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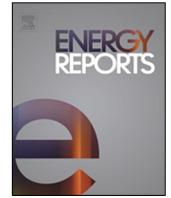
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Research paper

Effects of the move towards renewables on the power system reliability and flexibility in South Korea



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ABSTRACT

The plan to shift towards renewable energy has recently become the central part of the energy policy on the power system in South Korea. The sudden shift towards renewable energy has raised questions regarding the reliability and flexibility of the power system. This paper proposes a research framework to evaluate the new policy in South Korea from various aspects using three simulation models in a series. The first optimal generation model finds the optimal electricity generation mix and provides the total generation cost and environmental impact of the given long-term capacity expansion plan. The other two simulation models assess the reliability and flexibility of power systems, respectively. Within the research framework, we introduce a new probabilistic index to quantitatively measure the flexibility. The results of applying the framework into the new policy show that the policy fails to guarantee the target reliability level and increases costs and emissions. Achieving target system reliability will require additional capacity, and system flexibility is very sensitive to the type of capacity added. If the Korean government decides to add more capacity, natural gas turbine power plants turn out to be a good option from the point of economic, environmental, and flexibility considerations.

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1. Introduction

The Korean government has been establishing a 15-year plan for long-term electricity supply and demand biennially since 2002 (KPX, 2015, 2017). Since the plan has an enormous influence on the society and economy of the country, it is devised by experts in diverse fields by taking economic, social, and environmental issues into consideration. Nevertheless, over the past few years, South Korea has endured large social costs and inefficiencies in the power market caused by erroneous decisions by the government in establishing the plan. For example, there were power blackout risks because of power supply shortages from 2011 to 2014, following which the government has dramatically increased the approval of new power plants.

In 2017, a new energy policy that aims to phase out not only coal power plants because of the recent air quality issue but also nuclear power plants because of the public acceptance issue was announced. The new policy is aligned with the global energy transition movements toward renewable energy (Child et al., 2019). Accordingly, the most recent plan for long-term electricity supply

and demand, announced in December 2017 (hereafter “the 8th plan”), aims to reduce the dependence of the country’s electricity supply on coal and nuclear power to about 60% by 2030 from more than 75% in 2017 (KPX, 2017). The 8th plan also aims to dramatically increase the share of renewable energy from the current level of about 6% to 20% by 2030, replacing coal and nuclear power. The target share of renewable energy in 2030 is about 7% higher than that of the former plan announced in 2015 (called “the 7th plan”) (KPX, 2015; Choi et al., 2015). That is, South Korea needs to add 30.8 GW of solar power plants and 16.5 GW of wind power plants, which is about 10 times more than the current capacity of 2.7 GW and 1.2 GW, respectively.

The new policy has created a great deal of controversy within the electricity sector community. Many experts have concerned that the shift towards renewable energy and nuclear power phase-out could have negative effects on the economic efficiency and reliable operation of the power system. More importantly, the experts have expected that the adoption of large-size renewable energy sources, mainly solar and wind energy, will create a challenge of balancing supply and demand for the power system. This is owing to the stochastic nature of major renewable energy sources and the low ability of a power system to increase (or decrease) the amount of power generated within a certain time

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frame in response to a change in the net load (Bouffard and Ortega-Vazquez, 2010; Lannoye et al., 2012).

The Korean government has been mainly using a commercial software package (WASP¹) to develop and evaluate its long-term electricity supply and demand plans. The WASP software has been effective so far because it has successfully estimated the benefits of the plan from an economic perspective. In addition, since the share of solar and wind power is negligible in Korea, the technical limitations in assessing the reliability and flexibility of the power system integrated with large-scale renewable energy have not been such an important issue yet. However, a shift towards renewable energy, as mentioned in the 8th plan, requires a transformation of the way that the power system is planned to incorporate an assessment of its *reliability* and *flexibility*.

This study, therefore, has a twofold purpose: First, we extensively review the literature, that quantitatively evaluates the long-term capacity expansion plan in terms of power system reliability and flexibility, and propose a research framework modified for the Korean power system. Second, we use the proposed methodology to empirically evaluate the new energy policy (i.e., the 8th plan) in Korea. On the basis of this evaluation, we highlight the important policy issues in the new plan and provide several suggestions for potential amendments.

The rest of this paper is organized as follows. Section 2 reviews the previous literature on power system capacity expansion planning considering power system reliability and/or flexibility. In this section, we will clearly state the differences between previous methodologies and our proposed one clearly. Section 3 describes the revised methodology suggested in this paper. Section 4 describes data, basic assumptions, and test scenarios, and Section 5 presents the results of the analysis. Finally, Section 6 concludes by summarizing the key policy implications.

2. Literature review

As electric power systems in developed countries have undergone rapid expansion, which has been occurring since the early 1970s, research on long-term power system capacity expansion planning has emerged (Bessiere, 1970; Anderson, 1972; Peterson, 1973). The earliest research established basic optimization models that considered only cost-efficiency. From the late 1970s to mid-1980s, much research extended the basic models to include system reliability (Scherer and Joe, 1977; Noonan and Giglio, 1977; Cote and Laughton, 1980; Bloom, 1982; Stremel, 1982), uncertainty in forecasting demand, and unexpected failures in power plants. For example, probabilistic constraints were employed to formulate the probability of unsatisfied demand occurring during a peak period. However, the computational burden hindered the practical use of optimization models that explicitly include uncertainty. To overcome computational limitations, an approximation method was widely adopted for practical electric power systems (Cote and Laughton, 1980; Bloom, 1982; Stremel, 1982). Moreover, several software packages, such as WASP, have now been commercialized and actively implemented in several developing countries, including Korea. Despite their popularity, these models have ignored the details of operating costs and constraints associated with uncertainty because they mostly employed deterministic programming models (Dagoumas N.E. Koltsaklis, 2018). For example, deterministic demand profiles are assumed based on historical patterns to represent uncertain demand realizations. The costs and constraints employed by deterministic models decrease the computational burden but fail to provide additional meaningful information.

After earlier studies, variants of models were developed to effectively address growing uncertainty (Hobbs, 1995). In particular, a growing body of literature has used stochastic programming models to include uncertainty associated with demand because of the growing concerns about power system reliability (Jin et al., 2011; Feng and Ryan, 2013; Min and Chung, 2013; Pineda et al., 2014; Pisciella et al., 2016; Pineda and Morales, 2016; Pineda et al., 2016; Park and Baldick, 2016; Min et al., 2018). Most of these papers considered power system reliability as a penalty cost for not satisfying demand, and the penalty cost is included in their optimization models (Jin et al., 2011; Feng and Ryan, 2013; Pineda and Morales, 2016; Pineda et al., 2016; Park and Baldick, 2016; Jin et al., 2014). However, it is difficult to estimate the penalty costs because of its ambiguity so that the costs may vary according to assumptions. Other literature instead included a constraint explicitly representing reliability measures such as CVaR (Conditional Value-at-Risk) or LOLP (Loss of Load Probability) (Pisciella et al., 2016; Min et al., 2018).

More recently, a few studies in the literature have begun to consider short-term variability as one of the critical operational constraints in long-term capacity expansion decisions. Shortt et al. (2013) evaluated the importance of utilizing operational constraints in long-term planning models. Khodaei et al. (2011) proposed a framework for the optimal expansion planning of fast-response thermal units under a given level of wind integration. Jonghe et al. (2011) developed a long-term planning model that includes the optimal annual operational scheduling of a power system. Jin et al. (2014) developed a stochastic model that includes not only the short-term operational characteristics of thermal power plants but also the long-term uncertainty in the availability of and variability in the weekly wind pattern.

Meanwhile, various flexibility measures have been proposed to accommodate the short-term variability in both power generation and demand from multi-aspects. Heggarty et al. (2019) categorized the flexibility measures into three types depending on their role; a resource's ability to provide flexibility, a system's ability to provide flexibility and a system's needs for flexibility. For example, Ma et al. (2013) defined the flexibility of a power system as the ability of a power system to cope with variability and uncertainty in both power generation and demand. Sarrinen et al. (2015) used an energy storage volume and a balancing power measure to quantify the flexibility needs induced by variable renewable energy sources. Papaefthymiou et al. (2018) presented the flexibility tracker, an assessment method for monitoring and comparing the readiness of power systems for high variable renewable energy shares.

Although some aforementioned studies have investigated the short-term operational flexibility as constraints and devised flexibility measures in the long-term planning model, only a few studies have explicitly defined an index for measuring and quantifying the operational flexibility (Abdin and Zio, 2018). Moreover, industry practitioners have difficulties in measuring power system flexibility and deciding how much and which type of capacity should be added to achieve the target flexibility level. Accordingly, we attempt to make a contribution to the current literature by introducing a new index for measuring operational flexibility in the context of the long-term planning model. Based on the idea of power system reliability such as LOLP, this study proposed a flexibility index that measures the failure probability in balancing demand and supply because of the lack of operational flexibility. By doing so, we believe that the proposed flexibility index will provide practitioners with clear information on the degree of flexibility in long-term planning.

To the best of our knowledge, little research has been conducted on how to measure power system flexibility in the context of long-term capacity expansion planning, and many practitioners

¹ The WASP package was originally developed by the Tennessee Valley Authority and the Oak Ridge National Laboratory in the U.S. and is currently maintained by the International Atomic Energy Agency (IAEA)

currently use mathematical models and/or commercial software packages only for assessing a pre-designed plan from various aspects in Korea. Our recent study proposed a method for finding an optimal long-term capacity expansion plan while considering the large-scale integration of renewable energy, but it evaluated the power system only from the reliability perspective. This study extends our previous study (Min et al., 2018) by including power system flexibility. In addition, we aim to evaluate reliability and flexibility of given capacity expansion plans instead of finding an optimal capacity expansion plan that guarantees target reliability or flexibility level.

3. Research methodology

In this section, we aim to propose a framework for the quantitative evaluation of the long-term capacity expansion plan in terms of power system reliability and flexibility. The framework proposes three models to measure the desired outputs, including not only system flexibility and reliability but also generation costs and environmental impacts. First, the optimal generation model is used to determine the optimal electricity generation mix in any given capacity expansion scenario and based on technology characteristics data. The generation model estimates the total generation costs and environmental impacts (e.g., GHGs and air pollutant emissions) under the optimal electricity generation mix. The optimal mix is then fed into the simulation models, which evaluate the probabilistic indices for reliability and flexibility of the power system. We have incorporated random factors into the three models to account for system uncertainty associated with the demand and availability of generation technologies. Fig. 1 illustrates the framework with all its constituent components and their interactions. For further descriptions of the models, we have used the notations summarized in Table 1.

3.1. The optimal generation simulation model

We formulate the optimal generation decisions using a stochastic programming model by modifying our previous work (Min et al., 2018) (see Eqs. (1)–(8)). However, according to the research purpose, the proposed optimal generation model only determines the electricity generation mix for a given capacity expansion plan without considering the constraint for a reliability measure, LOLP. That is, unlike our previous model, the capacity expansion plan, which is defined in the model as z_{it} , z_{jt} , y_{it} , and y_{jt} , is assumed to be given as parameters because we decided to focus on evaluating the given plan instead of finding an optimal decision.

Referring to the literature (Jonghe et al., 2011; Ma et al., 2013), we particularly include a critical operational constraint (Eq. (6)) on upward operating reserve that can affect flexibility index. Both ramp-up and ramp-down rates of a generation technology are generally identical, and the operational constraint for the downward operating reserve is mirrored to that for the upward operating reserve. Furthermore, the preliminary analysis on hourly net load shows that the Korean power system requires a higher ramp-up rate than a ramp-down rate to meet the demand satisfactorily. Therefore, our model considers only the operational constraint for the upward operating reserve in order to reduce the computational burden.

The objective of the model is to minimize the total expected cost discounted at the rate of γ (Eq. (1)). The annual cost in year t (π_t) consists of the annualized upfront investment costs ($\sum_{i=1}^I c_i^u z_{it} k_{it} + \sum_{j=1}^J c_j^u z_{jt}$), the fixed costs for operating capacity ($\sum_{i=1}^I c_i^f z_{it} y_{it} + \sum_{j=1}^J c_j^f y_{jt}$), and the variable costs for generating electricity ($c_i^v \sum_{\tau=1}^L x_{i\tau t}^{\xi} + c_j^v \sum_{\tau=1}^L x_{j\tau t}^{\xi}$). The optimal amount of power generation should meet the demand for each time-slice

τ in year t (Eq. (3)) while being constrained by the available capacity (Eqs. (4) and (5)). In Eq. (4), we formulate $g_{it\tau}^{\xi}$, which represents the number of available plants using technology i , as a binomial random variable to accommodate the possibility of forced outages in conventional generation technologies. If the forced outage rate (q_i) represents only a preventive outage schedule, the availability of a plant possibly depends on its outage status in the previous period. However, we assume the time-independence of outage events because q_i should include not only a preventive outage but also other unexpected outage events (IEEE, 2007).

Eq. (6) represents the upward operating reserve and constrains the changes in electricity generation in conventional power plants. The changes are determined by taking the minimum between residual capacity ($z_i g_{iht}^{\xi} - x_{ih-1t}^{\xi}$) and ramp up capacity ($R_i^{up} x_{ih-1t}^{\xi} + R_i^{up} N_i^{up} (z_i g_{iht}^{\xi} - x_{ih-1t}^{\xi})$) under a given capacity mix in the power system. The residual capacity represents the amount of non-committed capacity (non-spinning reserve) in the previous hour, and the ramp-up capacity is defined as the sum of the ability to change the output from the committed capacity (spinning reserve) in the previous hour and ability to change the output from non-committed capacity in the previous hour. The total amount of electricity generated during the ramp-up period should be the same as the amount of electricity generated at the time-slice for the ramp-up period (Eq. (7)). Finally, Eqs. (8) and (9) show the capacity transfer constraints.

Optimal Generation Model:

$$\min \pi_0 + \frac{1}{(1+\gamma)} E_{\xi^1} \left[\min \pi_1 + \frac{1}{(1+\gamma)} E_{\xi^2 | \xi^1} \right. \\ \left. \times \left[\min \pi_2 + \dots + \frac{1}{(1+\gamma)} E_{\xi^T | \xi^1, \dots, \xi^{T-1}} [\min \pi_T] \right] \right] \quad (1)$$

$$\text{s.t. } \pi_t = \sum_{i=1}^I [c_i^u z_{it} k_{it} + c_i^f z_{it} y_{it} + c_i^v \sum_{\tau=1}^L x_{i\tau t}^{\xi}] + \sum_{j=1}^J [c_j^u z_{jt} \\ + c_j^f y_{jt} + c_j^v \sum_{\tau=1}^L x_{j\tau t}^{\xi}] \quad (2)$$

$$\sum_{i=1}^I x_{i\tau t}^{\xi} + \sum_{j=1}^J x_{j\tau t}^{\xi} \geq D_{\tau t}^{\xi}, \forall \tau, t \quad (3)$$

$$x_{i\tau t}^{\xi} \leq z_i g_{it\tau}^{\xi} \eta_{\tau} \text{ where } g_{it\tau}^{\xi} \sim B(y_{it}, 1 - q_i), \forall i, \tau, t \quad (4)$$

$$x_{j\tau t}^{\xi} \leq A_{j\tau}^{\xi} \eta_{\tau}, \forall i, \tau, t \quad (5)$$

$$x_{iht}^{\xi} - x_{ih-1t}^{\xi} \leq \min [z_i g_{iht}^{\xi} - x_{ih-1t}^{\xi}, R_i^{up} x_{ih-1t}^{\xi} \\ + R_i^{up} N_i^{up} (z_i g_{iht}^{\xi} - x_{ih-1t}^{\xi})], \forall i, h, t \quad (6)$$

$$\sum_{h=1}^H x_{iht}^{\xi} = x_{i2t}^{\xi}, \forall i \quad (7)$$

$$y_{it} = y_{it-1} + k_{it}, \forall i, t \quad (8)$$

$$y_{jt} = y_{jt-1} + z_{jt}, \forall j, t \quad (9)$$

$$x_{i\tau t}^{\xi}, x_{j\tau t}^{\xi} \geq 0, \forall i, j, t \quad (10)$$

We use the sample average approximation (SAA) method to determine the optimal electricity generation mix with an objective to minimize the total costs. The SAA method first transforms the original stochastic optimal generation model into the deterministic equivalent model by applying a finite set of samples (sample size of N). We then solve the deterministic model multiple times (M iterations) to achieve better solution quality. By running preliminary experiments, we set N and M to be 200 and 30, respectively. Readers can refer to our previous works for the details of the SAA method (Min and Chung, 2013; Min et al., 2018).

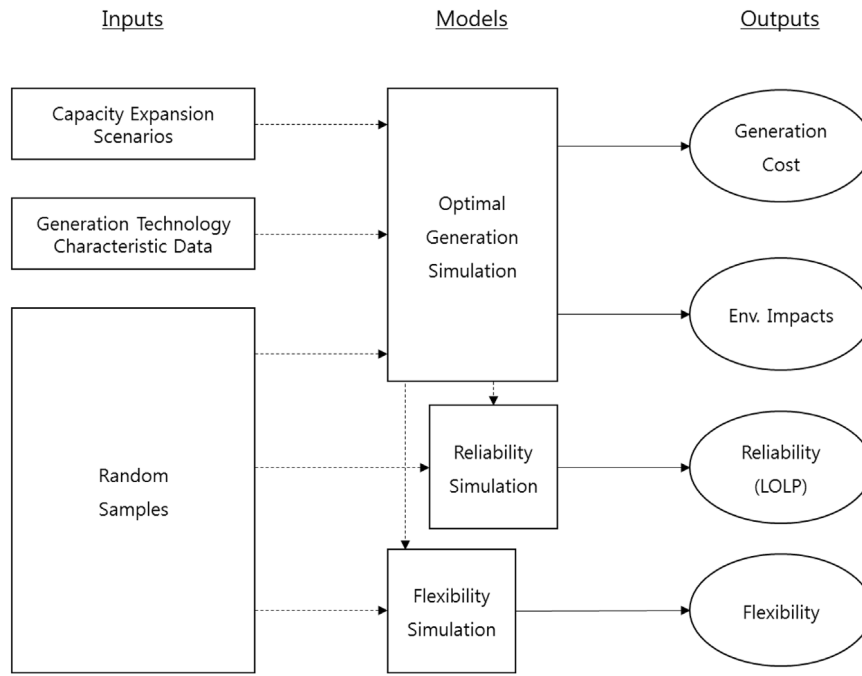


Fig. 1. Research framework: three models and their inputs/outputs.

Table 1

Notation summary.

Set and indices	
$i \in I$	Conventional generation technologies (e.g., nuclear, coal, LNG, etc.)
$j \in J$	Renewable energy technologies (e.g., solar PV, wind etc.)
$t = 1, 2, \dots, T$	Years over the planning horizon
$\tau = 1, 2, \dots, L$	Time-slices within a year (let $\tau = 1$ to correspond to the peak period and $\tau = 2$ To correspond to the ramp-up period)
$h = 1, 2, \dots, H$	Hours over the ramp-up period
$\xi^t \in \Xi^t$	Random scenario in year t
Decision variables	
π_t^ξ	Total costs in year t under scenario ξ (e.g. USD, KRW)
$X_{i\tau t}^\xi$ ($X_{j\tau t}^\xi$)	Amount of electricity generated using technology i (or j) at time-slice τ in year t (MWh)
X_{iht}^ξ	Amount of electricity generated using technology i at hour h in year t (MWh)
Input parameters	
z_i	Reference nameplate capacity of a plant using conventional generation technology i (MW)
z_{jt}	Nameplate capacity of renewable energy technology j and newly installed in year t (MW)
k_{it}	Number of plants using conventional technology i and newly installed in year t (units)
y_{it}	Total number of plants using conventional technology i in year t (units)
$g_{i\tau}^\xi$	Number of available plants using technology i at time-slice τ (units)
y_{jt}	Total capacity of renewable energy technology j in year t (MW)
$D_{\tau t}^\xi$	Demand at time-slice τ in year t under scenario ξ (MWh)
D_{ht}^ξ	Demand at hour h in year t under scenario ξ (MWh)
η_τ	Length of time-slice τ (hours)
c_i^u (c_j^u)	Annualized capital investment cost of technology i (or j) (KRW/MW)
c_i^f (c_j^f)	Annual fixed cost of technology i (or j) (KRW/MW)
c_i^v (c_j^v)	Variable O&M cost of technology i (or j) (KRW/MWh)
q_i	Forced outage rate of technology i (%)
A_τ^ξ	Availability factor of renewable energy technology j at time-slice τ under scenario ξ (%)
A_h^ξ	Availability factor of renewable energy technology j at hour h under scenario ξ (%)
R_i^{up}	ramp-up rate for the committed capacity of technology i (%/h)
N_i^{up}	Discount factor of the ramp-up rate for the non-committed capacity of technology i (%)

We calculate the total costs from the optimal mix and evaluate the economic effectiveness of each capacity expansion scenario. In addition to the economic validity, the environmental impact of the scenario has recently drawn much attention in society. We measure GHGs (in terms of CO₂eq.) and air pollutants (NO_x, SO_x, and PM10) emissions by applying emission factors to the generation amounts. Let e_i^c denote the emission factor for GHGs emission from generation technology i . Then, the amount of GHGs emission in year t becomes $E_t^c = \sum_i e_i^c \sum_{\tau} x_{i\tau t}$.

The simulation-based solution approach (i.e., SAA) provides an optimal solution but it does not mean that the optimal solution always satisfies the constraints in all possible scenarios. Therefore, the solution should be evaluated by running a simulation procedure with a separate set of samples that is independent of the samples used for the optimal generation model (Jin et al., 2011; Feng and Ryan, 2013; Pineda et al., 2014; Pisciella et al., 2016; Pineda and Morales, 2016; Pineda et al., 2016; Park and Baldick, 2016). The use of an independent set of samples possibly results in some violations of constraints about demand satisfaction and ramp up capacity. The next sections describe the simulation models that evaluate the optimal solution by measuring system reliability and flexibility.

3.2. Reliability simulation model

Similar to previous studies (Scherer and Joe, 1977; Noonan and Giglio, 1977; Cote and Laughton, 1980; Stremel, 1982), we use a conventional probabilistic index, LOLP, to measure power system reliability. LOLP is generally defined as the probability of the peak load exceeding the given available capacity. The greater the available generation capacity, the lower the failure probability. Therefore, a low target value of LOLP requires a large reserve margin (i.e., more capacity) so that it prevents the system from failing to meet the peak load. Eq. (11) formally defines power system reliability for a capacity expansion scenario s ($\Phi_t(s)$), which represents the probability that the peak load D_{1t}^{ξ} is more than the total available capacity.

$$\Phi_t(s) = \Pr(D_{1t}^{\xi}/\eta_1 > \sum_{j=1}^J A_{j1}^{\xi} y_{jt}^{\xi} + \sum_{i=1}^I z_i g_{it\tau}^{\xi}) \quad (11)$$

As an additional probabilistic reliability index, we subsequently consider the expected energy not supplied (EENS) with aims to measure the amount of load shedding. EENS is generally defined as the accumulation of the curtailed load over the period (Huang and Nair, 2002; Taljan and Gubina, 2009; Motaleb et al., 2016). Eq. (12) is used to calculate the EENS:

$$\Pi_t(s) = E_{\xi} [(D_{1t}^{\xi} - \sum_{j=1}^J A_{j1}^{\xi} y_{jt}^{\xi} - \sum_{i=1}^I z_i g_{it\tau}^{\xi})^+] \quad (12)$$

Renewable energy sources are known to be unreliable and uncertain, which has a significant impact on the overall power system reliability. To consider the technical limitations of renewable energy, we take a finite discrete probability distribution $A_{j\tau}^{\xi}$ that is developed from historical data as the availability factor of each generation technology. We generate random samples from the distribution of $A_{j\tau}^{\xi}$ and apply the samples to Eqs. (11) and (12). This simulation approach explicitly represents the uncertainty in electricity supply from renewable energy as a part of the reliability index. Furthermore, the proposed model considers the possibility of forced outage in conventional technologies. As mentioned in Section 3.1, the number of available plants $g_{it\tau}^{\xi}$ is randomly sampled using a binomial distribution.

To assess the power system reliability (i.e., LOLP and EENS) for scenario s , we design the following four-step simulation procedure:

Step 1. Initialization

- Choose initial sample size K , the number of iterations M
- Set the iteration index $m = 1$
- Set the counter $co_t^m = 0$ and $en_t^m = 0$

Step 2. Random Sampling

- Generate K samples of demand $D_{\tau t}^{\xi}$, renewable energy generation $A_{j\tau}^{\xi}$, and the number of available conventional power plants $g_{it\tau}^{\xi}$

Step 3. Reliability Evaluation

- For the k -th sample, evaluate $\Phi_t^k(s) = D_{1t}^k/\eta_1 - \sum_{j=1}^J A_{j1}^k y_{jt} - \sum_{i=1}^I z_i g_{it}^k$
If $\Phi_t^k(s) > 0$, set $co_t^m \leftarrow co_t^m + 1$ and $en_t^m \leftarrow en_t^m + \Phi_t^k(s)$
- For K samples, evaluate $\Phi_t^m(s) = \frac{co_t^m}{K} \times 100\%$ and $\Pi_t^m(s) = \frac{en_t^m}{K}$
- If $m < M$, then go to Step 2. Otherwise, go to Step 4.

Step 4. Reliability Estimation

- Estimate the reliability as:
 $\hat{\Phi}_t(s) = \frac{1}{M} \sum_{m=1}^M \Phi_t^m(s)$ and $\hat{\Pi}_t(s) = \frac{1}{M} \sum_{m=1}^M \Pi_t^m(s)$

3.3. Flexibility simulation model

This paper defines the power system flexibility index as the probability of failure to adjust power outputs in response to the rapid change in the net load in an hour because of the poor ramp-up ability of the power system (Eq. (13)).

$$F_t(s) = \Pr(\Delta_t), \forall t \quad (13)$$

where Δ_t is an event satisfying $\exists h$ such that $D_{ht}^{\xi} - \sum_{j=1}^J A_{jh}^{\xi} y_{jt}^{\xi} > \sum_{i=1}^I x_{iht}^{\xi}$ under the constraint:

$$x_{iht}^{\xi} - x_{ih-1t}^{\xi} \leq \min [z_i g_{iht}^{\xi} - x_{ih-1t}^{\xi}, R_i^{up} x_{ih-1t}^{\xi} + R_i^{up} N_i^{up} (z_i g_{iht}^{\xi} - x_{ih-1t}^{\xi})], \forall i, h, t \quad (14)$$

The flexibility index measures the probability of the hourly electricity net load exceeding the electricity supply from conventional power plants. Here, the hourly electricity supply from a conventional technology is subject to the constraint for upward operating reserve (Eq. (14)), which is determined by residual capacity ($z_i g_{iht}^{\xi} - x_{ih-1t}^{\xi}$) and/or ramp-up capacity ($R_i^{up} x_{ih-1t}^{\xi} + R_i^{up} N_i^{up} (z_i g_{iht}^{\xi} - x_{ih-1t}^{\xi})$) as described in Section 3.1. According to the definition, the lower the value of the flexibility index the power system has, the more flexibility it has.

It is well-known that flexibility varies across generation technologies. For example, Jonghe et al. (2011) classified the technologies into four categories: high peak load (e.g., natural gas turbine), peak load (e.g., natural gas combined cycle), mid load (e.g., coal steam turbine), and base load (e.g., nuclear) technologies. Each of these categories has different ramp-up abilities. Despite their high price, high peak load technologies are likely to improve flexibility. On the other hand, mid-load and base-load technologies tend to lower system flexibility, even though they are usually cost-competitive. The difference in ramp-up ability in different technologies indicates that the power system flexibility highly depends on the capacity mix. Therefore, the power system could temporally fail to meet the demand despite a large enough

reserve margin because power output can be constrained by the ramp-up ability.

The following simulation model is proposed to measure power system flexibility. The simulation starts by generating random samples of demand, renewable energy generation, and the number of available conventional power plants. Then, we apply the random samples to measure the flexibility $F_t(s)$ where the ramp-up ability is constrained by capacity and/or ramp-up rates. Repeated evaluations provide an estimate of flexibility. The details are as follows:

Step 1. Initialization

- Choose the initial sample size K , the number of iterations M
- Set the iteration index $m = 1$
- Set the counter $co_t^m = 0$

Step 2. Random Sampling

- Generate K samples of demand D_{ht}^k , renewable energy generation A_{jh}^k , and the number of available conventional power plants g_{ith}^k

Step 3. Flexibility Evaluation (Jonghe et al., 2011, Ma et al., 2013)

- For the k -th sample, evaluate $F_t^k(s) = D_{ht}^k - \sum_{j=1}^J A_{jh}^k y_{jt}^h - \sum_{i=1}^I x_{iht}^k \forall h = 1, 2, \dots, H$ with ramping constraints $x_{iht}^k - x_{ih-1t}^k \leq \min[z_i g_{iht}^k - x_{ih-1t}^k, R_i^{up} x_{ih-1t}^k + R_i^{up} N_i^{up} (z_i g_{iht}^k - x_{ih-1t}^k)]$, where $g_{iht}^k \sim B(y_{it}, 1 - q_i)$
- If $F_t^k(s) > 0$, set $co_t^m = co_t^m + 1$
- For K samples, evaluate $F_t^m(s) = \frac{co_t^m}{K} \times 100\%$
- If $m < M$, then go to Step 2. Otherwise, go to Step 4.

Step 4. Flexibility Estimation

- Estimate the flexibility as $\hat{F}_t(s) = \frac{1}{M} \sum_{m=1}^M F_t^m(s)$

In Step 3, we use the result from the optimal generation simulation model to determine x_{iht}^k (i.e., the electricity generation levels from conventional power plants at the beginning of the ramp-up period). The electricity generation levels during the following hours are simulated by considering ramping constraints.

4. Assumptions, data, and scenarios

For the purpose of evaluation, this section introduces capacity expansion scenarios that describe when, how much, and which type of generation capacity should be expanded. Referring to the Korean electric power system, we first state the assumptions and data used in the further analysis.

4.1. Basic assumptions and data

We establish assumptions and collect data mainly from the 8th plan (KPX, 2017) and/or the former 7th plan (KPX, 2015). We set a 16-year planning horizon for our proposed model, from 2015 to 2030 (i.e., $T = 16$), and the annual discount rate and the target LOLP level are set as 2.4% and 0.08%, respectively. The adequacy of power system reliability is evaluated in comparison with the target LOLP level of 0.08%.

For both reliability and flexibility simulations, we iterate the simulation procedure for 30 times (i.e., $M = 30$) with a sample size of 1000 (i.e., $K = 1000$). The preliminary test reveals that the standard error with these two values of K and M becomes less than 0.1% of the sample mean.

Table 2

Empirical probability distribution of demand in the peak period.

Probability (%)	Demand in 2015 (MW)	Demand in 2030 (MW)
1.35	78,790	100,500
9.12	69,018	82,696
22.27	65,881	78,937
54.86	62,744	75,178
9.72	56,470	67,660
1.78	50,195	60,142
0.90	43,921	52,625

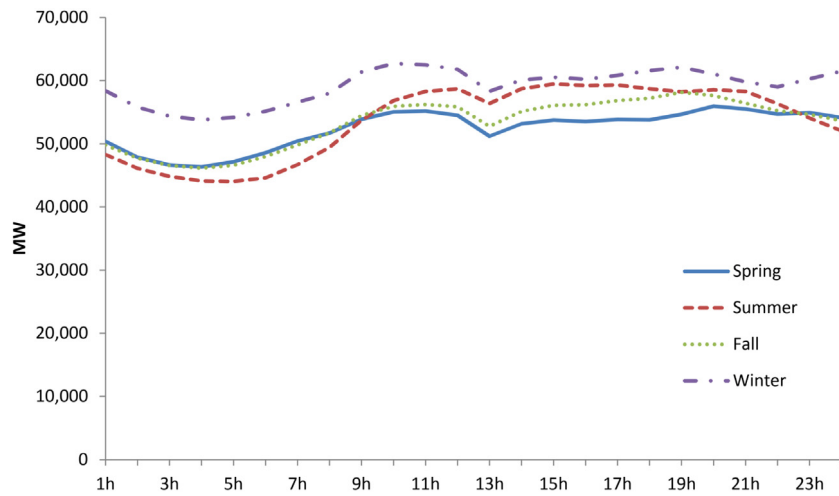
4.1.1. Demand

In order to define the time slices within a year, we analyze the expected net load patterns from various angles over the planning horizon. The future expected patterns are constructed on the basis of the data for hourly electricity load and hourly electricity generation from RETs in 2013 provided by KPX (Korea Power Exchange). We assume that the amounts of annual electricity demand and annual electricity generation from RETs increase according to the projections reported in the 8th plan, but the hourly variations for both will not change over the entire horizon. Based on the data availability and assumptions, we obtain the net load by subtracting the demand served by renewable energy from the total demand during a day. Then, we analyze the hourly average net load patterns for four seasons in 2013 and 2030, as illustrated in Fig. 2. Because of the integration of large-size renewable energy, the net load in 2030 can be lower than that in 2013. From the analysis, we define four time slices (i.e., $L = 4$): peak period ($\eta_1 = 408$ h), ramp-up period ($\eta_2 = 2920$ h), nighttime period ($\eta_3 = 4015$ h), and daytime period ($\eta_4 = 1417$ h).

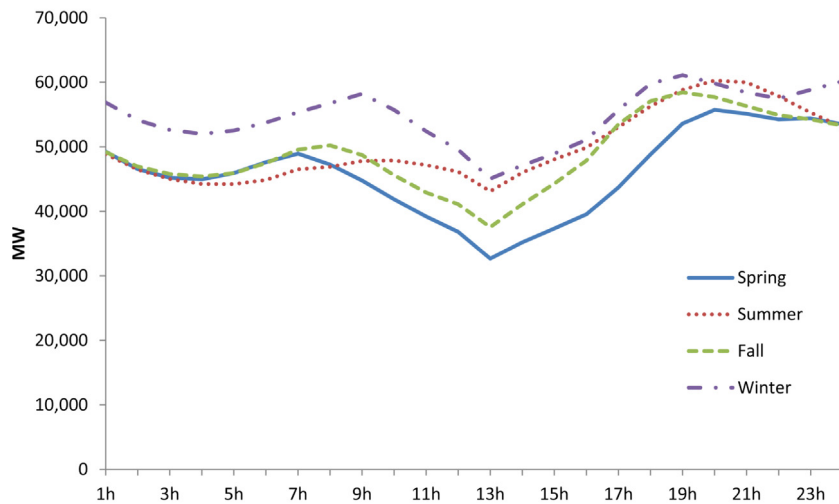
In the 8th plan, the historical data for the annual demand and peak load levels in 2015 are provided as 483,655 MWh and 78,790 MW, respectively. Assuming an invariant load pattern, the average load level for each time-slice in 2015 becomes 68,000 MW for the peak period, 63,425 MW for the ramp-up period, 60,724 MW for the daytime period, and 56,448 MW for the night-time period. Considering the annual growth rates of annual demand and peak load level to be 1.0% and 1.3% respectively, as mentioned in the 8th plan, the levels would reach 579,500 MWh and 100,500 MWh in 2030, respectively. Again, using these projections and assuming an invariant hourly load pattern, we determine the empirical probability distribution of demand for each time-slice in order to consider uncertainty in demand. For example, Table 2 represents the empirical probability distribution of demand in the peak period.

4.1.2. Renewable energy supply

Electricity generation from RETs is known to be highly uncertain and unreliable. For our simulation models, the empirical distributions of the availability factors (AFs) of RETs are also used to determine the uncertainty and unreliability in power supply. Based on the data for hourly electricity generation from RETs in 2013 provided by KPX, we analyze the AFs of wind, solar PV, and others as shown in Table 3. Thereafter, we construct empirical distributions for wind and solar PV for each time-slice as shown in Table 4. Again, we assume that the empirical probability distributions are constant over the entire planning horizon, and the amount of annual electricity generation from RETs increases according to the projections reported in the 8th plan. In the 8th plan, the nameplate capacities of RETs combined are projected to increase to 58.5 GW, including 33.5 GW for solar PV and 17.7 GW for wind. The solar PV and wind are expected to account for about 88% of the total electricity generation using renewable energy in 2030.



(a) Hourly average net load patterns in 2013



(b) Hourly average net load patterns in 2030

Fig. 2. Hourly average net load (demand minus renewable energy) patterns in the Korean electric power system.**Table 3**
Mean availability factor of RETs (%).

Technology	time-slice				Annual Avg.
	Peak	Ramp up	Daytime	Night-time	
Wind	30.2	23.7	20.5	25.8	25.2
Solar PV	27.5	25.7	30.8	0.1	15.7

Table 4
Probability distribution of the availability factor in the peak period (%).

AF(%)	0	10	20	30	40	50	60	70	80	
Probability	Wind	6.1	16.1	17.8	21.7	17.8	12.8	5.2	2.4	0.1
	Solar	13.8	24.7	13.1	12.4	11.8	11.3	8.3	3.8	0.8

4.1.3. Technology characteristics

The 8th plan considers six conventional generation technologies: nuclear, bituminous coal steam turbine (BCST), anthracite coal steam turbine (ACST), natural gas combined cycle (NGCC), natural gas turbine (NGT), and pumped storage (PS). RETs are divided into four types: wind, solar PV, and others (e.g., waste, fuel cell, tidal, byproduct gases, etc.).

We estimate the costs and other parameters of conventional generation technologies by mainly referring to the 7th plan (KPX, 2015), the internal report of the Korea Energy Economics Institute (KEEI), and other supplementary documents (Black and Veatch, 2012). The technology profiles of renewable energy are from the database provided by two government-funded research institutes, the Korea Institute of Energy Research (KIER) and the Korea Institute of Energy Technology Evaluation and Planning (KETEP). We refer readers to our recent publications about the database (Choi et al., 2015; Park et al., 2016). Table 5 summarizes the technology profiles. In Table 5, the values for other renewable energy and group technologies are omitted because the available data is insufficient.

Finally, we need emission factors to measure the amount of GHG and dust emissions. This study applies the same emission factors as mentioned in the 7th plan (KPX, 2015). The emission factors used in this study are summarized in Table 6.

4.2. Test scenarios

This paper considers four test scenarios that represent the 8th plan and other comparative plans. Table 7 describes the

Table 5

Key characteristics data of generation technologies.

Technology	Ref. nameplate capacity (MW)	# of plants ^d (units)	AF ^b (%)	FOR ^c (%)	Cap. Cost (\$/kW)	Fixed O&M cost (\$/kW-yr)	Var. O&M cost (\$/MWh)	Lifetime (years)	1-h ramp up rate ^d (%/h)	Peak Cont. factor (%)
Conventional generation technologies										
Pumped Storage	650	7	25	5	2565	17.93	0	55	100(100%)	100
ACST	200	6	89	5	1588	101.17	0.0007	30	50(60%)	100
BCST	500	50	87	5	1445	42.07	0.0001	30	50(60%)	100
NGT	250	4	87	6	1051	34.20	0.0009	30	100(100%)	100
NGCC	450	57	87	6	593	37.47	0.0009	30	80(60%)	100
Nuclear	1000	21	77	5	2590	150.5	1.26	40	33(60%)	100
Nuclear APR	1400	0	77	5	2365	122.0	1.26	40	33(60%)	100
Renewable energy technologies										
Wind	1	600	25.2	0	2890	75.14	0	22	–	2
Solar PV	1	1790	15.7	0	4370	46.24	0	25	–	15
Others	1	3860	38.3	7	–	–	–	–	–	42

1\$ = 1000 KRW

^aNumber of plants in the base year of 2015.^bAF = Availability Factor.^cFOR = Forced Outage Rate.^dThe data are given in the form of $R_i^{up}(N_i^{up})$.**Table 6**

Emission factors.

	Coal	Natural gas (LNG)	Oil
SO _x (kg/MWh)	0.317	–	0.460
NO _x (kg/MWh)	0.497	0.386	0.985
PM10 (kg/MWh)	0.015	–	0.012
CO ₂ eq. (kg/MWh)	823	362	702

test scenarios, and Table 8 shows the capacity mix for each test scenario.

First, we consider the 8th plan, which is developed under the new energy policy, as the baseline scenario (Scenario 1). The second test scenario (Scenario 2) is designed to evaluate the effect of the coal and nuclear power phase-out policy on system reliability and flexibility. For this purpose, Scenario 2 uses the same capacity mix as defined in the 7th plan, without any change in other parameters, which are used as mentioned in the 8th plan. The 7th plan includes more nuclear and coal power plants but less use of renewable energy than the 8th plan. We expect that the baseline scenario worsens the system's reliability and flexibility because of the large-scale integration of renewable energy.

Based on our preliminary analysis, we expect Scenarios 1 and 2 to fail in achieving the target level of power system reliability. Therefore, Scenario 3 is designed to answer the following research question: how much more capacity is required to improve the power system reliability up to the target level? We assume that, in Scenario 3, the power system expands by the same capacity as in Scenario 1. Scenario 3 only adds NGCC power plants to achieve the target reliability level.

In Scenario 4, we aim to show the possibility of improving the power system flexibility not by increasing capacity but by changing the capacity mix. Scenario 4 uses the same capacity as Scenario 1, but it only considers NGT power plants for additional capacity to achieve the target level of the system reliability. We expect Scenario 4 to provide better flexibility than Scenario 3 because NGT has a better ability to ramp up production quickly.

5. Results and discussions

This section summarizes the outputs of the three proposed models under four test scenarios. It should be mentioned that the proposed models were validated by comparing the simulation results with the 8th plan (KPX, 2017), and the comparison reveals that the simulation results are very close to the 8th plan.

5.1. Power system reliability

We run the simulation model described in Section 3.2. Table 9 includes a summary of the simulation results of the power system reliability over the planning horizon. In Table 9, the average and max reliability mean are $\frac{1}{T} \sum_{t=1}^T \hat{\phi}_t(s)$ and $\max_t \hat{\phi}_t(s)$, respectively. The installed reserve margin is calculated by discounting the capacity of renewable energy using the peak contribution factors. Consequently, Scenarios 1 and 2 have similar installed reserve margins (e.g., about 21.8% in 2030) although there is a large difference in their total nameplate capacity as shown in Table 8.

It is noteworthy that Scenario 2 has lower LOLP and EENS (i.e., better reliability) than Scenario 1. This means that the plan for coal and nuclear power phase-out and a shift towards renewable energy lowers the system reliability. Moreover, the system is likely to fail to reach the target system reliability level of LOLP in both Scenarios 1 and 2. On average, the LOLP levels in Scenarios 1 and 2 are 0.355% and 0.249%, respectively, which are above the target level of 0.08%.

Based on the LOLP level, the target system reliability can be achieved by adding more capacity so that the peak load may not exceed the available capacity. Both Scenarios 3 and 4 accommodate additional capacity, which reduces the possibility of the peak load exceeding the available capacity so that they have lower LOLP and EENS. The required additional capacity starts from 2025, and it increases from about 1800 MW in 2025 to 5000 MW in 2030. Both Scenarios 3 and 4 assume having more than 25% installed reserve margins with the additional capacity, and the resulting LOLP levels in both scenarios are about 0.02% on average, which are below the target level of 0.08%.

5.2. Power system flexibility

Power system flexibility is measured by using the simulation model shown in Section 3.3. Recall that we defined the flexibility index as the failure probability in response to changes in the short-term net load (see Eq. (13)). Table 9 also includes a summary of simulation results for the power system flexibility over the planning horizon in each test scenario.

Scenarios 1 and 2 have similar flexibility levels, despite having significant differences in the capacity mix and reliability. The results show that the power system flexibility is very sensitive to the reserve margin. A higher reserve margin contributes to improvement in the system flexibility by lowering the failure

Table 7
Test scenarios.

Scenarios	Description
Scenario 1 (Baseline scenario)	· Use the same plan for capacity expansion as given in the 8th plan · A plan for coal and nuclear power phase-out and a dramatic increase in renewable energy
Scenario 2	· Use the sample plan for capacity expansion and mix as defined in the 7th plan · Evaluate the new energy policy for coal and nuclear power phase-out and renewable shift
Scenario 3	· No change in the plan for capacity expansion in Scenario 1 · Increase the capacity through NGCC to achieve the target level of power system reliability
Scenario 4	· No change in the plan for capacity expansion in Scenario 1 · Increase the capacity through NGT and expect the same level of power system reliability as in Scenario 3 · Evaluate the effect of changes in the capacity mix on the power system flexibility

Table 8
Annual capacity mix(%) and capacity (MW).

Technology	Baseline scenario					Scenario 2				
	2015	2018	2020	2025	2030	2015	2018	2020	2025	2030
Pumped storage	4.65	3.75	3.39	2.99	2.62	4.65	3.75	3.45	3.11	2.95
Coal	28.27	28.65	28.65	25.86	22.48	27.81	28.27	29.15	26.91	25.28
Natural gas	28.38	27.32	26.08	25.30	24.82	28.38	27.32	26.53	22.02	20.03
Nuclear	22.50	20.77	19.85	16.01	11.76	22.50	20.77	20.19	21.99	22.69
Wind	0.75	2.20	3.35	6.82	10.12	0.75	2.20	2.72	4.02	5.22
Solar PV	2.40	4.54	6.24	13.10	19.19	2.40	4.54	5.03	8.52	10.74
Others	13.05	12.77	12.44	9.92	9.01	13.51	13.15	12.93	13.43	13.09
Total nameplate capacity	97,790	121,325	134,030	152,373	173,478	97,790	120,600	131,750	141,880	149,720

Table 9
Summary of simulation results: reserve margin and reliability.

Scenario		Installed reserve margin (%)	Reliability (LOLP, %)	Reliability (EENS, MWh)	Flexibility (%)
1	avg.	25.812	0.355	611,191	0.023
	max	31.222	1.160	2,322,731	0.163
	min	21.338	0.000	0	0.001
2	avg.	25.472	0.249	436,154	0.020
	max	30.887	0.810	3,223,566	0.185
	min	21.018	0.000	0	0.001
3	avg.	28.019	0.023	277,907	0.017
	max	31.221	0.057	1,630,577	0.160
	min	25.584	0.00	0	0.000
4	avg.	28.019	0.024	226,907	0.011
	max	31.221	0.053	1,963,083	0.092
	min	25.584	0.000	0	0.000

The target LOLP level = 0.08%.

probability. This means that we need more capacity to improve system flexibility. We measure the power system flexibility by varying reserve margins, which indicates that the flexibility index converges to almost zero when the reserve margin is over 25% in all test scenarios. According to the baseline scenario designed by the Korean government, a reserve margin of 21.2% is expected in 2030, which corresponds to approximately 0.1% of the failure probability (i.e., flexibility).

These interesting findings highlight the importance of considering not only how much capacity should be expanded but also which capacity should be included in the mix when improving the flexibility. This result can be observed by comparing Scenarios 3 and 4, which have the same capacity but a different capacity mix. Scenario 3, where the capacity is expanded mostly with NGCC, shows a very marginal improvement in flexibility. On the other hand, Scenario 4 achieves better flexibility than Scenario 3 because NGT has a better ramp-up rate than NGCC (see Table 5).

Fig. 3 represents the projection of the average ramp-up ability, which is determined by taking the minimum between residual capacity and ramp-up capacity as given in Eq. (14). As shown previously, since Scenarios 3 and 4 have more capacity, they are

more capable of adjusting the power generation than are Scenarios 1 and 2. Fig. 3 also shows the effect of the capacity mix on the system flexibility. Scenario 4 has the largest ramp-up ability because, in this scenario, the capacity is mainly expanded with the most flexible technology, NGT. We can achieve approximately 5000 MW additional ramp-up ability by simply adding capacity with NGT power plants instead of NGCC power plants.

5.3. Generation costs and environmental impacts

The optimal generation simulation model provides the total generation costs and environmental impacts using the optimal electricity generation mix. From Table 10, which summarizes the results, we observe that Scenario 2 has a cost of 393,160 billion KRW, which is lower than that of the baseline scenario (Scenario 1) by 25,503 billion KRW. Scenario 1 represents the 8th plan under the new Korean energy policy to phase out coal and nuclear power plants and replace them mainly with renewable energy and natural gas power plants. The shift towards renewable energy causes a significant increase in the fixed costs of capital investment, and the relatively expensive natural gas leads to higher fuel costs. Under Scenarios 3 and 4, the additional capacity

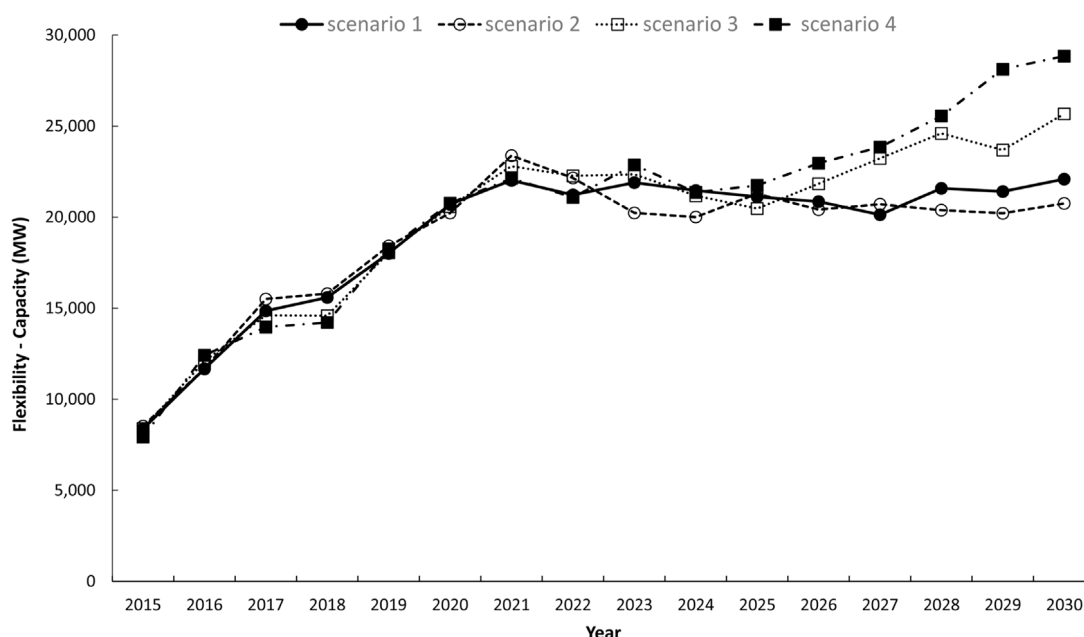


Fig. 3. Projection of the average ramp up ability of the power system.

to achieve the target reliability level inevitably results in higher total costs.

In addition to the generation cost, we evaluate the environmental impacts by measuring GHGs and air pollutant emissions as summarized in Table 10. An interesting finding is that Scenario 2 has the least emissions of all test scenarios, which is contrary to our expectations. Scenario 2 has more coal power plants and uses a smaller amount of renewable energy than other scenarios, but it has many more nuclear power plants. These results imply that the intensive use of nuclear power plants is very important in reducing emissions.

6. Conclusions

The recent plan following a new energy policy direction, which aims to phase out coal and nuclear power and shift towards large-scale integration of renewable energy, has provoked huge controversy in South Korea. There are concerns not only about poor economic efficiency but also about low reliability and flexibility of the power system. In particular, industry practitioners have been recently confronted with difficulties in measuring operational flexibility in accordance with the shift towards renewable energy. Against this background, this paper proposes a research framework with the purpose of evaluating the plan from the aspect of not only the total generation cost and environmental impact but also the reliability and flexibility of the power system.

Despite the growing needs of flexibility measurement, little research effort was devoted to designing an index for measuring and quantifying power system flexibility in the context of long-term capacity expansion planning. This paper introduces a new index for measuring operational flexibility in the long-term planning model by employing the idea of a power system reliability index. The newly designed flexibility index measures the failure probability in balancing demand and supply because of the lack of operational flexibility. We believe that this index provides industry practitioners with better information on the degree of flexibility.

We apply our proposed framework to evaluate four test scenarios, and the evaluation provides three meaningful implications. First, the new plan for long-term capacity expansion (i.e.,

Table 10

Total generation costs and environmental impacts.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Electricity generation mix (%) ^a				
RETs	9.62	7.34	9.62	9.62
Nuclear	27.40	32.61	27.40	27.40
LNG	13.87	11.04	13.89	13.89
Coal	47.42	47.33	47.41	47.40
Others	1.69	1.68	1.68	1.69
Total generation costs (Billion KRW)				
Total cost ^b	418,663	393,160	424,647	420,286
Fixed cost ^c	129,092	122,801	118,017	130,160
Variable cost ^d	289,571	270,359	306,630	290,126
Environmental impacts ^e (1000 ton/year)				
CO ₂ eq.	260,720	254,185	260,747	260,784
SO _x	88.97	88.80	88.97	88.97
NO _x	171.19	164.44	171.22	171.26
PM ₁₀	4.21	4.20	4.21	4.21

^aAnnual average.

^bCost over the 16-year planning horizon.

^cCapital investment and fixed O&M costs.

^dVariable O&M and fuel costs.

^eAnnual average.

8th plan) in Korea may lower the reliability and flexibility of the power system. The power system is likely to fail in meeting the target reliability level if the new plan is implemented. In South Korea, the peak contribution factors of renewable energy have been used very conservatively. Thus, the 8th plan requires about 15% more total nameplate capacity than the previous 7th plan so that both plans have a similar installed reserve margin. Nevertheless, our analysis shows that the large-size integration of renewable energy increases the probability of the peak load exceeding the given available capacity by 42.5%.

Second, the analysis reveals that the type of capacity added is very important in improving power system flexibility. More generally, including the system flexibility in the decision could change the optimal capacity mix. We find that achieving the target reliability level requires about 5000 MW additional capacity by 2030. If the Korean government decides to increase

the capacity with NGT, then the power system flexibility can be improved by about 36% compared to when the government chooses NGCC. We also find that the additional capacity with NGT is large enough for the flexibility if we compare the measure with the target level of reliability, too.

Finally, the new 8th plan might be less eco-friendly than the 7th plan. Improving air quality is one of the main considerations in designing the new energy policy. However, we observe that the 8th plan fails to reduce GHGs and air pollutant emissions. Despite the decrease in the share of coal power plants and the extensive use of clean renewable energy, our analysis shows that a sharp reduction in nuclear power plants might disturb the reduction in the utilization of coal and natural gas power plants. Consequently, the total amount of emissions increases under the new 8th plan when compared with the 7th plan. This means that nuclear power has a critical role in reducing emissions, and the government should regulate the use of coal power plants as well.

The main contribution of this study is to provide answers to the questions that have emerged recently in the Korean electricity sector. However, this study has some limitations. For example, the results of the analysis could not be officially approved because some of the official data owned by the government are not accessible. We also ignored the costs and environmental impacts incurred by radioactive waste from nuclear power plants, which are recently arguable in industry. Nevertheless, we have shown that the proposed research framework provides insightful information that is beneficial to policymakers and power system planners in making more informed and better decisions. We also believe that the proposed research framework can be easily applied in many other countries confronting similar policy issues.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Daiki Min: Methodology, Formal analysis, Writing - original draft. **Jong-hyun Ryu:** Validation, Formal analysis, Supervision, Writing - review & editing. **Dong Gu Choi:** Conceptualization, Data curation, Funding acquisition, Methodology, Project administration, Writing - review & editing.

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References

- Abdin, I.F., Zio, E., 2018. An integrated framework for operational flexibility assessment in multi-period power system planning with renewable energy production. *Appl. Energy* 222, 898–914.
- Anderson, D., 1972. Models for determining least-cost investments in electricity supply. *Bell J. Econ. Manage. Sci.* 3, 267–299.
- Bessiere, F., 1970. The investment 85 model of electricite de france. *Manage. Sci.* 17, 192–211.
- Black and Veatch, 2012. Cost and Performance Data for Power Generation Technologies Prepared for the National Renewable Energy Laboratory. Technical report.
- Bloom, J.A., 1982. Long range generation planning using decomposition and probabilistic simulation. *IEEE Trans. Power Appar. Syst.* PAS-101, 797–802.
- Bouffard, F., Ortega-Vazquez, M., 2010. The value of operational flexibility in power systems with significant wind power generation. In: *Proceedings in 2011 IEEE Power and Energy Society General Meeting*, pp. 1–5.
- Child, M., Kemfert, C., Bogdanov, D., Breyer, C., 2019. Flexible electricity generation, grid exchange and storage for the transition to a 100% renewable energy system in europe. *Renew. Energy* 139, 80–101.
- Choi, D.G., Park, S.Y., Hong, J.C., 2015. Quantitatively exploring the future of renewable portfolio standard in the korean electricity sector via a bottom-up energy model. *Renew. Sustain. Energy Rev.* 50, 793–803.
- Cote, G., Laughton, M.A., 1980. Prediction of reserve requirements in generation planning. *Int. J. Electr. Power Energy Syst.* 2, 87–95.
- Dagoumas N.E. Koltsaklis, A.S., 2018. State-of-the-art generation expansion planning: A review. *Appl. Energy* 230, 563–589.
- Feng, Y., Ryan, S.M., 2013. Scenario construction and reduction applied to stochastic power generation expansion planning. *Comput. Oper. Res.* 40, 9–23.
- Heggarty, T., Bourmaud, J.Y., Girard, R., Kariniotakis, G., 2019. Multi-temporal assessment of power system flexibility requirement. *Appl. Energy* 238, 1327–1336.
- Hobbs, B.F., 1995. Optimization methods for electric utility resource planning. *European J. Oper. Res.* 83, 1–20.
- Huang, G.M., Nair, N.C., 2002. Voltage stability constrained load curtailment procedure to evaluate power system reliability measures. In: *Proceedings of IEEE Power Engineering Society Winter Meeting*, Vol. 2, pp. 761–765.
- IEEE, 2007. *IEEE Standard Definitions for Use in Reporting Electric Generating Unit, Reliability, Availability, and Productivity*. Technical Report.
- Jin, S., Botterud, A., Ryan, S.M., 2014. Temporal versus stochastic granularity in thermal generational capacity planning with wind power. *IEEE Trans. Power Syst.* 29, 2033–2041.
- Jin, S., Ryan, S.M., Watson, J.P., Woodruff, D.L., 2011. Modeling and solving a large-scale generation expansion planning problem under uncertainty. *Energy Syst.* 2, 209–242.
- Jonghe, C.D., Delarue, E., Belmans, R., D'haeseleer, W., 2011. Determining optimal electricity technology mix with high level of wind power penetration. *Appl. Energy* 88, 2231–2238.
- Khodaei, S., Kamalinia, A., Shahidehpour, M., 2011. Security-constrained expansion planning of fast-response units for wind integration. *Electr. Power Syst. Res.* 81, 107–116.
- KPX, 2015. The 7th basic plan for long-term electricity supply and demand (2015–2029). In: *Ministry of Trade, Industry and Energy*. MOTIE, <https://www.kpx.or.kr/eng/selectBbsNttView.do?key=328&bbsNo=199&nttNo=14547&searchCtgrY=&searchCnd=all&searchKwrd=&pageIndex=1&integrDeptCode=>.
- KPX, 2017. The 8th basic plan for long-term electricity supply and demand (2017–2031). In: *Ministry of Trade, Industry and Energy*. MOTIE.
- Lannoye, E., Flynn, D., O'Malley, M., 2012. Evaluation of power system flexibility. *IEEE Trans. Power Syst.* 27, 922–931.
- Ma, J., Silva, V., Belhomme, R., Kirschen, D.S., 2013. Evaluating and planning flexibility in sustainable power systems. *IEEE Trans. Sustain. Energy* 4, 200–209.
- Min, D., Chung, J., 2013. Evaluation of the long-term power generation mix: The case of South Korea's energy policy. *Energy Policy* 62, 1544–1552.
- Min, D., Ryu, J., Choi, D.G., 2018. A long-term capacity expansion planning model for an electric power system integrating large-size renewable energy technologies. *Comput. Oper. Res.* 96, 244–255.
- Motaleb, A., Bekdache, S.K., Barrios, L.A., 2016. Optimal sizing for a hybrid power system with wind/energy storage based in stochastic environment. *Renew. Sustain. Energy Rev.* 59, 1149–1158.
- Noonan, F., Giglio, R.J., 1977. Planning electric power generation: a non-linear mixed integer model employing benders decomposition. *Manage. Sci.* 23, 946–956.
- Papaefthymiou, G., Haesen, E., Sach, T., 2018. Power system flexibility tracker: Indicators to track flexibility progress towards high-res systems. *Renew. Energy* 127, 1026–1035.
- Park, H., Baldick, R., 2016. Multi-year stochastic generation capacity expansion planning under environmental energy policy. *Appl. Energy* 186, 737–745.
- Park, S.Y., Yun, B.-Y., Yun, C.Y., Lee, D.H., Choi, D.G., 2016. An analysis of the optimum renewable energy portfolio using the bottom-up model: Focusing on the electricity generation sector in south korea. *Renew. Sustain. Energy Rev.* 53, 319.
- Peterson, E.R., 1973. A dynamic programming model for the expansion of electric power systems. *Manage. Sci.* 20, 656–664.
- Pineda, S., Morales, J.M., 2016. Capacity expansion of stochastic power generation under two-stage electricity markets. *Comput. Oper. Res.* 70, 101–114.
- Pineda, S., Morales, J.M., Boomsma, T.K., 2016. Impact of forecast errors on expansion planning of power systems with a renewables target. *European J. Oper. Res.* 248, 1113–1122.
- Pineda, S., Morales, J.M., Ding, Y., Østergaard, J., 2014. Impact of equipment failures and wind correlation on generation expansion planning. *Electr. Power Syst. Res.* 116, 451–458.

- Pisciella, P., Vespucci, M.T., Bertocchi, M., Zigrino, S., 2016. A time consistent risk averse three-stage stochastic mixed integer optimization model for power generation capacity expansion. *Energy Econ.* 53, 203–211.
- Sarrinen, L., Dahlbäck, N., Lundin, U., 2015. Power system flexibility need induced by wind and solar power intermittency on time scales of 1–14 days. *Renew. Energy* 83, 339–344.
- Scherer, C.R., Joe, L., 1977. Electric power system planning with explicit stochastic reserve constraint. *Manage. Sci.* 23, 978–985.
- Shortt, A., Kiviluoma, J., O'Malley, M., 2013. Accommodating variability in generation planning. *IEEE Trans. Power Syst.* 28, 158–169.
- Stremel, J.P., 1982. Production costing for long-range generation expansion planning studies. *IEEE Trans. Power Appar. Syst.* PAS-101, 526–536.
- Taljan, G., Gubina, A.F., 2009. Energy-based system well-being analysis for small systems with intermittent renewable energy sources. *Renew. Energy* 34, 2651–2661.