

Article

# Integration of Smart Grid Resources into Generation and Transmission Planning Using an Interval-Stochastic Model

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**Abstract:** In the power industry, the deployment of smart grid resources in power systems has become an issue of major interest. The deployment of smart grid resources represents an additional uncertainty in the integrated generation and transmission planning that raises uncertainties in investment-related decision making. This paper presents a new power system planning method for the integration of electric vehicles (EVs) and wind power generators into power systems. An interval-stochastic programming method is used to account for the heterogeneous uncertainties attributable to natural variability and lack of knowledge. The numerical results compare the multiple integration scenarios and verifies the effectiveness of the proposed method in terms of cost distribution and regret cost.

**Keywords:** smart grid; integrated generation and transmission planning; interval-stochastic programming; wind power; electric vehicle

## 1. Introduction

The prominent trend toward smart grid development is the increasing integration of new energy resources into power systems. Such resources—which include renewable energy, electric vehicles (EVs), demand response (DR), and energy storage systems (ESSs)—have the potential to enable high-efficiency operation of power systems utilizing clean, secure energy sources [1]. The studies for integrating new energy resources have been conducted. An open source-based hardware platform [2] and monitoring, control system was developed [3,4]. While digitalizing the power grid, a secure authentication for new energy sources was also studied [5]. A comparison of several forecasting methods is presented [5]. The integration and application of new resources is summarized in [6].

As smart grid resources become more widely integrated into the power system, the system operators face critical challenges to balance the supply and demand in the power system. They have to develop ways to balance supply and demand while considering the distinctive and stochastic characteristics of smart grid resources [7]. Furthermore, these challenges also take place in an integrated generation and transmission planning [8,9]. In turn, the risk of potential losses associated with non-optimal investment decisions in power system planning will increase.

It is important to develop a comprehensive understanding of the uncertainties involved in new energy resources [10,11]. However, existing power system planning methods involving smart grid resources [12,13] take into account only uncertainties associated with natural variability. The focus of this paper is to present a new integrated generation and transmission planning method that also reflects risks arising from increased uncertainties caused by major smart grid resources such as EVs and wind power generators.

In this study, stochastic programming is used to model the uncertainty attributable to the natural variability of smart grid resources. Probabilistic distributions associated with the new energy resources

are estimated by means of entropy pooling (EP) [14,15], which is a scenario analysis method based on the Bayesian perspective. Furthermore, interval programming is used to model uncertainties attributable to the lack of knowledge and minimax regret criterion for minimizing potential losses of the interval optimization problem. In addition, an interval-stochastic programming method [16,17] is used to simultaneously account for both interval and stochastic variables in an integrated generation and transmission planning problem.

The remainder of this paper is organized as follows: In Section 2, an integrated generation and transmission planning problem involving smart grid resource models is formulated. The proposed interval-stochastic power system expansion planning method based on the entropy pooling is presented in Section 3. The effectiveness of the proposed method is shown under multiple EV charging price scenarios in Section 4.

## 2. Problem Formulation

The proposed method is designed to determine the investment location, timing and capacity of generator and transmission, considering the uncertainties of deployment and generation pattern of smart grid resources. Figure 1 presents the schematic diagram of the proposed method.

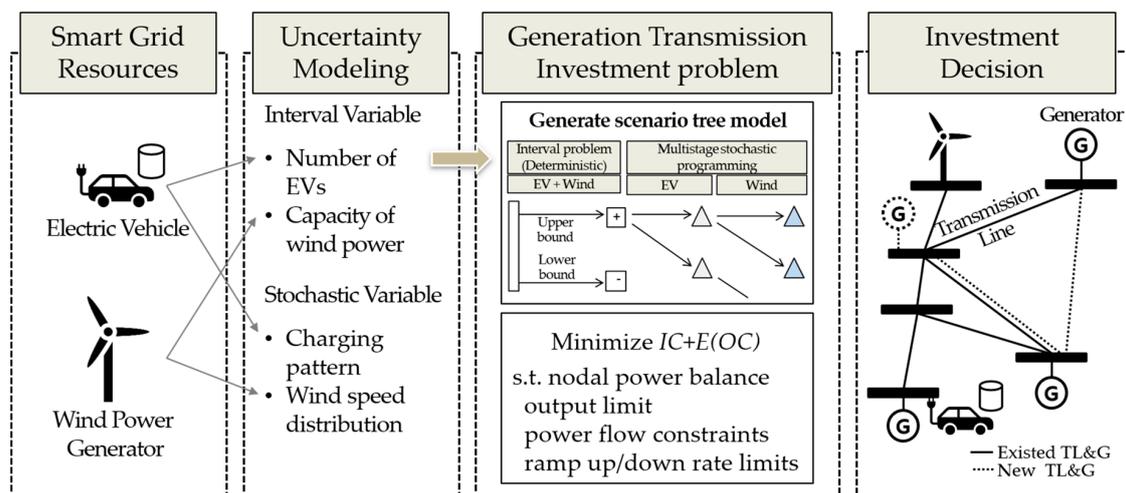


Figure 1. Schematic diagram of the proposed method.

In this section, the problem formulation of the generation and transmission planning problem is presented. First, the hourly generation of new energy resources is modeled with the consideration of their uncertainties. Then, the master and slave problem of the proposed optimization problem using Benders' decomposition is discussed.

### 2.1. New Energy Resource Model Under Uncertainty

In this study, interval-stochastic models of new energy resources such as EV charging loads and wind power are formulated. Because the impact on the power grid of wind power is significant due to its capacity, the uncertainty of wind power is considered before other renewable energy sources. In the EV charging load model, the key factors influencing the EV charging loads generally include the number of EVs, the daily energy consumed by EVs, and the hourly charging patterns of EVs [13,18,19]. Likewise, the key factors influencing the wind power generations generally include the wind speed, the conversion rate from wind to electrical energy, and the annual diffusion rate of wind power capacity [12,20]. Uncertain factors regarding the deployment of each new energy resource, for which probabilistic distributions are hard to obtain, are modeled as interval variables, whereas other uncertain factors are modeled as stochastic variables.

## EV Charging Load

The anticipated annual market diffusion rate of EVs in future year  $y$  ( $\omega_y^\pm$ ) within vehicle markets is expressed as follows:

$$\omega_y^\pm = \frac{M^\pm}{1 + \exp(\kappa \cdot t) \cdot \exp(-\kappa \cdot y)}, \forall y, \quad (1)$$

where  $\pm$  is the index for interval variables,  $M$  is the saturation level of the diffusion curve,  $t$  is the parameter of the inflection point, and  $\kappa$  is the delay factor characterizing the shape of the deformed exponential function. The anticipated annual market share rate of EVs has been modeled as a logistic curve ("s-shaped curve") [19,21]. Based on the diffusion rate  $\omega_y^\pm$ , the number of EVs at each bus in every year can be calculated. The EV charging load during hour  $h$  in year  $y$  at bus  $i$  ( $EV_{yhi\psi}^\pm$ ) in an anticipated power system is presented as follows:

$$EV_{yhi\psi}^\pm = \sum_{v=1}^{NEV_{yi}^\pm} \left( \left( \frac{C_v^{\max}}{R_v^{\max}} \cdot R_{v\psi}^{day} \cdot \eta_v \right) \cdot \rho_{h\psi} \right), \forall y, h, i, \psi. \quad (2)$$

where  $NEV_{yi}^\pm$  is the number of EVs in future  $y$  year at bus  $i$ ,  $v$  is the index for EVs,  $R_v^{\max}$  is the maximum driving distance of an EV with a fully charged battery,  $C_v^{\max}$  is the capacity of an EV battery,  $R_{v\psi}^{day}$  is the daily driving distance per EV, and  $\eta_v$  is the EV charging efficiency,  $\rho_{h\psi}$  is the distribution of EVs by charging state during certain hour.

## 2.2. Formulation of Integrated Generation and Transmission Expansion Planning with Smart Grid Resources

The objective of conventional integrated resource planning (IRP) is to minimize investment costs, subject to planning and operational constraints. New energy resources under uncertainties are modeled as interval-stochastic variables. The uncertainties, such as load growth and fuel price, were taken into account [22], however, to restrict the focus of this study to the effect of smart grid resources, only the effects of smart grid resources are considered. A Benders' decomposition technique is used to determine both deterministic and stochastic variables simultaneously [23].

### 2.2.1. Wind Power Generation

In this study, wind speed is estimated using a stochastic variable that follows a Weibull distribution [12]. A discontinuous function ( $P_{yhw\psi}$ ) for the output of a single wind turbine at hour  $h$

$$P_{yhw\psi} = \begin{cases} 0, & 0 \leq v \leq v_c, v \geq v_s \\ P_w^{\max} \cdot \left( Z_w + U_w(v_{yhw\psi}^A) + Q_w(v_{yhw\psi}^A)^2 \right), & v_c \leq v \leq v_r \\ P_w^{\max}, & v_r \leq v \leq v_s \end{cases}, \forall y, h, w, \psi. \quad (3)$$

where  $Z$ ,  $U$ , and  $Q$  are the parameters that describe the conversion rate from wind to electrical energy. In addition,  $w$  is the index for wind power turbines,  $P_w^{\max}$  is the maximum output of the wind power turbine, and  $v_c$ ,  $v_r$ , and  $v_s$  are the cut-in wind speed, rated wind speed, and the cut-off wind speed of the wind power turbine, respectively. Based on the model of new energy resources that can be formulated, an integrated generation and transmission planning problem is presented in the following subsection.

### 2.2.2. Benders' Master Problem

The optimization problem for integrated generation and transmission planning defined for a deterministic stage can be represented using the following equations. The objective function ( $Z$ ) for minimizing the investment cost and expected mean value of operational cost is given by:

$$\text{Min. } Z^\pm = IC^\pm(xg^\pm, xt^\pm) + \phi^\pm, \quad (4)$$

where  $xg$  and  $xt$  represent the investment decisions in generating capacity and transmission lines, respectively;  $IC$  represents the investment cost function; and  $\varphi$  represents the expected mean value of the operational cost from the dual function. The investment cost  $IC$  can be represented as follows:

$$IC^\pm(xg^\pm, xt^\pm) = \sum_{y=1}^{NY} \left( \left( \sum_{g \in G+} ICG_g \cdot xg_{gy}^\pm + \sum_{ij,t \in T+} ICT_{ij} \cdot xt_{ijty}^\pm \right) \cdot (1+m)^{-(y-1)} \right) - SC^Y, \quad (5)$$

where  $NY$  is the length of the planning horizon in years;  $i-j$  are the index for bus pairs;  $g$  and  $t$  are the generation unit transmission line indices, respectively;  $m$  is the discount rate;  $SC^Y$  is the salvage cost in the final planning year  $Y$ ;  $G+$  and  $T+$  are the candidate sets of the generation units and transmission lines to be built; and  $ICG$  and  $ICT$  are the investment cost coefficient of building the generation and transmission line, respectively.

The first constraints for a master problem are the dual constraints due to the Bender's decomposition technique.

$$\phi^\pm = E^\pm(OC_\psi^\pm(xg^\pm, xt^\pm)) \geq \sum_{y=1}^{NY} \left( (o_{y\psi}^\pm)^{(n-1)} - (\xi_{y\psi}^{(n-1)} \cdot xg_{gy}^\pm + \pi_{y\psi}^{(n-1)} \cdot xt_{ijty}^\pm) \right), \forall n. \quad (6)$$

where  $E(OC(\cdot))$  represents the expected value of the operational cost function  $OC$ ,  $n$  is the iteration index number, and  $o$ ,  $\pi$ , and  $\xi$  are the dual values of the objective function, the generation capacity limit, and the transmission capacity limit, respectively, in the slave problem. The other constraints are investment constraints, and equality constraints.

### 2.2.3. Benders' Slave Problem

Consequently, the slave optimization problem for system operation defined for each probabilistic scenario can be represented using the following equations. The objective function for minimizing operational cost can be expressed as follows:

$$\text{Min.}_{xp^\pm} OC_\psi^\pm = \sum_{y=1}^{NY} \left( \sum_{h=1}^{NH} \sum_{g \in G} (OCG_{gy} \cdot xp_{gyh}^\pm) \cdot (1+m)^{-(y-1)} \right). \quad (7)$$

where  $NH$  is the number of the hours in the year,  $G$  is the set of the available generation units,  $xp$  is the generation schedule of generation units, and  $OCG$  is the generation cost coefficient of the generation unit.

The constraints of the slave problems include constraints such as:

- The nodal power balance equation
- The upper and lower limit constraints for generator output and line flow
- The power flow constraints
- The thermal unit ramp up/down rate limits
- The equality constraint for power flow variables

In the proposed planning problem, investment decisions are scheduled at yearly intervals, while electricity demand is met at hourly intervals. The dual constraint in Equation (6) is represented in terms of the expected marginal mean values of the system operational constraints and indicates the optimality and feasibility of the slave problems. The solution technique incorporating minimax criterion is presented in the following section.

### 3. Integrated Generation and Transmission Planning Method Incorporating New Energy Resources under Uncertainties

To deal with interval variables, the proposed problem has to be reformulated. Additionally, a method to fix an interval solution into one value is needed. On the other hand, due to the complexity of stochastic programming, the sampling technique is needed to reduce the scenarios which are considered. In this section, the two-step method with minimax regret criterion for interval variable and EP for sampling the stochastic variables are presented.

#### 3.1. Risk-Based Decision-Making Method for Interval Planning Problem with Minimax Regret Criterion

In this study, the uncertainties involved in the deployments of smart grid resources—such as the diffusion rates of EVs and the projected capacity of installed wind generators—are represented as interval parameters. A two-step method [17] is used to deal with the interval parameters by reformulating the proposed interval power system planning model into two deterministic submodels: upper and lower bound models. By transforming the interval variables into deterministic variables and solving each submodels, the interval bound of investment solution can be obtained. To deal with interval-valued solutions, a minimax regret criterion for minimizing potential losses is incorporated as a decision-making criterion for the interval optimization problem. To obtain the minimax regret solution within infinite alternative sets, a bi-objective optimization method incorporating both upper and lower bound models is used in this study. Consequently, the objective function of the proposed master problem (4) can be rewritten as follows [24]:

$$\text{Min. } Z = Z^+ + Z^- \quad (8)$$

$xg, xt, \phi$

The investment decision variable in both submodels are set to the same value, to share an identical investment result for both cases; however, operational decision variables are decoupled. Consequently, investment solutions that minimize the opportunity costs can be obtained. These solutions also satisfy the feasibility conditions of both upper and lower bound models.

#### 3.2. Interval-Stochastic Programming Method with Entropy Pooling

In this subsection, the uncertainty attributed to the natural variability of smart grid resources is considered using an appropriate stochastic model. Previous studies [25,26] have shown that consideration of the multiple distributions could help manage the risks associated with forecasting errors in the decision-making problem. In this study, EP is employed to consider the multiple distributions for forecasting the introduction of smart grid technologies. EP, a novel scenario analysis technique for portfolio optimization, estimates the posterior probabilistic distributions of stochastic variables by minimizing the relative entropy of their prior (reference) and posterior PDFs. In the EP model, the posterior PDFs  $\bar{f}(\cdot)$  of stochastic variables ( $\phi_\psi$ ) can be estimated by solving the following optimization problems:

$$\bar{f}(\phi_\psi) \equiv \arg \min_{\bar{f} \in \Omega} \left\{ \varepsilon(\bar{f}(\phi_\psi) | \underline{f}(\phi_\psi)) \right\}, \quad \forall \psi. \quad (9)$$

where  $\underline{f}(\cdot)$  represents the prior PDFs of stochastic variables;  $\Omega$ , the set of alternative distributions on stochastic variables; and  $\varepsilon(\cdot)$ , the relative entropy between the prior and the posterior model. By estimating the Bayesian PDFs of stochastic variables, the proposed method incorporates a wide-spectrum distribution for forecasting smart grid resources. The relative entropy between the prior and the posterior model ( $\varepsilon(\cdot)$ ) can be expressed as follows:

$$\varepsilon(\bar{f}(\phi_\psi) | \underline{f}(\phi_\psi)) \equiv \int \bar{f}(\phi_\psi) [\ln \bar{f}(\phi_\psi) - \ln \underline{f}(\phi_\psi)] d\mu, \quad \forall \psi. \quad (10)$$

The relative entropy minimization procedure of the EP model can prevent the distorted estimation of the posterior distributions. Moreover, the EP provides accurate estimates in low-probability results; therefore, it can be adopted in tail simulations for testing the robustness of the determined solutions. In this study, the estimated posterior model of stochastic variables, in which multiple PDFs are integrated, provides wider distributions than those provided by the prior model. In other words, the proposed Bayesian PDF model estimates the area of high uncertainties, but not the specific values.

The consideration of stochastic samplings of EV charging loads and wind generation could result in a large number of scenarios. The fast-backward scenario reduction algorithm in [27] is used to approximate a smaller number of scenarios with corresponding probabilities. This algorithm determines the interval of a set of scenarios and assigns new probabilities, with possible outcomes of uncertain parameters.

The proposed power system planning problem is solved using an interval-stochastic model that reflects the uncertainties of multiple variables. The probabilistic scenario tree approach [27] is used to deal with a series of rare events generated by adopting the multiple probabilistic distributions of smart grid resources. The finite sets of probabilistic scenarios are represented by nodes, and these nodes are arranged in terms of the stages of the probabilistic variables. Branches connect nodes from different stages, and they are then used to calculate the conditional probability between connected nodes. The proposed power expansion planning method involving the use of the interval-stochastic smart grid resource model can be summarized as Figure 2.

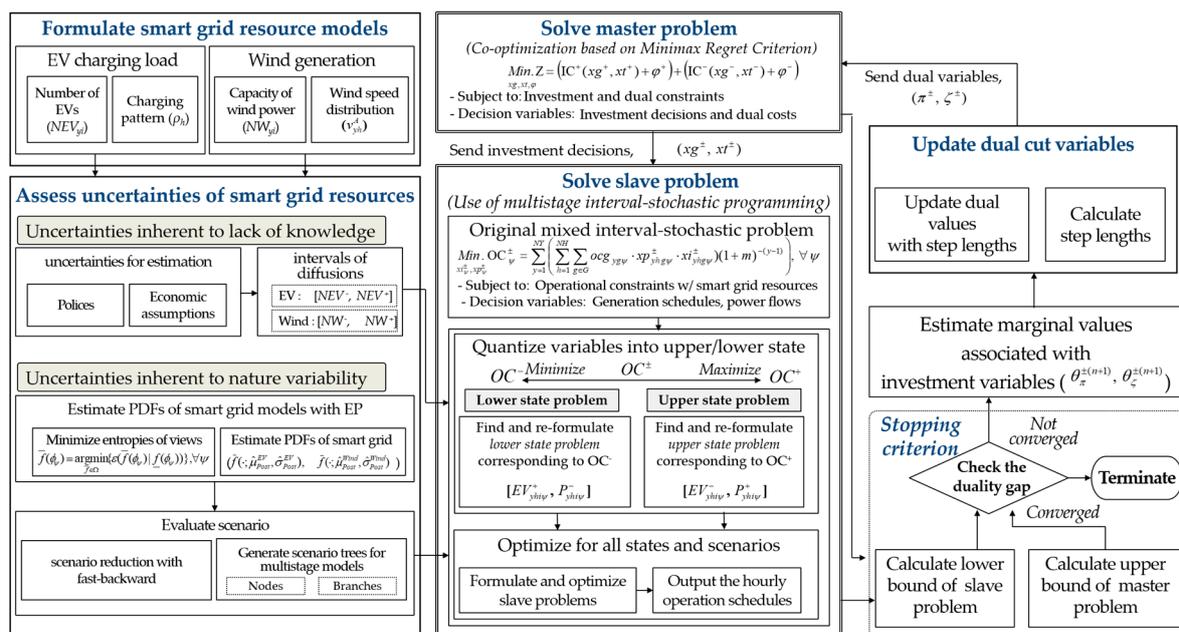


Figure 2. Framework of proposed method with smart grid resources.

#### 4. Numerical Results

The proposed method is tested using projected Korean power system growth between 2020 and 2027 [28]. The base year and discount rate for present-value calculations are assumed to be the year 2020 and 5.0%, respectively. Chronological load curve (CLC) data are represented by polling two typical days (highest demand peak in each month) per month to obtain 576 h/year of data. Table 1 shows the data for the candidate generation units [28]. From Table 1, it can be seen that peaking candidate generation facilities, such as LNG-fired units, could be located within metropolitan areas in which electricity demand is concentrated. By contrast, the candidate base-load and intermediate generation facilities, such as nuclear and coal-fired units, could be located in nonmetropolitan areas. Data for candidate transmission lines are shown in Table 2, from which it can be seen that the characteristics of

candidate transmission lines are determined by their length. The output pattern of hydro generations is created from a historic hourly hydro generation profile of the Korean power system.

**Table 1.** Data for Candidate Generation Unit.

Fuel Type and Capacity (MW *)	Candidate Sites (Area)	Capacity (MW)	Construction Cost Coefficient (k\$/MW)	Incremental Heat Rate (kcal/kWh)
LNG-fired#500	Metro	500	741	1558
LNG-fired#700	South West	700	730	1521
Coal-fired#500	South East	500	1145	1893
Coal-fired#800	Central	800	1058	1985
Coal-fired#1000	Central	800	1058	1985
Nuclear#1000	South East	1000	2122	2084
Nuclear#1400	South East	1400	1790	2217

\* MW: MegaWatt ( $10^6$  Watt).

**Table 2.** Data for Candidate Transmission Line.

Line Type	Capacity (MW)	Reactance (p.u./km)	Construction Cost Coefficient (k\$/km)
Line#1	466	$1.06 \times 10^{-4}$	926
Line#2	518	$9.16 \times 10^{-5}$	1057

In this research, the following scenarios will be used to study how smart grid resources such as EVs and wind power generators influence integrated generation and transmission planning:

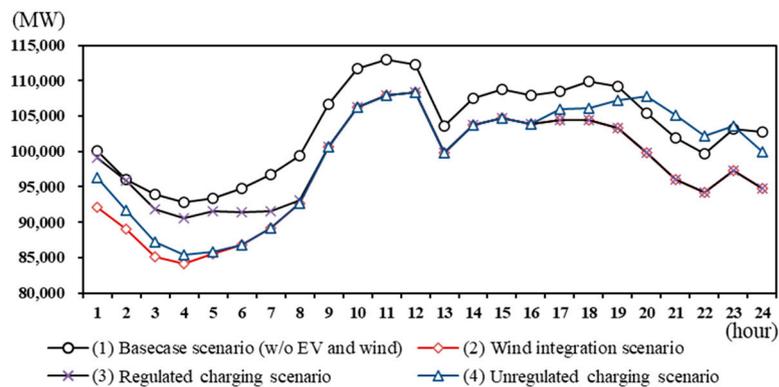
- (1) Basecase scenario—this scenario assumes integration of neither wind nor EVs
- (2) Wind integration scenario—in which only wind power generation is integrated
- (3) Regulated charging scenario—in which the time-of-use charging price of EV is set to be low in off-peak time and the schedule of EV charging is managed to occur when the system net load (i.e., system load minus wind power) is lowest. In this scenario, charging of a vehicle takes place only when it reaches the home of the user.
- (4) Unregulated charging scenario—in which the charging price is uniform, so that the EVs are charging freely just after their trip. In this scenario, charging of a vehicle occurs twice, when it reaches the office and their home.

The key influencing factors and the patterns of EV charging loads can be estimated using statistical data obtained from the Korean National Statistics Office [29] and from Korea's EV demonstration project. It is assumed that the ratio of new vehicle to total vehicle registrations over the past few years will be equivalent to that in future years, and that dissemination scenarios from previous studies [30,31] can be used to estimate the annual diffusion rate of EVs into the vehicle market. Table 3 provides interval data representing a broad spectrum of views on the anticipated annual penetration of smart grid resources, EVs, and wind. From this, a reasonable inference can be made that, in 2024, approximately 1.4 to 3.6 million EVs will be integrated into Korean power systems. In scenario (3) and (4), the EV is assumed as the classic EV which can only charge from the grid. To obtain an hourly charging load, it is assumed that EV charges 8.7 kWh in a day on average with a 2.3 kW converter, therefore, they charge for 4 hours per day on average. Candidate sites selected for the installation of wind power generation capacity can be found in the southwest part of the country and on Jeju Island; parameters of a Weibull function for wind speed variation can be estimated from historical data recorded on the island by the Korea Meteorological Administration (2009).

**Table 3.** Interval Data for Yearly Projected Deployment of Smart Grid Resources.

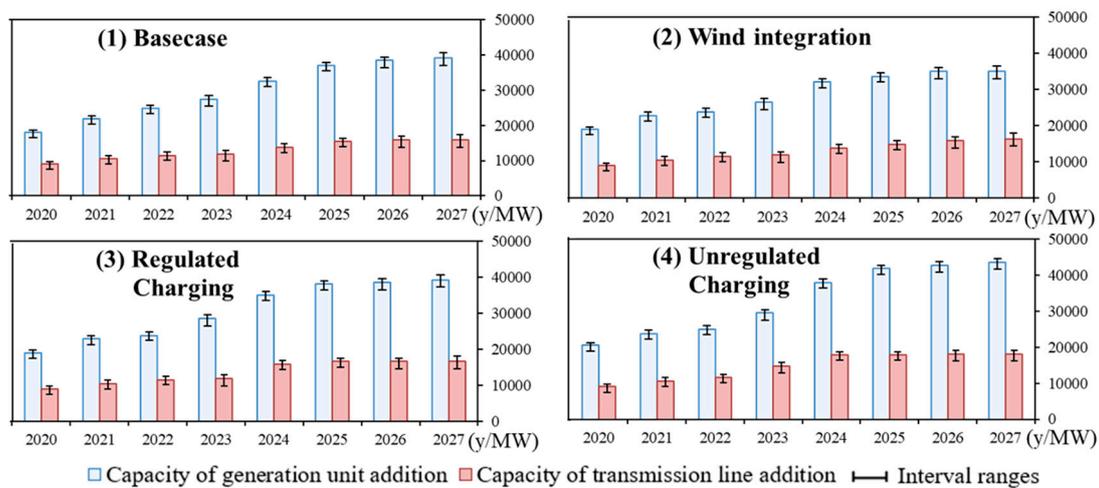
Year		2020	2021	2022	2023	2024	2025	2026	2027
Volume of electric vehicles (EVs)	Lower	903,003	1,059,057	1,195,502	1,311,020	1,404,234	1,504,074	1,611,014	1,725,557
	Upper	2,347,808	2,753,548	3,108,304	3,408,652	3,651,007	3,910,594	4,188,637	4,486,449
Cap. of wind (MW)	Lower	7971	9861	11,177	11,492	11,492	11,492	11,492	12,009
	Upper	14,803	18,313	20,757	21,342	21,342	21,342	21,342	22,302

Under the Renewable Portfolio Standard (RPS), 12.0% of Korean electricity should be supplied by renewable resources in 2027 [28], although various studies [32,33] anticipate that the actual annual renewable energy investment could differ from policy objectives. Figure 3 shows the representative hourly system load profiles of each scenario for one day (24 h) of the first week in 2027.



**Figure 3.** System net-load profiles of each scenario.

The proposed planning method is applied to obtain an optimal investment decision, with respect to integrated generation and transmission planning. The numerical computation takes about an hour for each scenario, with a i3-4000M CPU and 4GB RAM laptop using the GAMS with the Matlab. The generation and transmission investment decision results in 2027 for each smart grid deployment scenario are shown in Table 4. Figure 4 shows the annual accumulated installed capacity and its interval range for each scenario.



**Figure 4.** Annual accumulated installed capacity and its interval range for each scenario (2020–2027).

It can be seen that the generation and transmission investment decision results in each scenario vary, owing to differing levels of smart grid resource incorporation. In the basecase scenario, multiple

transmission lines are established to supply metropolitan demand, resulting in a relatively large quantity of electrical power flowing to the north.

In the wind integration scenario (2), an increase in required ramping rates combines with a decrease in off-peak system loads to stimulate a greater investment in candidate-peaking generation than in any other scenario. The integration of wind power generation in non-metropolitan areas results in the addition of more transmission lines, because wind-powered generators are located far from metropolitan areas and thus cause transmission congestion between metropolitan and non-metropolitan areas at off-peak times.

**Table 4.** Generation Unit and Transmission Line Addition by Smart Grid Deployment Scenario.

Scenario	Basecase Scenario (w/o SG * Resources)	Wind Integration Scenario	Regulated Charging Price Scenario	Unregulated Charging Price Scenario
Number of Generation Unit Addition by Fuel Y\Type in 2027				
LNG **-fired#500	7	8 (▲1)	6 (▼1)	9 (▲2)
LNG-fired#700	6	8 (▲2)	6 (-)	6 (-)
Coal-fired#500	3	3 (-)	3 (-)	4 (▲1)
Coal-fired#800	5	3 (▼2)	6 (▲1)	7 (▲2)
Coal-fired#1000	2	1 (▼1)	2 (-)	2 (-)
Nuclear#1000	4	3 (▼1)	5 (▲1)	5 (▲1)
Nuclear#1400	7	6 (▼1)	8 (▲1)	7 (-)
Number of Transmission Line Addition in 2027				
Transmission line	32	33 (▲1)	34 (▲2)	37 (▲5)

\* SG: Smart Grid, \*\* LNG: Liquefied Natural Gas.

In the regulated charging scenario (3), an increase in minimum system loads owing to EV charging load at off-peak times results in more investment in candidate base-load generation units than in the wind integration scenario. Because the EV charging load in this scenario reduces required ramping rates and does not cause an increase in peak load, there are comparatively fewer candidate transmission lines in the southwest corridor and in other areas.

In the unregulated charging scenario (4), a greater number of new generation units and transmission lines are added than in the regulated charging scenario, while the proportion of peaking capacity is slightly higher. Owing to the increase in uncertainty at peak times, the interval range of investment decisions in this scenario is higher than in the regulated charging scenario.

In order to show the effectiveness of proposed power expansion planning, cases using a minimax regret criterion that incorporate the interval-stochastic method is compared with cases that do not, as follows:

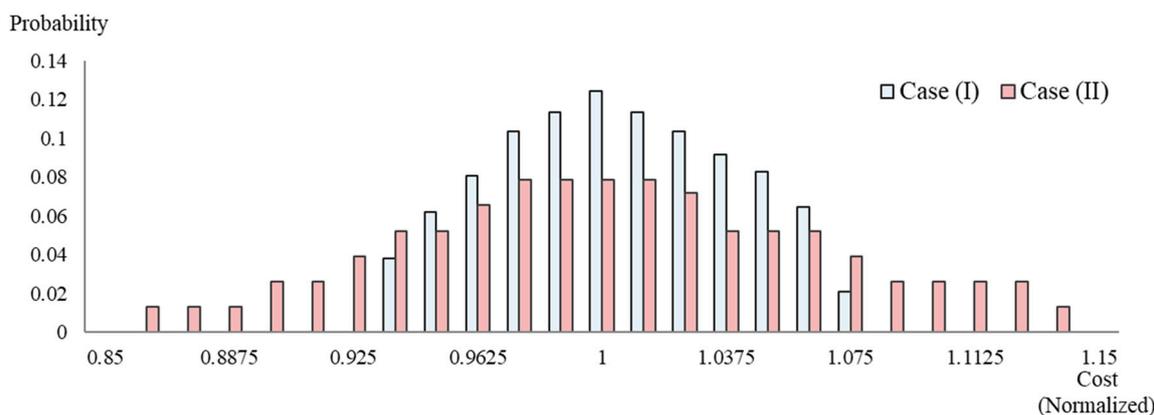
(I) Case using interval-stochastic method—power expansion planning with the proposed interval-stochastic optimization method is used. Formulation is as described in Section 2, and the minimax regret criterion is used as described in Section 3.

(II) Case using deterministic method—power expansion planning with the deterministic optimization method [34] is used. Stochastic variables, as described in Section 2, turn into the deterministic variables with fixed expect values of PDFs. Interval variables are set to values of medians.

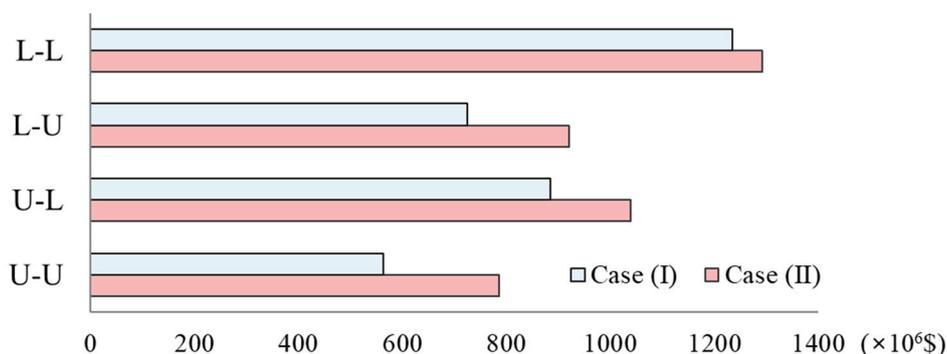
Figure 5 shows cumulative and probabilistic distributions of the total costs based on the fixed investment decisions in 2027 owing to each case, with incorporating probabilistic distributions of smart grid resources. It can be seen from Figure 5 that a slope of the probabilistic distribution associated with case (I) shows less variance than case (II); this is because the proposed method is designed to take into account the set of stochastic scenarios pertaining to the adoption of new smart grid technologies.

In addition, Figure 6 shows annual regret costs [35] of cases (I) and (II), under four different interval states. The regret cost of each interval state presents the differences between the total cost

based on fixed investment decisions owing to each case, and the local optimum objective value at a certain interval point. It can be seen from Figure 6 that the regret cost of case (II) is greater than that of case (I) at lower and upper boundaries. This is because the incorporation of the proposed multistage can help reduce the potential losses associated with making non-optimal decisions regarding smart grid resources. Therefore, the adoption of the proposed power expansion planning method may not guarantee that the outcome of a particular risky decision will be optimal, but it could reduce the risk of prediction errors concerning new resources.



**Figure 5.** Probabilistic distribution of the total costs based on fixed investment decisions in year 2027 owing to each case (x-axis: normalized total costs based on each case; average value is 1, y-axis: probability).



**Figure 6.** Regret costs of case (I) and (II) under different interval states. Note: “L-L”, “L-U”, “U-L”, “U-U” denote interval values of wind generation and EV is fixed to “lower and lower”, “lower and upper”, “upper and lower”, “upper and upper” respectively.

### 5. Conclusions

In this study, the interval-stochastic programming based integrated generation and transmission planning problem is proposed. The proposed method considers the uncertainties of EVs and wind power generation, which are modeled through the EP technique. Additionally, the minimax regret criterion is applied to handle interval solutions into a deterministic manner.

The proposed problem is formulated through the interval and stochastic variables associated with EVs and wind power generation. The numerical test is conducted on the Korean power system, with multiple renewable integration scenarios to observe the influence of the charging price policy of EVs. The result shows that the investment cost of the power grid could be reduced with reasonable pricing, by comparing regulated and unregulated charging scenarios.

By comparing cumulative and probabilistic distributions of the total costs, the result shows that the stochastic approach of the proposed method can reduce the risk from uncertainty, comparing the

result of the deterministic IRP problem. Additionally, with the regret cost at the boundary condition of each interval variable, it is shown that the minimax regret criterion successfully reduces the potential losses from a non-optimal decision.

If a sufficient number of sample observations can be collected, the presented Bayesian probabilistic model for smart grid resources can be further improved. Therefore, the selection of an appropriate investment time frame can be useful in managing innovation risks imposed by a lack of data on new resources. In future work, the integration of more renewable energy sources, such as PV and energy storage systems, and an assessment of the reliability associated with the power system expansion should be tackled.

**Author Contributions:** G.-H.M. performed the research and wrote the paper. R.K. helped with the original draft and revision the paper. S.-K.J. provided guidance for the research and revised the paper. All authors have read and agreed to the published version of the manuscript.

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**Conflicts of Interest:** The authors declare no conflict of interest.

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