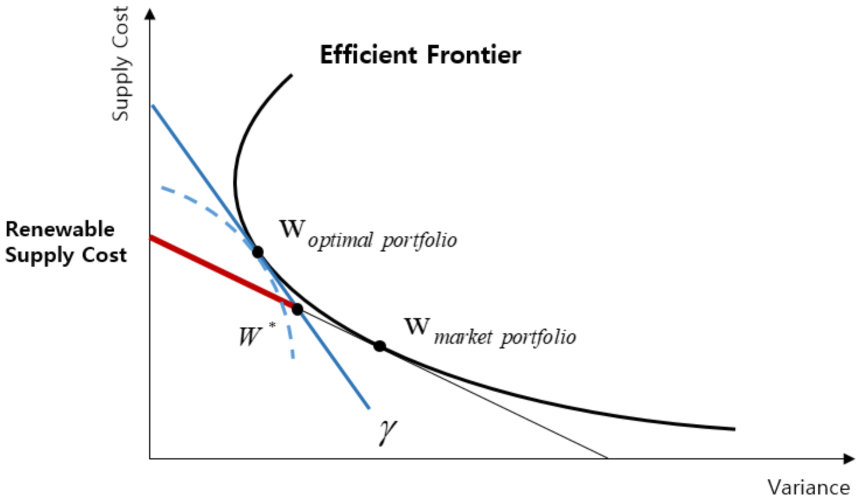


Figure 27. Superior portfolio set when renewable options are available (Case2)

However, as in the case of Figure 27, the situation is different in which the supply cost of renewable energy is lower than the y-intercept of the tangent with the estimated MRS as the slope. In this case, the points on the red straight line of the portfolio above the capital market line are superior to the optimal portfolio $W_{optimal}$ that does not contain renewable energy. In addition, according to the weak axiom of the theory of revealed preference, the W* point where the capital market line meets the MRS connection point is the portfolio that has the minimum ratio of renewable energy in the superior portfolio set. This is because the red straight section is superior to $W_{optimal}$. That is, when estimating MRS from the utility function of policy makers, it provides information on how much it is superior to include renewable energy.

In this background, this study tried to calculate the appropriate ratio of renewable energy by using renewable costs and the estimated MRS in Korea. Figure 28 shows the investment cost trend of the solar and wind power generation in Korea during 2006-2015. In the case of wind power generation, it did not show much change, but solar power fell sharply due to a decrease in solar cell module prices.

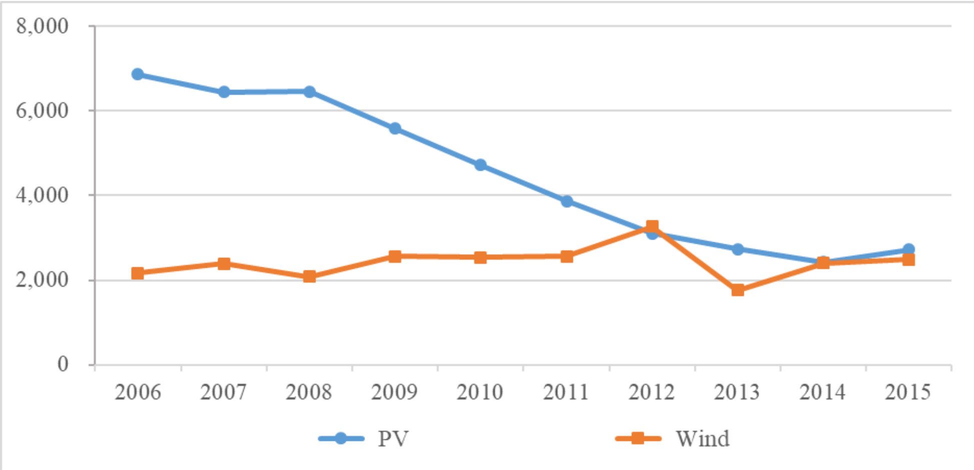


Figure 28. Investment cost trend of PV and wind turbine in Korea, 2006-2015

The annual supply cost of renewable energy includes the annualized investment cost and the fixed O&M costs. To simplify the discussion, renewable energy is considered as only PV, which is the most important source of power for the Korean government. Investment costs were referred to Korea Power Exchange(KPX, 2019). The annual operating and maintenance cost was applied as 37,365 KRW/kW according to the actual survey results of Lee(2017)'s 100kW facility(C. Lee, 2017).

Unlike traditional power generation facilities, renewable energy shows a low capacity factor, so the cost was adjusted according to the difference of capacity factors between them. In the data details of Section 4.1, the traditional power sources assume a capacity factor of 85% to estimate the annual supply cost per kW, so they produce about 5.31 times more electricity than renewable energy that has about 15% utilization rate. Therefore, the scale was adjusted by multiplying the renewable energy cost by 5.31 times.

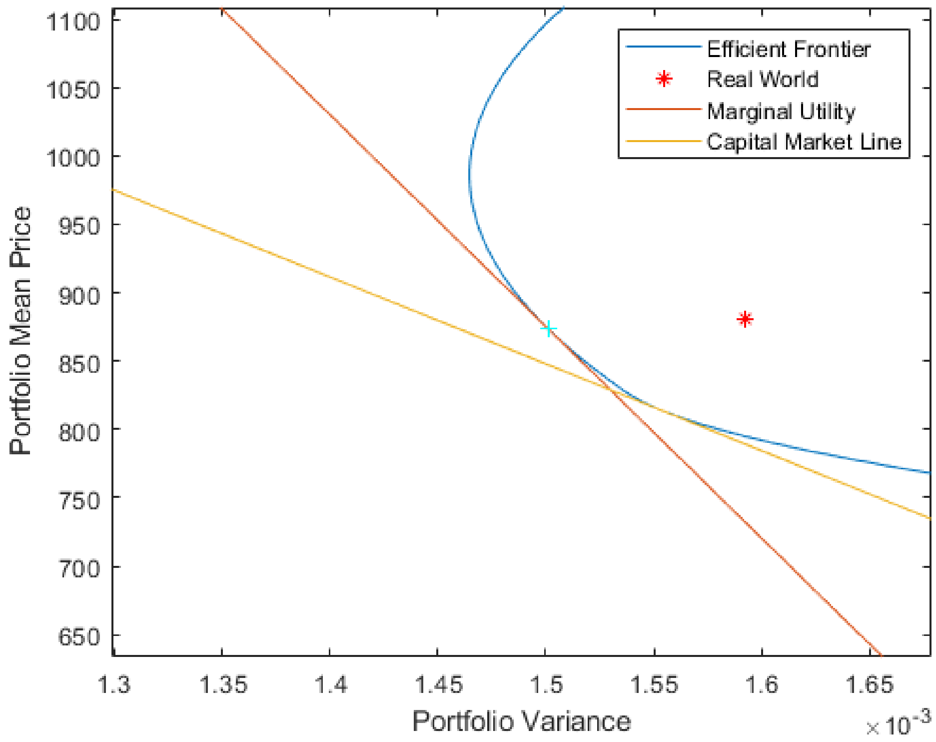


Figure 29. Comparison between Capital Market Line and the MRS tangent

As a result, the annual supply cost of photovoltaic power generation gradually decreased from 3,932 thousand KRW/kW in 2006 to 1,761 thousand KRW/kW in 2014, which decreased to about 1/2 level for 10 years. As a result of analyzing the market portfolio facing the efficiency frontier with 1,311 thousand KRW/kW as the cost of a risk-free asset, 32.9% of nuclear power, 42.7% of coal, 24.3% of LNG, and 0% of other thermal power were recorded as market portfolio. In addition, as shown in Figure 29, the share of renewable energy at the point W* where the estimated MRS tangent meets the capital market line was found to be 16.7%. This means that based on the empirically estimated MRS, it is a superior option to include more than 16.7% of renewable energy. In the Korean government's eighth Basic Plan for Power Supply and Demand, the ratio of renewable energy capacity to 33% in 2030 is considered a good choice if it is expected that the cost of renewable energy will fall further than now.

Table 16. Future portfolio comparison between optimal and government plan

	Nuclear	Coal	LNG	Oil	Renewable
8^{th} Plan	11.7%	23.0%	27.3%	0.8%	33.7%
1-risk Optimal	20.7%	26.9%	15.3%	0.0%	33.7%

Note. In the eighth Basic Plan for Power Supply and Demand, the share 3.5% of pumping storage power generator is included in addition to the above-mentioned power sources.

Table 16 shows the proportion of each power source in the eighth Basic Plan for Power Supply and Demand and the proportion of the optimal portfolio based on portfolio theory. In the eighth plan, nuclear power was about 9%p more than optimal portfolio, and LNG was about 12%p less. This seems to be because the current government's policy direction has been making a policy shift to abolish nuclear power unlike the previous government. If the phase-out of the nuclear power plant was not decided in the eighth Basic Plan for Power Supply and Demand, the share of nuclear power in 2029 was about 23.4% according to the seventh supply and demand plan. It looks so similar to the optimal portfolio.

4.4.2 Intermittency of Renewable Energy

Renewable energy is a risk-free asset in terms of volatility risk. Therefore, the more renewables the policymaker includes, the more volatility risk he can reduce. In the power system, however, there is a structural difficulty, which cannot include renewable energy indefinitely. Some storage facilities such as pumping hydro generators and ESS exist, but electricity is not easy to store. Therefore, in order for the hourly power supply to match the power load, the generators should be able to control their own output by themselves, and must prepare a certain level of reserve power capacity.

However, renewable energy has a characteristic that it cannot control its own power generation. Since the output of the renewable energy generator is determined according to the natural environment, it is difficult to react to the power load in real time. For this reason, when renewable energy is gradually expanded, many generators with fast-acting characteristics are needed for real-time balancing. Mostly, small-sized gas turbines or pumping hydro generators do so because of the rapid ramping-up and -down of the output. Therefore, the more renewable energy is expanded into the power system, the more gas generators are needed. This suggests that the proportion of optimal power capacity may change if reliability risk is considered in a power generation portfolio that includes renewables.

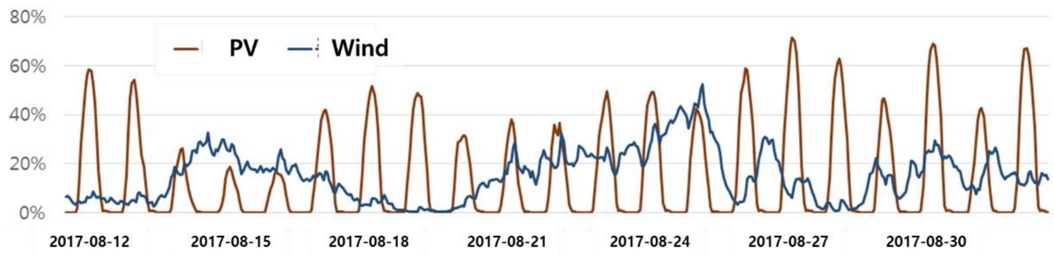


Figure 30. Generation output pattern of PV and wind turbine in summer

To this end, it is necessary to identify intermittent features of renewable energy generation. In order to identify the output distribution of Korea's intermittent renewable generation sources, hourly output data of solar PV and wind turbine generators was obtained from the Korea Power Exchange. The data period is from January 1, 2013 to December 31, 2017. The total generator capacity was 2,062MW for solar PV and 1,284MW for wind power generator, and the total number of sites was 1,807 for solar power and 98 for wind power.

Figure 30 shows the generation patterns of solar PV and wind power generators in Korea's power system over the three weeks of August 2017. In the case of solar PV, the output of day and night is regular, whereas the wind power generator shows the appearance of random and difficult to find regularity of the output pattern of day and night.

Figure 31 shows the distribution of hourly capacity factor of solar and wind power. Both solar PV and wind had skewed distributions compared to the normal distribution, but solar PV had a long tail on the left, while wind turbine had a long tail on the right.

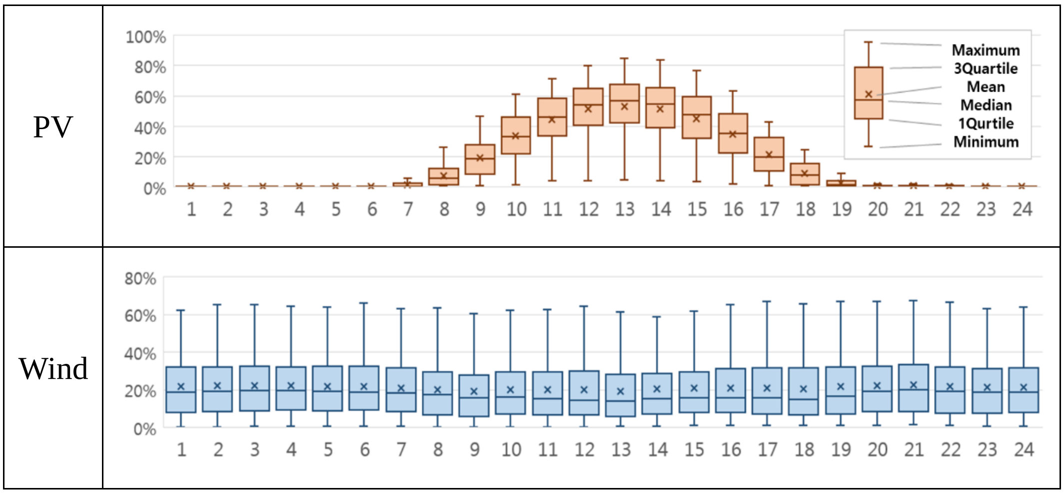


Figure 31. Distribution of PV and wind turbine by time groups, 2013-2017

In order to simulate the effect of intermittence of renewable energy on the reliability of the power system, the capacity factor at 15 hour, which is the peak time period in Korean power system, is displayed as a histogram, as shown in Figure 32 below. The reason for using the capacity factor data rather than the power generation output is that it should be normalized to one to eliminate the increase effect of the power generation due to the increase in the renewable capacity. As shown in the figure, the distribution of the output pattern at 15 hour is a multi-modal distribution with several peaks.

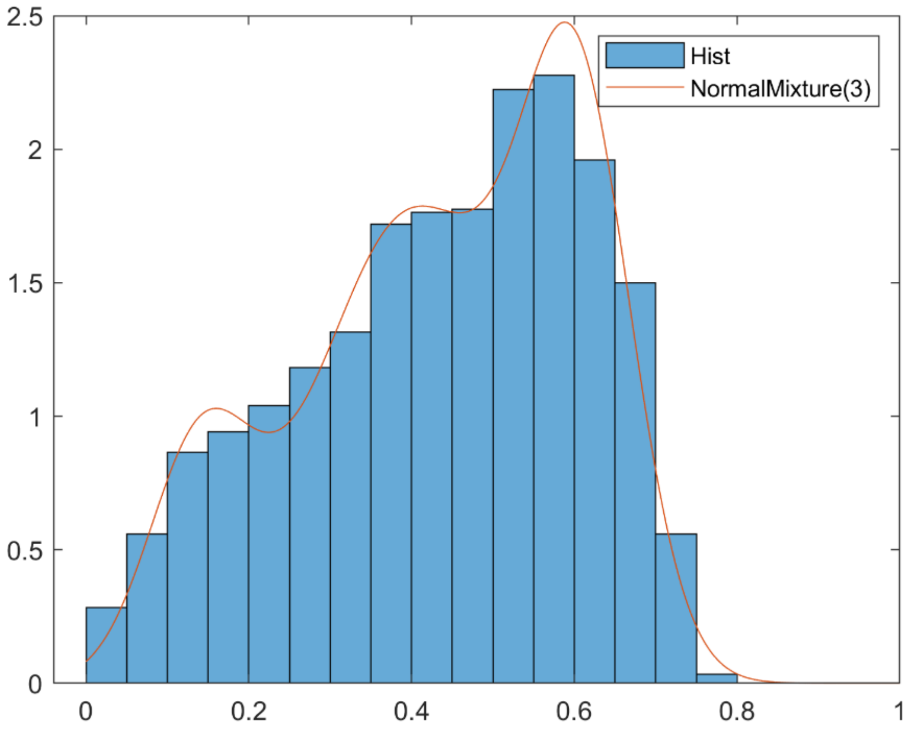


Figure 32. Power output distribution of renewable energy at time 15h in Korea

In order to perform stochastic simulation, it is necessary to define the distribution using the histogram obtained from sampled data. In this study, the distribution of renewable energy was approximated by assuming a multi-modal distribution in which several normal distributions were synthesized.

The approximation results are shown in Table 17 and Figure 33. It was found that the multi-modal distribution, which is the closest to the histogram from sample data set, is the 3-modal distribution. In the case of AIC, as the number of peaks increases, it tends to decrease more and more, but in the case of BIC, it has the smallest value in three modes. However, AIC also declined significantly from one to three and then decreased flatly from four. Based on these two facts, we assume that the renewable output distribution approximate a tri-modal distribution.

Table 17. Approximation of multi-modal distribution using normal distribution.

# of Mode	Mean					Variance				
1	0.435	-	-	-	-	0.032	-	-	-	-
2	0.581	0.320	-	-	-	0.006	0.021	-	-	-
3	**0.401**	**0.603**	**0.140**	-	-	**0.014**	**0.005**	**0.004**	-	-
4	0.380	0.570	0.670	0.132	-	0.013	0.004	0.001	0.004	-
5	0.665	0.098	0.406	0.241	0.558	0.002	0.002	0.004	0.006	0.003

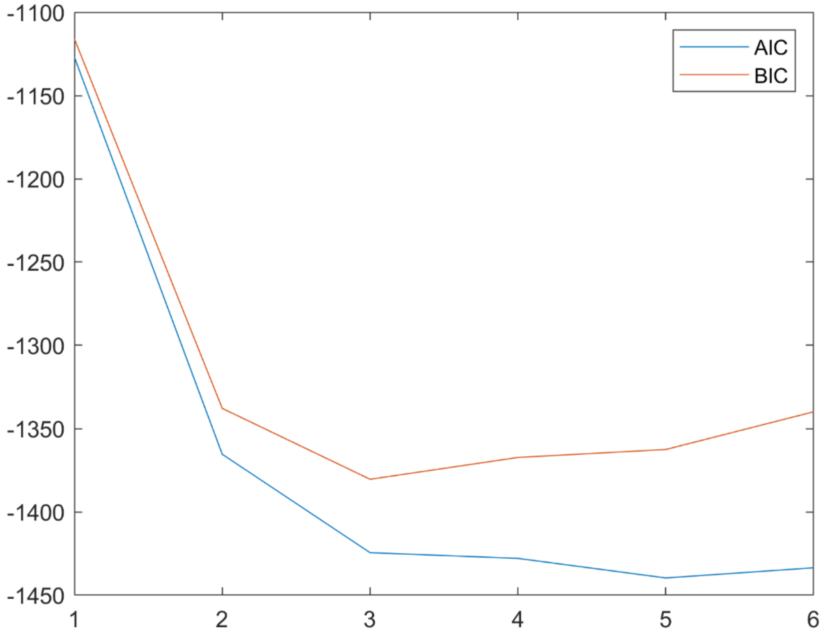


Figure 33. AIC and BIC to approximate the distribution by the number of mode

4.4.3 Future Portfolio Including Renewable Energy

In order to derive the optimal portfolio in 2030 using the two-risk model, the reliability risk when the proportion of renewable energy was 33.7%, which is the share of the eighth Basic Plan for electricity supply and demand, was simulated. The reliability risk, LOLP, was calculated by Monte Carlo simulation using a portfolio composed of 66.3% of traditional power generation sources and 33.7% of renewable energy with an intermittent power generation pattern with a tri-modal distribution as shown in Figure 32. From this simulation, the beta, the first derivative of the reliability risk in 2030 is calculated, and then applied to Eq. (4.7), the optimal portfolio in the two-risk model is derived.

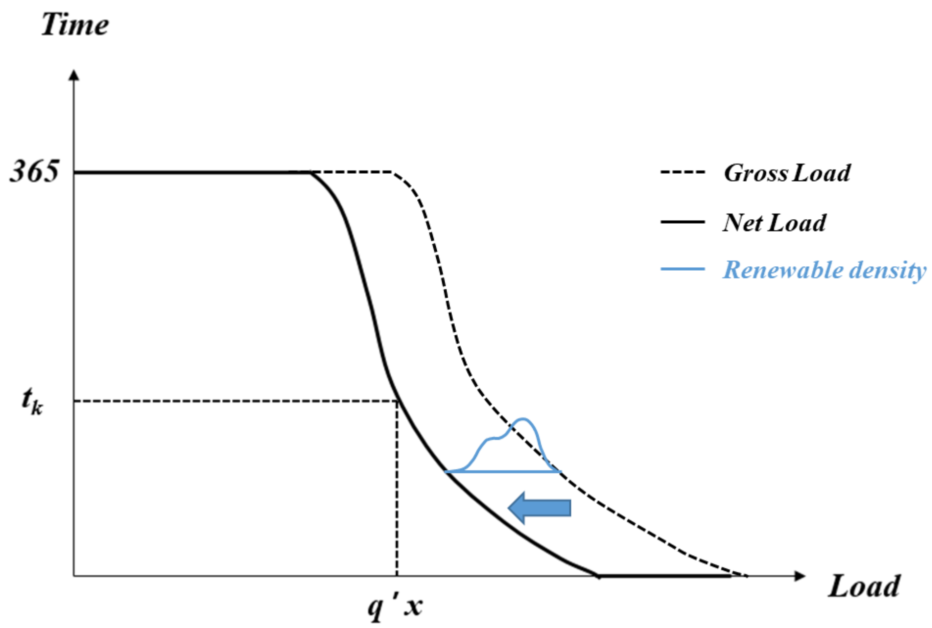


Figure 34. Concept to apply renewable intermittency to LOLP simulation

Figure 34 is a conceptual diagram of how to simulate the reliability risk including intermittent renewable energy in this study. Traditional power generation sources show multivariate binomial distribution due to the probability of failure, whereas renewable energy shows a different distribution than these, so simulation was performed using a net load, which subtracts the renewable energy from the power load, and stochastic traditional power generation sources. Electricity demand was used in 2030, as suggested by the eighth Basic Plan for Electricity Demand.

As a result of the analysis, LOLP in 2030 was found to be 0.94 day/year, which is similar to the reliability in 1994. The optimal portfolio of 2-risk model using the beta derived from this simulation and the tau estimated in Section 4.3 was 29.8% for nuclear power, 37.8% for coal, 32.3% for LNG, and 0.1% for other thermal power. This shows 3.1%p and 4.9%p lower for nuclear and coal, respectively, than the optimal portfolio of 1-risk models, which has 32.9% of nuclear power, 42.7% of coal, 24.3% of LNG, and 0% of other thermal power. On the other hands, the share of LNG in 2-risk optimum increased by 8%p. This means that increasing the proportion of gas power generators, which are small power sources and good for coping with intermittency, are better for maximizing social welfare.

Table 18. Future portfolio comparison between two optimal and government plan

	Nuclear	Coal	LNG	Oil	Renewable
8th Plan	11.7%	23.0%	27.3%	0.8%	33.7%
1-risk Optimal	20.7%	26.9%	15.3%	0.0%	33.7%
2-risk Optimal	18.7%	23.7%	20.3%	0.0%	33.7%

Note. In the eighth Basic Plan for Power Supply and Demand, the share 3.5% of pumping storage power generator is included in addition to the above-mentioned power sources.

Table 18 shows the optimal portfolio when renewable energy occupies a 33.7% share, as in the eighth Basic Plan for Power Supply and Demand. In the case of the

1-risk model, the optimal portfolio showed 15.3% of LNG, but in the 2-risk model, it was 20.3%, 5%p higher, showing a result closer to reality.

However, it is still different from the results of the eighth Basic Plan for Power Supply and Demand. In the optimal portfolio of the two-risk model, the share of coal does not show much difference from the 8th Basic Plan for Power Supply and Demand, but the share of nuclear power is 7%p higher, and the share of LNG is about 7%p lower. This is because the current government has changed its policy toward gradually retiring nuclear power plants that have reached their end of life due to safety reasons.

Chapter 5. Summary and Conclusion

5.1 Concluding Remarks and Contribution

This dissertation developed a methodology for applying the portfolio theory widely used in general financial markets to the electric power industry, and estimated important parameters using actual data, thereby deriving practical policy implications. Prior to developing the methodology, this study established the microeconomic foundation for deriving the optimal portfolio in the power industry. We borrowed the main concept from the consumer's choice theory—how much power generation equipment each source should build for policy makers to maximize their social welfare goals.

By solving this optimization problem, we derive the social planner's optimal power share equation as the FOC equation. Many studies have attempted to apply portfolio theory to the power generation sector since the pioneering research by Awerbuch (2002). However, there might be no case in which the optimal portfolio was derived by an economically valid trade-off rate of mean and variance based on the social welfare function of the policymaker. To the best of our knowledge, this is the first study to contribute to this knowledge.

The second contribution of this study is the development of a methodology to derive the optimal portfolio by reflecting the characteristics of the power industry. Ordinary portfolio theory only looks at both price and volatility risk. However, this method cannot be fully covered in the electric power industry, which is a real asset.

Minimizing the cost and volatility risk are crucial decision factors for the optimal portfolio of the power generation facility, but it is also a very important decision to balance supply and demand factor to prevent power outages. This can be called the reliability risk of the power system, and this risk must be reflected in decision making to obtain an efficient portfolio. This study developed an optimal portfolio theory that fits the context of the power industry by incorporating the risk of reliability of the power system for the optimization problem.

Using this methodology, this study estimated the marginal rate of substitution for policy makers using Korea's power generation data from 1992 to 2014. The estimation model was constructed by adding the optimization error term in the first order condition for the social welfare maximization problem. This is because Korea's policy makers who have implemented power expansion planning have chosen the portfolio based on their own optimization rule, thus the MRS derived from this equation becomes the exchange rate between the risk and cost to the Korean government.

The estimation results of the methodology and policy implications for the Korean Electric Power Industry are as follows. First, as a result of the 1-risk model, the actual power generation portfolio had fewer base load power sources such as nuclear power and coal, and a higher proportion of peak energy sources such as gas and oil than the optimum. However, the gap between these optimal and actual portfolios gradually decreased over time, meaning that the government's optimization efforts were strengthened.

Second, the attitude of policy makers in Korea toward volatility risk has gradually changed over time to risk-taking tendencies. This can be observed as the elasticity of volatility to costs. The value of the final year fell to about half in the starting year. This change in attitude means that the proportion of peak power sources, which have a relatively high risk of volatility, gradually increased, and the actual proportion of LNG optimal power generation facilities has increased substantially from 12% in 1992 to 21% in 2014.

Third, the GHG emission trading system was not introduced during the sample period, therefore, carbon costs were not reflected. When considering these costs, however, the share of the optimal power composition was found to increase the gas power slightly and reduce the oil power.

Fourth, the MRS between cost and variance, cost and LOLP estimated through the 2-risk model was estimated reasonably, and the fit of the model was further improved. While comparing the estimation results of the 1-risk model, the study has shown a significant problem that the 1-risk model underestimates the volatility risk because of the relatively high elasticity to the volatility risk.

Fifth, the optimal power portfolio based on the 2-risk model did not show a significant difference in the base-load power sources such as nuclear power and coal, but the proportion of gas power plants increased. This characteristic is even more remarkable when the reliability of the power system has worsened, and the optimal proportion of gas has risen to around 30% at the time when the power crisis occurred.

Based on these results, this study draws the following policy implications: First, policy makers' attitude toward volatility risk in Korea is gradually shifting toward a direction that is tolerant of volatility. This in reality appears toward further expansion of high volatility gas power plants. In this case, we can predict that fluctuations in the retail price of electricity for consumers will gradually increase. However, in Korea, retail consumer rates have been rigidly regulated for a long time. This is the reason that exacerbates the financial difficulties of social welfare, accordingly a transparent link between retail rates and wholesale price, which means power generation cost, is necessary.

Second, when considering the reliability risk, the proportion of gas power generation should be higher than when it is not, which means that gas power generation has a negative effect on volatility but a positive effect on reliability. The Korean government is pursuing a policy to expand renewable power generation in the future, which will increase the reliability risk of the electricity system. To prepare for this increase in reliability risk, gas generation is expected to expand further.

5.2 Limitation and Future Studies

This paper classifies power generation sources into nuclear power, coal, LNG, and others (petroleum). In recent years, renewables are being actively considered in the construction of power sources in Korea and abroad, therefore including the renewable as a type of power generation is a way to consider the recent trend. However, it has not been long since renewables were introduced in Korea, such as the RPS system starting in 2012, and renewable energy development cost statistics have not yet been compiled. In the future, as the electricity generation cost (LCOE) statistics for renewables will become reliable time series data, it is necessary to take it a step further with a model that includes renewable power.

In addition, this model is a supply-oriented model. Considering the reliability risk, this model assumes that only the supply sector is stochastically distributed. In fact, not only the supply but also the power demand is probabilistic. If the volatility of demand can be added to establish the LOLP function, it is expected that the 2-risk model can better explain the reality.

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Appendix 1: Deriving Optimal Share Equation

$$\underset{q_t}{Max} \quad U\,[E(Cost_t \mid I_t),\ Var(Cost_t \mid I_t)]$$

$$s.t. \quad i'q_t = Q_t, \quad q_t \geq 0$$

(Lagrangian) $$L = U(\ \mu_t' \cdot \mathrm{q}_t,\ \ \mathrm{q}_t' \cdot \Sigma_t \cdot \mathrm{q}_t\ ) \ + \ \lambda(Q_t - \iota' \cdot \mathrm{q}_t)$$

(FOC) $$\frac{\partial L}{\partial \mathrm{q}_t} = U_1 \cdot \mu_t' \ + \ 2U_1 \cdot \mathrm{q}_t' \cdot \Sigma_t \ - \lambda \cdot \iota' = 0$$

- Multiply both sides by $\Sigma_t^{-1} \cdot \iota$,

$$U_1 \cdot \mu_t' \cdot (\Sigma_t^{-1} \cdot \iota) + \ 2U_1 \cdot \mathrm{q}_t' \cdot \Sigma_t\,(\Sigma_t^{-1} \cdot \iota) \ - \lambda \cdot \iota' \cdot (\Sigma_t^{-1} \cdot \iota) = 0$$

$$U_1 \cdot \mu_t' \cdot (\Sigma_t^{-1} \cdot \iota) + \ 2U_1 \cdot \mathrm{q}_t' \cdot \iota \ = \lambda \cdot \iota' \cdot (\Sigma_t^{-1} \cdot \iota)$$

$$U_1 \cdot \mu_t' \cdot (\Sigma_t^{-1} \cdot \iota) + \ 2U_1 \cdot \mathrm{Q}_t \ = \lambda \cdot \iota' \cdot (\Sigma_t^{-1} \cdot \iota)$$

$$\lambda = \frac{U_1 \cdot \mu_t' \cdot (\Sigma_t^{-1} \cdot \iota) + \ 2U_1 \cdot \mathrm{Q}_t}{\iota' \cdot (\Sigma_t^{-1} \cdot \iota)}$$

- Assign λ to FOC

$$2U_1 \cdot \mathrm{q}_t' \cdot \Sigma_t \quad = -U_1 \cdot \mu_t' \ + \ \frac{U_1 \cdot \mu_t' \cdot (\Sigma_t^{-1} \cdot \iota) + \ 2U_1 \cdot \mathrm{Q}_t}{\iota' \cdot (\Sigma_t^{-1} \cdot \iota)} \cdot \iota'$$

- Multiply both sides by Σ_t^{-1}

$$2U_1 \cdot q_t{}' \;\; = -U_1 \cdot \mu_t{}' \cdot \Sigma_t^{-1} + \;\; \frac{U_1 \cdot \mu_t{}' \cdot (\Sigma_t^{-1} \cdot \iota) \; + \; 2U_1 \cdot Q_t}{\iota' \cdot (\Sigma_t^{-1} \cdot \iota)} \cdot \iota' \cdot \Sigma_t^{-1}$$

$$q_t{}' \;\; = -\frac{U_1}{2U_1} \cdot \mu_t{}' \cdot \Sigma_t^{-1} + \;\; \frac{U_1 \cdot \mu_t{}' \cdot (\Sigma_t^{-1} \cdot \iota)(\iota' \cdot \Sigma_t^{-1})}{2U_1 \cdot \iota' \cdot (\Sigma_t^{-1} \cdot \iota)} \cdot + \frac{Q_t \cdot \iota' \cdot \Sigma_t^{-1}}{\iota' \cdot (\Sigma_t^{-1} \cdot \iota)}$$

$$= \frac{Q_t \cdot \iota' \cdot \Sigma_t^{-1}}{\iota' \cdot (\Sigma_t^{-1} \cdot \iota)} + \mu_t{}' \cdot \left(-\frac{U_1}{2U_1} \right) \cdot \left(\Sigma_t^{-1} - \frac{(\Sigma_t^{-1} \cdot \iota)(\iota' \cdot \Sigma_t^{-1})}{\iota' \cdot (\Sigma_t^{-1} \cdot \iota)} \right)$$

- Transpose both sides

$$q_t \;\; = \frac{Q_t \cdot \Sigma_t^{-1} \iota'}{\iota' (\Sigma_t^{-1} \iota)} + \left(-\frac{U_1}{2U_1} \right) \left(\Sigma_t^{-1} - \frac{(\Sigma_t^{-1} \iota\iota' \cdot \Sigma_t^{-1})}{\iota' \Sigma_t^{-1} \iota} \right) \cdot \mu_t$$

Appendix 2: Deriving Derivatives of LOLP Function

❖ The Leibniz rule

$$\frac{d}{dt}\left(\int_{g(t)}^{h(t)} F(x,t)dx\right)$$

$$=\left\{F(h(t),t)\cdot\frac{d\,h(t)}{d(t)}-F(g(t),t)\cdot\frac{d\,g(t)}{d(t)}\right\}+\int_{g(t)}^{h(t)}\frac{\partial F(x,t)}{\partial t}dx$$

❖ The expansion of vector space of Leibniz rule(Flanders, 1973)

$$Let\quad \mathbf{x}=(x^1,\, x^2,\, x^3)\quad \mathbf{v}=(v^1,\, v^2,\, v^3)=d\mathbf{x}/dt$$

$$\frac{d}{dt}\left(\iiint_{D_t} F(\mathbf{x},t)\; dx^1\, dx^2\, dx^3\right)$$

$$=\iiint_{D_t}\left\{div(F\cdot\mathbf{v})+\frac{\partial F(\mathbf{x},t)}{\partial t}\right\}dx^1\, dx^2\, dx^3$$

$$=\iiint_{D_t}\left\{grad(F)\cdot\mathbf{v}+F\cdot div(\mathbf{v})+\frac{\partial F(\mathbf{x},t)}{\partial t}\right\}dx^1\, dx^2\, dx^3$$

❖ Application to LOLP function

- It is equivalent considering each element of vector **q** as t and applying the Leibniz rule of vector space

$$Let\qquad \mathbf{q}=(q_1,\, q_2,\cdots,\, q_j,\cdots)$$

- When defining a vector with each element as the first term in equation as ϕ , a vector with each element as the second term as ρ, and a vector with each element as the third term as φ, the vectors are expressed as follows.

$$\frac{d\,R(\mathbf{q})}{d\,q_j} = \sum_{i=0}^{n-1} \int_{A_i} grad\left(G(\mathbf{x})\right) \cdot \frac{\partial\,\mathbf{x}}{\partial\,q_j} d\,\mathbf{x}$$

$$+ \sum_{i=0}^{n-1} \int_{A_i} G(\mathbf{x}) \cdot div\left(\frac{\partial\,\mathbf{x}}{\partial\,q_j}\right) d\,\mathbf{x} + \sum_{i=0}^{n-1} \int_{A_i} \frac{\partial\,G(\mathbf{x},\,\mathbf{q})}{\partial\,q_j} d\,\mathbf{x}$$

$$where \quad G(\mathbf{x},\,\mathbf{q}) = \left(b_i(\mathbf{q}'\mathbf{x}) + c_i\right) \cdot g(\mathbf{x})$$

$$A_i = \left\{x | z_i \le \mathbf{q}'_{\mathbf{t}}\mathbf{x} \le z_{i+1}\right\}$$

$$\phi = \begin{pmatrix} \sum_{i=0}^{n-1} \int_{A_i} grad\left(G(\mathbf{x})\right) \cdot \frac{\partial\mathbf{x}}{\partial q_1} d\,\mathbf{x} \\ \sum_{i=0}^{n-1} \int_{A_i} grad\left(G(\mathbf{x})\right) \cdot \frac{\partial\mathbf{x}}{\partial q_2} d\,\mathbf{x} \\ \vdots \\ \sum_{i=0}^{n-1} \int_{A_i} grad\left(G(\mathbf{x})\right) \cdot \frac{\partial\mathbf{x}}{\partial q_m} d\,\mathbf{x} \end{pmatrix}, \quad \rho = \begin{pmatrix} \sum_{i=0}^{n-1} \int_{A_i} G(\mathbf{x}) \cdot div\left(\frac{\partial\mathbf{x}}{\partial q_1}\right) d\,\mathbf{x} \\ \sum_{i=0}^{n-1} \int_{A_i} G(\mathbf{x}) \cdot div\left(\frac{\partial\mathbf{x}}{\partial q_2}\right) d\,\mathbf{x} \\ \vdots \\ \sum_{i=0}^{n-1} \int_{A_i} G(\mathbf{x}) \cdot div\left(\frac{\partial\mathbf{x}}{\partial q_m}\right) d\,\mathbf{x} \end{pmatrix}$$

$$
\varphi = \begin{pmatrix} \sum_{i=0}^{n-1} \int_{A_i} \frac{\partial G(\mathbf{x}, \mathbf{q_t})}{\partial q_1} \, d\mathbf{x} \\ \sum_{i=0}^{n-1} \int_{A_i} \frac{\partial G(\mathbf{x}, \mathbf{q_t})}{\partial q_2} \, d\mathbf{x} \\ \vdots \\ \sum_{i=0}^{n-1} \int_{A_i} \frac{\partial G(\mathbf{x}, \mathbf{q_t})}{\partial q_m} \, d\mathbf{x} \end{pmatrix} = \begin{pmatrix} \sum_{i=0}^{n-1} \int_{A_i} (b_i \cdot x_1) \cdot g(\mathbf{x}) \, d\mathbf{x} \\ \sum_{i=0}^{n-1} \int_{A_i} (b_i \cdot x_2) \cdot g(\mathbf{x}) \, d\mathbf{x} \\ \vdots \\ \sum_{i=0}^{n-1} \int_{A_i} (b_i \cdot x_m) \cdot g(\mathbf{x}) \, d\mathbf{x} \end{pmatrix}
$$

- The $\partial \mathbf{x}/\partial q_j$, which in included in the vector ϕ, ρ means a change in the probability of each power source available when the capacity of a specific power source increases. It is reasonable to assume that the value is 0 in reality.

$$
\begin{aligned}
\frac{d R(\mathbf{q})}{d q_j} &= \sum_{i=0}^{n-1} \int_{A_i} \cancelto{zero}{grad\left(G(\mathbf{x})\right) \cdot \frac{\partial \mathbf{x}}{\partial q_j}} \, d\,\mathbf{x} \\
&\quad + \sum_{i=0}^{n-1} \int_{A_i} \cancelto{zero}{G(\mathbf{x}) \cdot div\left(\frac{\partial \mathbf{x}}{\partial q_j}\right)} d\,\mathbf{x} + \sum_{i=0}^{n-1} \int_{A_i} \frac{\partial G(\mathbf{x}, \mathbf{q})}{\partial q_j} \, d\,\mathbf{x} \\
&= \sum_{i=0}^{n-1} \int_{A_i} \{b_i \mathbf{x}\} \cdot g(\mathbf{x}) \, d\mathbf{x} \quad = \sum_{i=0}^{n-1} b_i \int_{A_i} \mathbf{x} \cdot g(\mathbf{x}) \, d\mathbf{x} \\
&= \sum_{i=1}^{n} b_i \cdot E_i(\mathbf{x}) \\
&\qquad \textit{where} \;\; E_i(\mathbf{x}) = \int_{A_i} \mathbf{x} \cdot g(\mathbf{x}) \, d\mathbf{x},
\end{aligned}
$$

Appendix 3: Data Set

1. Capacity(MW)

	Nuclear	Icoal	Dcoal	Oil	LNG CC	LNG ST	Other
1990	7,616	2,680	1,020	3,662	840	2,550	2,653
1991	7,616	2,680	1,020	3,662	760	2,550	2,823
1992	7,616	2,680	1,020	3,662	3,706	2,550	2,886
1993	7,616	4,740	1,020	4,425	5,173	1,788	2,893
1994	7,616	5,800	1,020	5,825	5,334	388	2,768
1995	8,616	6,800	1,020	4,675	6,184	1,538	3,352
1996	9,616	6,800	1,020	4,665	8,719	1,538	3,359
1997	10,316	9,300	900	4,340	11,269	1,538	3,380
1998	12,016	10,240	1,091	4,340	10,785	1,538	3,397
1999	13,716	11,740	1,291	4,340	10,935	1,538	3,419
2000	13,716	12,740	1,291	4,490	11,257	1,538	3,420
2001	13,716	14,240	1,291	4,490	11,436	1,538	4,149
2002	15,716	14,740	1,191	4,280	12,186	1,538	4,151
2003	15,716	14,740	1,191	4,280	13,086	1,538	5,503
2004	16,716	16,340	1,125	4,309	14,313	1,538	5,621
2005	17,716	16,840	1,125	4,309	15,015	1,538	5,717
2006	17,716	17,340	1,125	4,389	16,004	1,538	7,403
2007	17,716	19,340	1,125	4,489	16,511	1,538	7,550
2008	17,716	22,580	1,125	4,489	17,556	1,538	7,488
2009	17,716	23,080	1,125	4,479	18,087	888	8,096
2010	17,716	23,080	1,125	4,479	19,946	888	8,846
2011	18,716	23,080	1,125	4,479	21,160	888	9,895
2012	20,716	23,409	1,125	3,950	21,305	888	10,413
2013	20,716	23,409	1,125	3,950	25,209	888	11,672
2014	20,716	25,149	1,125	2,950	30,189	388	12,700

2. Investment Cost (KRW/kW)

	Nuclear	Icoal	Dcoal	Oil	LNG CC
1990	1,343,000	695,023	978,937	978,937	483,988
1991	1,697,779	695,023	1,065,039	1,065,039	474,644
1992	1,728,561	815,136	1,151,141	1,151,141	474,644
1993	1,853,171	850,394	1,237,244	1,237,244	488,005
1994	1,853,171	833,173	1,323,346	1,323,346	397,381
1995	1,853,171	1,034,753	1,409,448	1,409,448	388,149
1996	1,920,154	1,077,088	1,409,448	1,409,448	426,753
1997	1,920,154	1,048,622	1,439,224	1,439,224	472,547
1998	1,876,019	1,155,754	1,439,224	1,439,224	621,150
1999	1,878,014	1,155,754	1,439,224	1,439,224	589,091
2000	1,747,466	1,101,140	1,469,000	1,469,000	572,578
2001	1,747,466	1,101,140	1,524,250	1,524,250	572,578
2002	1,747,466	1,070,589	1,579,500	1,579,500	500,005
2003	1,884,000	1,098,865	1,634,750	1,634,750	591,929
2004	1,884,000	1,005,598	1,690,000	1,690,000	591,929
2005	2,344,283	967,639	1,690,000	1,690,000	646,580
2006	2,574,425	967,639	1,690,000	1,690,000	703,506
2007	2,592,892	972,993	1,690,000	1,690,000	781,718
2008	2,592,892	1,041,012	1,745,250	1,745,250	807,725
2009	2,592,892	962,841	1,800,500	1,800,500	959,545
2010	2,657,378	1,443,441	1,855,750	1,855,750	1,224,061
2011	2,657,378	1,461,681	1,911,000	1,911,000	1,218,523
2012	2,657,378	1,588,579	1,966,250	1,966,250	1,174,569
2013	2,724,264	1,661,007	2,021,500	2,021,500	1,130,373
2014	2,724,264	1,661,007	2,076,750	2,076,750	1,039,595

Note. Icoal means Bituminous coal from import and Dcoal means hard coal by domestic from domestic coal industry

Appendix 4: 8th Basic plan for supply and demand

1. Installed Capacity Trend, 2019-2031(MW)

	Nuclear	Coal	LNG	Renewable	Oil	Pumping	Total
2019	26,050	36,031	39,964	15,361	3,991	4,700	126,096
	20.7%	28.6%	31.7%	12.2%	3.2%	3.7%	100.0%
2020	26,050	37,281	42,050	17,761	3,991	4,700	131,832
	19.8%	28.3%	31.9%	13.5%	3.0%	3.6%	100.0%
2021	26,050	39,911	42,050	20,451	3,991	4,700	137,152
	19.0%	29.1%	30.7%	14.9%	2.9%	3.4%	100.0%
2022	27,450	42,041	42,050	23,341	2,791	4,700	142,372
	19.3%	29.5%	29.5%	16.4%	2.0%	3.3%	100.0%
2023	28,200	42,041	40,250	26,431	2,791	4,700	144,412
	19.5%	29.1%	27.9%	18.3%	1.9%	3.3%	100.0%
2024	27,250	40,921	43,310	30,696	1,391	4,700	148,267
	18.4%	27.6%	29.2%	20.7%	0.9%	3.2%	100.0%
2025	25,350	39,921	44,310	34,761	1,391	4,700	150,432
	16.9%	26.5%	29.5%	23.1%	0.9%	3.1%	100.0%
2026	23,700	39,921	44,310	38,826	1,391	4,700	152,847
	15.5%	26.1%	29.0%	25.4%	0.9%	3.1%	100.0%
2027	22,050	39,921	46,110	43,326	1,391	4,700	157,497
	14.0%	25.3%	29.3%	27.5%	0.9%	3.0%	100.0%
2028	21,100	39,921	47,460	48,226	1,391	4,700	162,797
	13.0%	24.5%	29.2%	29.6%	0.9%	2.9%	100.0%
2029	20,400	39,921	47,460	53,126	1,391	5,500	167,797
	12.2%	23.8%	28.3%	31.7%	0.8%	3.3%	100.0%
2030	20,400	39,921	47,460	58,461	1,391	6,100	173,732
	11.7%	23.0%	27.3%	33.7%	0.8%	3.5%	100.0%
2031	20,400	39,921	47,460	58,611	1,391	6,700	174,482
	11.7%	22.9%	27.2%	33.6%	0.8%	3.8%	100.0%

2. Installed Capacity(Peak Contribution) Trend, 2019-2031(MW)

	Nuclear	Coal	LNG	Renewable	Oil	Pumping	Total
2019	26,050	35,098	39,961	3,704	3,853	4,700	113,366
	23.0%	31.0%	35.2%	3.3%	3.4%	4.1%	100.0%
2020	26,050	36,222	42,047	4,045	3,853	4,700	116,917
	22.3%	31.0%	36.0%	3.5%	3.3%	4.0%	100.0%
2021	26,050	38,852	42,047	4,398	3,853	4,700	119,901
	21.7%	32.4%	35.1%	3.7%	3.2%	3.9%	100.0%
2022	27,450	40,982	42,047	4,756	2,653	4,700	122,588
	22.4%	33.4%	34.3%	3.9%	2.2%	3.8%	100.0%
2023	28,200	40,982	40,247	5,117	2,653	4,700	121,899
	23.1%	33.6%	33.0%	4.2%	2.2%	3.9%	100.0%
2024	27,250	39,862	43,307	5,799	1,253	4,700	122,171
	22.3%	32.6%	35.4%	4.7%	1.0%	3.8%	100.0%
2025	25,350	38,862	44,307	6,245	1,253	4,700	120,717
	21.0%	32.2%	36.7%	5.2%	1.0%	3.9%	100.0%
2026	23,700	38,862	44,307	6,691	1,253	4,700	119,513
	19.8%	32.5%	37.1%	5.6%	1.0%	3.9%	100.0%
2027	22,050	38,862	46,107	7,191	1,253	4,700	120,164
	18.3%	32.3%	38.4%	6.0%	1.0%	3.9%	100.0%
2028	21,100	38,862	47,457	7,699	1,253	4,700	121,072
	17.4%	32.1%	39.2%	6.4%	1.0%	3.9%	100.0%
2029	20,400	38,862	47,457	8,208	1,253	5,500	121,680
	16.8%	31.9%	39.0%	6.7%	1.0%	4.5%	100.0%
2030	20,400	38,862	47,457	8,772	1,253	6,100	122,845
	16.6%	31.6%	38.6%	7.1%	1.0%	5.0%	100.0%
2031	20,400	38,862	47,457	8,796	1,253	6,700	123,468
	16.5%	31.5%	38.4%	7.1%	1.0%	5.4%	100.0%

3. Base Scenario Trend of Demand, 2016-2031(GWh, MW)

	Consumption		Peak Load			
	Annual	Growth	Summer	Growth	Winter	Growth
2016	497,039	2.8%	85,183	10.7%	83,657	0.8%
2017	508,994	2.4%	84,586	-0.7%	86,546	3.5%
2018	523,505	2.9%	87,523	3.5%	88,907	2.7%
2019	537,973	2.8%	89,750	2.5%	91,262	2.6%
2020	552,291	2.7%	91,955	2.5%	93,594	2.6%
2021	566,714	2.6%	94,173	2.4%	95,991	2.6%
2022	579,611	2.3%	96,174	2.1%	98,148	2.2%
2023	592,145	2.2%	98,122	2.0%	100,251	2.1%
2024	604,066	2.0%	99,985	1.9%	102,325	2.1%
2025	615,788	1.9%	101,819	1.8%	104,369	2.0%
2026	627,064	1.8%	103,591	1.7%	106,342	1.9%
2027	637,866	1.7%	105,297	1.6%	108,241	1.8%
2028	647,946	1.6%	106,902	1.5%	110,023	1.6%
2029	657,725	1.5%	108,466	1.5%	111,759	1.6%
2030	666,955	1.4%	109,954	1.4%	113,407	1.5%
2031	675,367	1.3%	111,327	1.2%	114,922	1.3%

4. Target Scenario Trend of Demand, 2016-2031(GWh, MW)

	Consumption		Peak Load			
	Annual	Growth	Summer	Growth	Winter	Growth
2016	497,039	2.8%	85,183	10.7%	83,657	0.8%
2017	506,981	2.0%	84,586	-0.7%	85,206	1.9%
2018	519,069	2.4%	86,114	1.8%	87,155	2.3%
2019	530,358	2.2%	87,084	1.1%	88,538	1.6%
2020	540,054	1.8%	88,779	1.9%	90,342	2.0%
2021	548,898	1.6%	90,382	1.8%	92,104	2.0%
2022	556,088	1.3%	91,464	1.2%	93,314	1.3%
2023	561,700	1.0%	92,553	1.2%	94,525	1.3%
2024	566,228	0.8%	93,527	1.1%	95,672	1.2%
2025	569,824	0.6%	94,359	0.9%	96,670	1.0%
2026	572,800	0.5%	95,104	0.8%	97,568	0.9%
2027	575,229	0.4%	95,797	0.7%	98,404	0.9%
2028	577,029	0.3%	96,399	0.6%	99,131	0.7%
2029	578,515	0.3%	96,986	0.6%	99,839	0.7%
2030	579,547	0.2%	97,533	0.6%	100,498	0.7%
2031	580,443	0.2%	98,010	0.5%	101,065	0.6%

Abstract (Korean)

지금까지 장기 전원계획은 주로 비용최소화를 바탕으로 이루어져왔다. 하지만, 2000 년대 이후부터 Markowitz 의 포트폴리오 이론을 발전설비의 포트폴리오에 적용하는 연구가 본격적으로 이루어지기 시작하면서 큰 변화가 나타났다. 그러나 선행의 많은 연구들은 발전비용의 평균과 분산을 통해 포트폴리오의 효율 경계를 찾는데 주된 목적을 두었고, 그 두 요소 간의 교환비율이 어떻게 되는지에 대한 연구는 이루어지지 않았다. 그래서 효율경계로부터 최적 전원구성의 찾아내는 방법은 시나리오 기법에 의존하거나, 전통적인 CAPM 모형을 이용하여 시장 포트폴리오를 도출하는데 그쳤다.

본 논문의 첫 번째 목적은 평균-분산 모형을 적용한 최적 전원 믹스를 분석함에 있어서, 비용의 평균과 그 변동성 간의 교환 비율, 즉 trade-off 관계를 합리적으로 추정하는데 있다. 두 번째 목적은 최적 전원구성을 고려함에 있어서, 전력산업에서 반드시 고려해야하는 신뢰도 위험을 분석 모형에 반영하는 것이다. 기존의 많은 연구들은 발전 자산이 마치 자본시장에서 거래되는 유가증권과 같은 방식으로 분석되었으나, 현실의 발전설비 투자는 비용최소화와 변동성 회피뿐만 아니라, 전력 신뢰도를 유지하는 것이 매우 중요하다. 본 논문에서는 신뢰도 위험을 공급지장확률(LOLP)로 정의하여, 전원계획을 수립하는 정책당국자의 효용함수의 한 요소로 반영하여 평균-분산 포트폴리오 모형을

확장시켰다. 모형의 미시적 기초는 변동성 위험만을 고려한 1위험 모형과 동일하며, 우리나라의 LOLP 함수를 산출하기 위하여 몬테카를로 시뮬레이션을 이용하였다.

이러한 연구목표와 방법론으로부터 얻은 결과는 다음과 같다. 첫째, 비용과 비용의 변동성의 관점에서 정책입안자가 바라보는 두 요소간의 대체 비율은 1992~2014 년 동안 점차 변동성을 허용하는 쪽으로 선호가 변경되었다. 이는 1970 년대 오일쇼크 이후 원자력과 석탄으로 발전원의 다각화를 시도하였다가, 1990 년대 이후부터 친환경적이고 발전효율이 지속적으로 개선된 LNG 복합발전이 확대된데 큰 이유가 있었다. 둘째, 실제 전원구성은 분석기간 동안 점차 최적 포트폴리오에 근접해지고 있었으나, 대규모 순환정전이 발생하였던 2011 년 이후로 LNG 복합발전의 비중이 최적에 비해 훨씬 늘어났다. 이는 2010 년대 초, 전력수급위기에 대응하여 건설 기간이 짧은 LNG 복합발전의 건설 승인이 상당수 늘어난데 그 원인을 찾을 수 있다. 셋째, 전력신뢰도를 고려할 경우 최적 전원구성 비율은 변동성만 고려한 모형보다 피크발전설비, 그 중에서도 특히 LNG 의 비중이 늘어나는 것으로 나타났다. 이는 복합발전 기술이 여러 대의 가스 터빈과 스팀터빈으로 이루어져, 발전기당 단위 기 용량이 작아 고장 발생에도 상당한 분산 효과가 있기 때문이다.

이러한 결과를 바탕으로 전원구성에의 정책적 시사점을 도출하면, 향후 전원구성에는 현재보다 LNG 의 비중이 더 늘어나야 할 것으로 보인다. 이는 정책입안자의 효용도 비용의 변동성을 점차 허용하는 관점으로

변하고 있고, 신뢰도 측면에서도 다른 전원에 비하여 우월한 특성이 있기 때문이다. 특히, 온실가스 배출 비용의 증가와 신뢰도 위험을 증가시킬 신재생 전원의 정책적 확대는 앞으로 더 많은 LNG 설비를 필요로 할 것으로 예상된다.

주요어: 포트폴리오 이론, 최적 전원구성, 변동성 위험, 신뢰도 위험, 전력수급기본계획, 공급지장확률
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