J Electr Eng Technol Vol. 8, No. 1: 1-10, 2013
http://dx.doi.org/10.5370/JEET.2013.8.1.001

ISSN(Print) 1975-0102
ISSN(Online) 2093-7423

Stochastic Integrated Generation and Transmission Planning Incorporating Electric Vehicle Deployment

**Guk-Hyun Moon*, Seong-Bae Kong*, Sung-Kwan Joo†,
Heon-Su Ryu** and Tae-Hoon Kim****

Abstract – The power industry is currently facing many challenges, due to the new environment created by the introduction of smart grid technologies. In particular, the large-scale deployment of electric vehicles (EVs) may have a significant impact on demand for electricity and, thereby, influence generation and transmission system planning. However, it is difficult to deal with uncertainties in EV charging loads using deterministic planning methods. This paper presents a two-stage stochastic decomposition method with Latin-hyper rectangle sampling (LHRS) to solve the integrated generation and transmission planning problem incorporating EV deployment. The probabilistic distribution of EV charging loads is estimated by Latin-hyper rectangle sampling (LHRS) to enhance the computational performance of the proposed method. Numerical results are presented to show the effectiveness of the proposed method.

Keywords: Electric vehicle (EV), Latin hyper-rectangle sampling (LHRS), Power system planning, Smart grid

1. Introduction

The power industry is currently facing many challenges, due to the new environment created by the introduction of smart grid technologies. One of the challenges faced by the power industry is the integration of smart grid resources with generation and transmission planning.

Among smart grid resources, electric vehicles (EVs) have been receiving increasing attention as the principal means of achieving the clean use of energy for transportation [1]. The impact of the charging of EVs and plug-in hybrid electric vehicles (PHEVs) on short-term power system operations has been analyzed in [2-7]. These studies have shown that the large-scale deployment of EVs may have an adverse influence on various aspects of a power system, including its reliability [3], operations [4, 5], and the cost of electricity [6, 7]. In particular, the reliability of a power system might be adversely affected if the charging loads of EVs exceed the capacity of existing power equipment [8].

Furthermore, the large-scale deployment of EVs may have a significant impact on demand for electricity and, thereby, influence generation and transmission system planning. Therefore, the integration of EV deployment into power system planning requires a new method to accommodate space-time varying EV charging loads in a generation and transmission system planning process. However, most power system planning methods do not take EV deployment into account. Only a few studies [9, 10] have attempted to evaluate the feasibility of PHEV integration into power systems.

It is a challenging task to incorporate EV charging loads into generation and transmission system planning [11]. The integration of EV deployment into power systems would be challenged by greater uncertainties in the estimation of EV charging loads [10], because of the insufficient historical data regarding the estimation of the these loads. It is difficult to deal with uncertainties in EV charging loads using deterministic planning methods. Such uncertainties associated with EV charging loads can be handled by using a probabilistic approach. Moreover, the integration of EV deployment into the generation and transmission planning problem involves both probabilistic and deterministic variables that cannot be simultaneously determined in the same optimization problem [12, 13].

This paper presents a two-stage stochastic decomposition method with Latin-hyper rectangle sampling (LHRS) to solve the integrated generation and transmission planning problem incorporating EV deployment. In this paper, the stochastic integrated generation and transmission planning for a power system with uncertain EV charging loads is formulated. The two-stage stochastic decomposition method [14] is applied to decompose the integrated optimization problem into a deterministic expansion problem and a stochastic operation problem. In this paper, a stochastic EV charging load model is also proposed to deal with the uncertainties involved in estimating EV charging loads. The probabilistic model of EV charging loads needs to be estimated using stochastic sampling.

† Corresponding Author: School of Electrical Engineering, Korea University, South Korea. (skjoo@korea.ac.kr)
* School of Electrical Engineering, Korea University, South Korea. (hellkeeper@korea.ac.kr, kong8306@korea.ac.kr)
** Power System Planning Team, Korea Power Exchange (KPX), South Korea. (maxima@kpx.or.kr, imu@kpx.or.kr)
Received: April 20, 2012; Accepted: August 24, 2012

Because of the complexity of probabilistic models of EV charging loads, however, the estimation of probabilistic distribution of EV charging loads requires a large computational effort with random sampling. In this paper, the probabilistic distribution of EV charging loads is estimated by LHRS [15] to reduce the computational effort of the proposed method. In this paper, the hourly chronological load curve (CLC) [16, 17] is used to study the effect of hourly charging patterns of EVs on the integrated generation and transmission planning problem.

The remainder of the paper is organized as follows: The stochastic generation and transmission planning problem with EVs deployment is formulated in Section 2. The two-stage stochastic generation and transmission planning method with LHRS is proposed in Section 3. Numerical results are presented to show the effectiveness of the proposed method in Section 4.

2. Problem Formulation

2.1 Electric vehicle charging load model

In this section, the probabilistic model of the EV charging load is described. In references [2, 18-20], deterministic methods have been developed for estimating electric drive vehicle charging loads. The PHEV charging load estimation method in [2] uses transportation survey data and the technical parameters of PHEVs to estimate the scales and patterns of these loads. The PHEV charging load estimation methods, however, are not appropriate for the power planning problem because these methods have not considered uncertainties in the prediction of future conditions that may have a direct impact on investment decisions.

In this study, a stochastic EV charging load model has been developed to evaluate the uncertainties involved in the prospective conditions used for estimating EV charging loads. The key factors influencing the scales and patterns of EV charging loads generally include (i) the volume of EVs, (ii) the daily energy consumed by EVs, and (iii) the hourly charging patterns of EVs [2, 20]. The proposed method to estimate the probabilistic EV charging load incorporating uncertainties in each of the prospective factors is described below.

The annual volumes of EVs in future years can be estimated on the basis of two types of prospective factors [11], namely, the estimated annual number of new vehicle registrations and the estimated EV penetration rates. Such prospective factors for estimating the annual volume of EVs are exposed by the uncertainties in the prediction of future conditions. In this study, these prospective factors are accounted for by using stochastic variables that follow their own probabilistic distributions.

The probabilistic volume of EVs in the future year y (NEV_y^{ω}) can be represented by the following equation:

$$NEV_y^{\omega} = (NV_y^{\omega} \cdot \rho_{EV,y}^{\omega}) + NEV_{y-1}^{\omega} - EV_y^{out} \;,\; \forall y, \forall \omega \quad (1)$$

where ω is the index for the probabilistic scenario, NV_y^{ω} is the probabilistic volume of vehicle registrations, $\rho_{EV,y}^{\omega}$ is the probabilistic annual penetration rate of new EVs, and EV_y^{out} is the volume of EVs disposed of in the year y.

It is anticipated in references [21, 22] that the shape of the annual market penetration growth rate of EVs would follow a "market-diffusion S-curve". In this paper, the Bass diffusion model [22] is adopted to characterize the S-curve shape of the annual penetration growth rate of EVs, which can be represented by the following equation:

$$\rho_{EV,y}^{\omega} = \frac{1 - e^{-(q^{\omega}+r^{\omega})\cdot y}}{1 + q^{\omega}\cdot (r^{\omega})^{-1} \cdot e^{-(q^{\omega}+r^{\omega})\cdot y}} \;,\; \forall y, \forall \omega \quad (2)$$

where q and r are parameters that characterize the S-curve shape.

It is assumed in this study that the daily electrical energy charged by EVs is equal to the amount of energy it consumes during its daily operation. Under this assumption, the daily electrical energy consumed by EVs can be estimated using the fuel efficiency and the daily driving distance of the EVs. Consequently, the daily electrical energy consumed by EVs in the year y ($L_{y,EV}^{\omega,daily}$) can be represented as follows:

$$L_{EV,y}^{\omega,daily} = \sum_{EV=1}^{NEV_y^{\omega}} \frac{1}{FE_{EV,t}^{\omega}} \cdot D_{EV}^{\omega} \;,\forall y, \forall \omega \quad (3)$$

where D_{EV}^{ω} is the daily driving distance of the EV, and $FE_{EV,t}^{\omega}$ is the fuel efficiency of the EV for type t.

Also, the fuel efficiency of the EV for type t can be calculated by using the following equation:

$$FE_{EV,t}^{\omega} = \frac{1}{NEV_t^{\omega}} \sum_{EV \in EV_t} \frac{(D_{EV}^{\max})^{\omega}}{(B_{EV}^{\max})^{\omega}}, \forall t, \forall \omega \quad (4)$$

where NEV_t is the number of EVs by type t; $D_{EV}^{\max}$ is the maximum driving distance of the EV when its battery is fully charged; $B_{EV}^{\max}$ is the capacity of the EV battery.

Another key consideration for estimating EV charging loads has been the time chosen by users to charge their EVs [2, 18]. If appropriate electricity price signals to regulate EV charging loads are provided, the best time for charging EVs would typically be at off-peak hours [18]. In this case, the integration of EV charging loads may not influence the peak-time loads of a power system. However, if appropriate EV tariff is not provided, the charging time would mostly be during peak hours. In order to analyze the impact of different charging patterns on power system planning, two EV charging scenarios are considered, as described below.

1) Regulated charging: In regulated charging scenario, EVs are assumed to start charging from midnight and continue charging until batteries are fully charged.
2) Unregulated charging: In unregulated charging scenario, EVs are charged to full capacity as soon as they arrive at work from home in the morning. Subsequently, the vehicles are charged again to full capacity when they arrive at home from work in the evening.

The time when EVs arrive daily at their charging stations can be estimated by analyzing hourly traffic patterns. The probabilistic distributions of the arrival time can be evaluated on the basis of the decrease in the traffic proportions on an hourly basis during the commute time. The charging speed of EV chargers can influence EV charging loads. In this research, the different charging speed of EV chargers is randomly selected from user-specified probability distribution as an input for the probabilistic model of EV charging loads. In particular, the effect of charging speed is reflected in estimating the charging duration of an EV in Eq. (5). Then, the probabilistic charging ratio of EVs during the hour h ($\varphi^{\omega}_{EV,h}$) can be represented by the following equation:

$$\varphi^{\omega}_{EV,h} = \frac{\sum_{h'=h_0-h^{\omega}_{dur}-h_{com}}^{h_0-h_{com}} \{\left|EV^{\omega}_{h'} - EV^{\omega}_{h'-1}\right| - (EV^{\omega}_{h'} - EV^{\omega}_{h'-1})\}}{\sum_{h'=h_0}^{NH} \{(EV^{\omega}_{h'} - EV^{\omega}_{h'-1}) + (EV^{\omega}_{h'} - EV^{\omega}_{h'-1})\}}, \quad \forall h, \forall \omega \tag{5}$$

where h_0 is the time when the EV starts charging, as determined by the EV charging scenario; h_{dur} is the charging duration of the EV; h_{com} is the travel time to commute of the EV; and EV_h is the number of vehicles being driven on the road during the hour h. Then, the probabilistic EV charging load during the hour h in year y ($L^{\omega}_{EV,yh}$) can be estimated by the following equation:

$$L^{\omega}_{EV,yh} = \left(\sum_{EV=1}^{NEV_y} \frac{D^{\omega}_{EV}}{FE^{\omega}_{EV,t}}\right) \cdot \frac{\sum_{h'=h_0-h^{\omega}_{dur}-h_{com}}^{h_0-h_{com}} \{\left|EV^{\omega}_{h'} - EV^{\omega}_{h'-1}\right| - (EV^{\omega}_{h'} - EV^{\omega}_{h'-1})\}}{\sum_{h'=h_0}^{NH} \{(EV^{\omega}_{h'} - EV^{\omega}_{h'-1}) + (EV^{\omega}_{h'} - EV^{\omega}_{h'-1})\}}, \quad \forall h, \forall y, \forall \omega \tag{6}$$

In this study, the EV charging load model is estimated by integrating a set of factors that follow their own distribution function. The integrated probabilistic distributions of the EV charging load model can be evaluated by using kernel density estimation [23]. Consequently, the PDF of the probabilistic EV charging load during the hour h in year y ($f(L^{\omega}_{EV,yh})$) can be represented by using the following kernel density estimator [23]:

$$f(L^{\omega}_{EV,yh}) = \frac{1}{NS \cdot b} \cdot \sum_{s=1}^{NS} K\left(\frac{X_s - L^{\omega}_{EV,yh}}{b}\right), \forall y, \forall h \tag{7}$$

where X_s , b , $K(\cdot)$, and NS are the statistical data sample, the window width of statistical data, the kernel density function from probabilistic models, and the number of statistical data samples, respectively. As the procedure to estimate the probabilistic model of the EV charging load has been described, the stochastic integrated resource planning (IRP) optimization problem for a power system with uncertain EV charging loads is presented in the following sub-section.

2.2 Two-Stage decomposed stochastic integrated generation and transmission planning problem

The integrated generation and transmission planning attempts to minimize the combined investment and operations costs of generation and transmission. The location, amount and timing of generation and transmission investment decisions can be formulated as a mixed integer programming (MIP) problem. The IRP framework and probabilistic models to incorporate the uncertainties in EV charging loads were employed in this study. The proposed stochastic IRP problem involves both probabilistic and deterministic variables, which cannot be simultaneously determined within the same optimization problem. Thus, the two-stage stochastic decomposition method is employed to decompose the original IRP problem into a first stage for the deterministic expansion problem and a second stage for the stochastic operation problem. The first stage of the power expansion planning problem can be derived as the following deterministic optimization problem (8-12). The objective of the first stage optimization problem is to determine the integrated generation and transmission investment decisions (wg_{iy} , wt_{mnky}) and dual variable (θ) that minimizes the total investment costs and dual costs subject to planning and dual constraints.

1) First-stage Problem for Power Expansion Planning:

a) Objective function for the power expansion planning problem:

$$\underset{wg,wt,\theta}{Minimize} \left[\sum_{y=1}^{NY} \{ \sum_{i \in G+} IG_i \cdot wg_{iy} + \sum_{m,n,k \in L+} IT_{mnk} \cdot wt_{mnky} + \theta_y \} \right] \tag{8}$$

where $m-n$ are the index node pairs, i and k are the indices for generation unit and transmission line, respectively; NY is the number of planning years, $G+$ and $L+$ are the set of candidate generation units and transmission lines, respectively; and IG_i and IT_{mnk} are the investment cost of building generation unit (i) and transmission line (m, n, k) respectively.

b) Dual constraint for investment variables:

$$\theta_y \geq \phi_y^{(\nu)} - (\xi_y^{(\nu)} \cdot wg_{iy} + \pi_y^{(\nu)} \cdot wt_{mnky}), \forall y \tag{9}$$

where ν is the iteration number index; ϕ, π, ξ are respectively the dual value of the objective function, the generation capacity limit, and the transmission capacity limit in the second stage problem; the dual constraint for investment variables (ϕ, π, ξ) is represented in terms of the expected marginal values of system operation constraints and these variables indicate the optimality and feasibility of second stage problems.

c) Generation and transmission investment constraint:

$$0 \leq wg_{iy} - wg_{iy-1}, \forall i, \forall y \tag{10}$$

$$0 \leq wt_{mnky} - wt_{mnky-1}, \forall mnk, \forall y \tag{11}$$

where wg_{iy} and wt_{mnky} are generation and transmission investment decisions in year y, respectively.

d) Transmission line variables equality equation:

$$wt_{mnky} = wt_{nmky}, \forall mnk, \forall y \tag{12}$$

Consequently, the second stage of the operation problem can be derived as the following optimization problem (13-19). In the second stage problem, the CLC model [16, 17] has been considered to analyze the impact of various EV charging scenarios with different charging patterns. Integrated generation and transmission investment decisions are determined at intervals of one year, while the time scale of operation problem is one hour interval. The objective of the second stage optimization problem is to determine the on/off status (I_{ith}) and generation schedules (P_{ith}) of generation units that minimize the total operational costs subject to various operations constraints.

2) Second-stage Problem for System Operation: For Each Stochastic Scenario, $\forall \Omega$

a) Objective function for the system operation problem:

$$\underset{I,\,P}{Minimize} \left[\sum_{y=1}^{NY} \sum_{h=1}^{NH} \sum_{i \in G} F_i(P_{iyh}) \cdot I_{iyh} \right] \tag{13}$$

where NH, G, and $F(\cdot)$ are, respectively, the number of hours of operations, the set of generation units, and the generation cost function of the generation unit (i).

b) Power balance equation at each node:

$$\sum_{i \in \Psi_m} P_{iyh} - \sum_{m,n,k \in \Phi_m} f_{mnkyh} = L_{myh} + L_{EV,myh}^{\omega}, \forall m, \forall y, \forall h \tag{14}$$

where f_{mnkyh}, L_{myh}, Ψ_m, Φ_m, and $L_{EV,myh}^{\omega}$ are, respectively, the power flow in transmission line (m, n, k), system load, the set of generation units and transmission lines connected at node (m), and the EV charging load at node (m).

c) DC power flow equation:

$$\begin{aligned} &-(1 - wt_{mnkyh})M_{mn} + B_{mnk}(\delta_{myh} - \delta_{nyh}) \leq f_{mnkyh}, \\ &f_{mnkyh} \leq (1 - wt_{mnkyh})M_{mn} + B_{mnk}(\delta_{myh} - \delta_{nyh}), \\ &\forall mnk, \forall y, \forall h \end{aligned} \tag{15}$$

where B_{mnk}, M_{mn}, and δ_{myh} are susceptance of transmission line (m, n, k), scaling factor for the equality, and the voltage angle at node (m), respectively.

d) Generation limits of thermal units:

$$P_i^{\min} \cdot WG_{iy} \leq P_{iyh} \leq P_i^{\max} \cdot WG_{iy}, \forall i, \forall y, \forall h \tag{16}$$

where $P_i^{\min}$, $P_i^{\max}$, and WG_{iy} are the minimum and maximum power output of generation unit (i), and generation invest decision determined in first stage problem, respectively.

e) Thermal limits of transmission lines:

$$\left| f_{mnkyh} \right| \leq WT_{mnky} \cdot f_{mnk}^{\max}, \forall mnk, \forall y, \forall h \tag{17}$$

where $f_{mnk}^{\max}$ and WT_{mnky} are the maximum capacity and investment decision of transmission line (m, n, k).

f) Commitment constraint of thermal units:

$$I_{iyh} \leq WG_{iyh}, \forall i, \forall y, \forall h \tag{18}$$

g) Power flow variables equality equation:

$$f_{mnkyh} = -f_{nmkyh}, \forall mnk, \forall y, \forall h \tag{19}$$

In the second stage problem, the EV charging load ($L_{EV,myh}^{\omega}$) is considered in the probabilistic model. As the stochastic IRP problem incorporating probabilistic EV charging loads has been formulated, the proposed stochastic solution technique with LHRS is presented in the following section.

3. Stochastic Integrated Generation and Transmission Planning Method Incorporating Electric Vehicle Charging Load

3.1 Probabilistic electric vehicle charging load model with latin hyper-rectangle sampling (LHRS)

The uncertainties of EV charging loads are represented by probabilistic models and estimated using stochastic sampling. When solving a stochastic problem, it is necessary to employ the appropriate sampling technique in order to estimate the probabilistic distributions of uncertain parameters. Because of the complexity of probabilistic models of EV charging loads, a large computational effort with random sampling is needed for estimating uncertainties. In this study, LHRS is employed to reduce the computational effort involved in the estimation of uncertainties. Conventional Latin hypercube sampling (LHS) with equal probability cells often tends to generate an insufficient number of samples in the low-probability area of non-uniform distributions.

LHRS is designed to partition PDFs into several cells with corresponding probabilities. With LHRS, the means and variances of the PDFs of EV charging loads can be estimated by following Eqs. (20) and (21):

$$\hat{\mu}_{LHRS}^{EV} = \sum_{c=1}^{NC} g(L_{EV,yh}^{\omega}[c]) \cdot p_c \tag{20}$$

$$(\hat{\sigma}_{LHRS}^{EV})^2 = \sum_{c=1}^{NC} \sigma[g(L_{EV,yh}^{\omega}[c])^2] \cdot p_c^2 \tag{21}$$

where c represents the index for non-equal probability cells and NC represents the total number of cells, $L_{EV,yh}^{\omega}[c]$ represents generated random EV charging load samples in cell (c), $g(\cdot)$ represents the estimated probabilistic function, and p_c is the corresponding probability of cell (c).

Further, by incorporating means of the PDFs, Eq. (21) can be rewritten as follows:

$$(\hat{\sigma}_{LHRS}^{EV})^2 = \sum_{c=1}^{NC} \left| E(L_{EV,yh}^{\omega}{}^2[c]) - (\hat{\mu}_{LHRS}^{EV})^2 \right| \cdot p_c^2 \tag{22}$$

By differentiating (22) with respect to each cell (c) and setting the derivatives to zero, the optimal boundary of the probability cell (a_c^{EV}), that minimizes the variance of the estimation, can be determined by the following equation:

$$a_c^{EV} = \frac{1}{p_c - p_{c+1}} \cdot \{(p_c \mu_c^{EV} - p_{c+1}\mu_{c+1}^{EV}) + \sqrt{(p_c\mu_c^{EV} - p_{c+1}\mu_{c+1}^{EV})^2 - (p_c - p_{c+1})(p_c E(L_{EV,yh}^{\omega}{}^2[c]) - p_{c+1}E(L_{EV,yh}^{\omega}{}^2[c+1])}\}, \quad \forall c \tag{23}$$

The probability of the c-th cell (p_c) can be estimated by the following equation:

$$p_c = \int_{a_{c-1}^{EV}}^{a_c^{EV}} f(L_{EV,yh}^{\omega})dL, \ \forall c \tag{24}$$

where $f(\cdot)$ represents the probabilistic density function (PDF). The size of non-equal probability cells affects on the means and variances of generated samples and, thereby, accuracy of estimation. The proper partitioning of the PDF into non-equal probability cells results in a sufficient number of samples in a low-probability area. This feature of LHRS can provide efficient and accurate estimation in low-probability areas.

The stochastic samplings of EV charging loads could result in a large number of scenarios, which in turn would cause computational burden. Thus, it is necessary to use an effective scenario reduction technique in a large-scale stochastic optimization problem. The fast-backward scenario-reduction technique [24] is adopted in this study to approximate a smaller number of scenarios with corresponding probabilities. The fast-backward scenario-

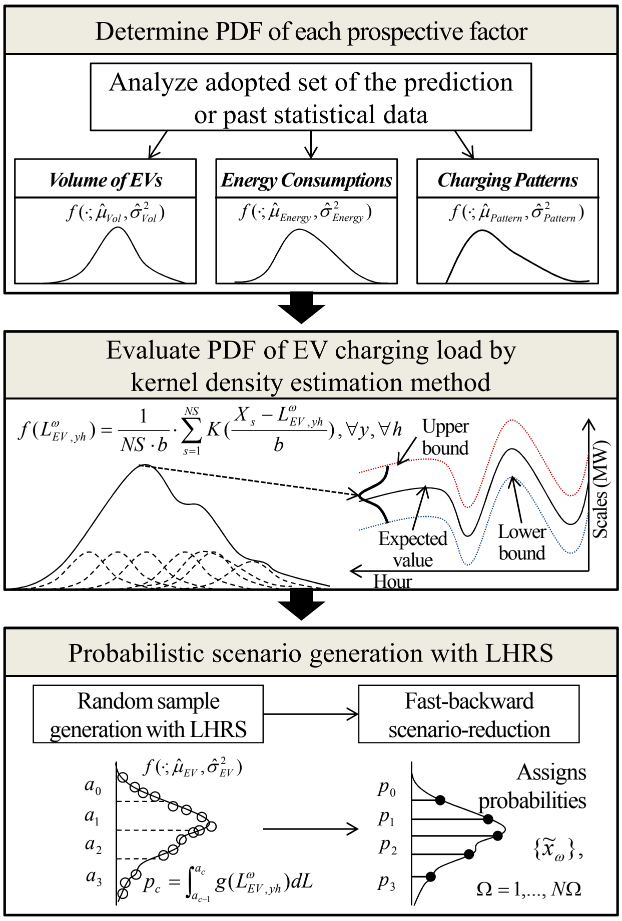

Fig. 1. Proposed procedure to evaluate probabilistic EV charging load model with LHRS

reduction technique attempts to determine an interval of a set of scenarios (Ω) and assigns new probabilities with possible outcomes for the uncertain parameters. The probability of each set of scenarios can be estimated by the following equation:

$$p^{\Omega} = \int_{a_{\Omega-1}^{EV}}^{a_{\Omega}^{EV}} f(L_{EV,yh}^{\Omega})dL, \forall\Omega \tag{25}$$

The proposed procedure to evaluate probabilistic models of EV charging loads with LHRS is illustrated in Fig. 1.

3.2 Stochastic integrated generation and transmission planning method with probabilistic electric vehicle charging model

Two-stage decomposition method is used to solve stochastic integrated generation and transmission planning problem with EV charging load. The procedures of the proposed two-stage decomposition method for the stochastic IRP problem with EV charging load can be summarized as follows:

Step 1) Initialize the iteration counter ν by setting it to 1. Also, set the primal variable to 0 and set the cut variables to arbitrary initial points.

Step 2) Compute the probabilistic annual volumes of EVs in future year y (NEV_y^{ω}) with annual number of new vehicle registrations and the EV penetration rates by using Eqs. (1) and (2).

Step 3) Compute the probabilistic daily electrical energy consumed by the EVs ($L_{y,EV}^{\omega,daily}$) with fuel efficiency and the daily driving distance of the EVs by using Eqs. (3) and (4).

Step 4) Compute the probabilistic charging ratio of EVs ($\varphi_{EV,h}^{\omega}$) based on EV charging scenarios by using Eq. (5).

Step 5) Evaluate the PDF of the probabilistic EV charging load $f(\cdot;\hat{\mu}_{LHRS}^{EV},\ \hat{\sigma}_{LHRS}^{EV})$ with prospective factors determined in Step 2 through Step 4 by using Eqs. (6) and (7).

Step 6) Generate the EV charging load samples according to the PDF $f(\cdot;\hat{\mu}_{LHRS}^{EV},\hat{\sigma}_{LHRS}^{EV})$ with LHRS. The probability of the c-th cell (p_c) can be estimated by Eq. (24).

Step 7) Determine the interval and probability of stochastic scenario (Ω) with possible outcomes for the uncertain parameters by using the fast-backward scenario-reduction technique [24].

Step 8) (First stage) Solve the deterministic power expansion problem subject to planning constraints and determine investment decision variables. The determined integrated generation and transmission investment decision variables are passed to the second stage problem.

Step 9) (Second stage) Solve the stochastic power operation problem subject to operation constraints and determine dual variables. The determined dual variables are passed to the step length calculation procedure.

Step 10) Update the dual constraint parameters in the first stage problem with step length for each dual variable of the second stage problem by using the following Eqs. (26, 27):

$$\pi^{(\nu+1)} = \pi^{(\nu)} + \sum_{\Omega=1}^{N\Omega} p^{\Omega} \cdot \lambda_{\pi}^{(\nu)}, \forall\nu \tag{26}$$

$$\zeta^{(\nu+1)} = \zeta^{(\nu)} + \sum_{\Omega=1}^{N\Omega} p^{\Omega} \cdot \lambda_{\zeta}^{(\nu)}, \forall\nu \tag{27}$$

where $N\Omega$ is the number of probabilistic scenarios, λ_{π} and λ_{ζ} are respectively, the dual values of constrained Eqs. (16) and (17).

Step 11) (Stopping criterion) Stop if the obtained duality gap is less than criterion value ε .

$$\frac{\sum_{y=1}^{NY}\sum_{h=1}^{NH}\sum_{i\in G} F_i(P_{iyh})\cdot I_{iyh} - \theta^{\nu}}{\theta^{\nu}} \le \varepsilon, \forall\nu \tag{28}$$

Otherwise, go back to Step 8 and repeat the process. The overall procedure of the proposed method is illustrated in Fig. 2.

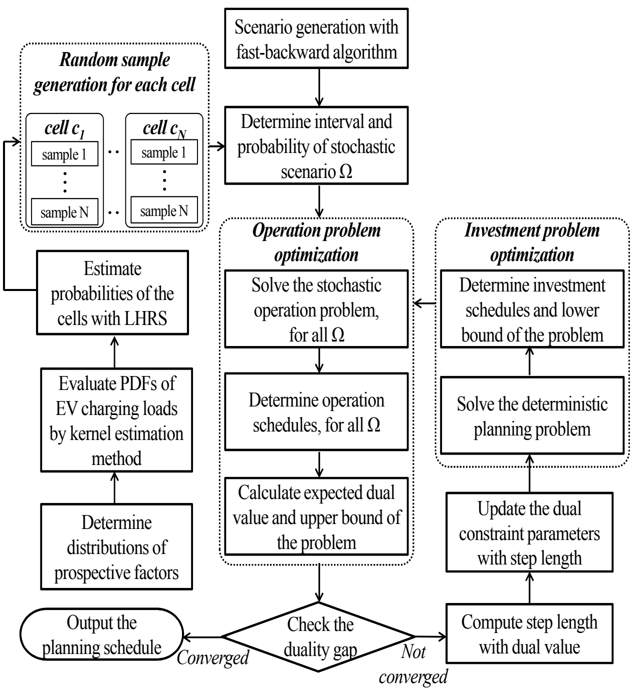

Fig. 2. Overall procedure of the proposed planning method

4. Numerical Results

In this section, the proposed method is tested on integrated generation and transmission planning for the future Korean power system. The planning horizon considered in this study is from the year 2010 to 2024 [25].

The CLC data are obtained from a historical load profile of Korean power system in 2009, which is then scaled to match annual peak demand projection. Due to the scale of the problem, the CLC data are represented by two typical days per month (576 h/year) in this study. The data for annual electricity peak demand of the Korean power system are shown in Table 1.

The electricity energy consumption is expected to continuously increase in Korea, and the average annual rate of increase in electricity peak demand is assumed to be 2.2 % during the planning horizon. Table 2 shows the data for installed generation capacity by fuel type in 2009, while Table 3 shows the data for the candidate generation unit.

It can be seen from Table 3 that new candidate peaking generation units such as LNG-fired units could be located in the metropolitan area where the demand is higher. In contrast, new base-load candidate generation units such as nuclear and coal-fired units could be located in non-metropolitan areas. In addition, the data for new candidate transmission lines are shown in Table 4.

Investment decisions on the candidate generation units and transmission lines that are already made during the planning period are treated as fixed variables. The output pattern of hydro generations is created from a historic hourly hydro generation profile of the Korean power system in 2009. The output pattern of wind generation is also estimated from historical wind power data in the Jeju Island of Korea in 2009.

Table 1. Forecasted annual electricity peak demand in Korea [25], (MW)

Year	2010	2011	2012	2013	2014	2015	2016
Peak load	70,457	73,713	76,161	79,784	83,360	86,754	89,629
2017	2018	2019	2020	2021	2022	2023	2024
92,281	95,075	97,405	99,653	101,640	103,644	105,615	107,437

Table 2. Data for installed generation capacity by fuel type

Fuel type	Capacity (MW)	Proportion (%)
Oil-fired	5,368	7.44
LNG-fired	17,850	24.73
Coal-fired	24,205	33.53
Nuclear	17,716	21.54
Hydro and Renewable	1,891	2.62
RCS (Regional Cogeneration System)	1,255	1.74
The others	3,900	5.40

Table 3. Data for new candidate generation unit

Fuel type	Capacity (MW)	Construction cost coefficient (k$/MW)	Generation cost coefficient ($/MWh)	Candidate sites (Area)
LNG-fired#1	500	741	83.68	Metro
LNG-fired#2	700	730	81.69	SW
Coal-fired#1	500	1,145	41.91	SE
Coal-fired#2	800	1,058	43.95	Central
Nuclear#1	1,000	2,122	2.69	SE
Nuclear#2	1,400	1,790	2.86	SE

Table 4. Data for new candidate transmission line

Line type	Capacity (MW)	Reactance (p.u./km)	Construction cost coefficient (k$/km)
Line#1	466	1.06×10^{-4}	926
Line#2	518	9.16×10^{-5}	1,057

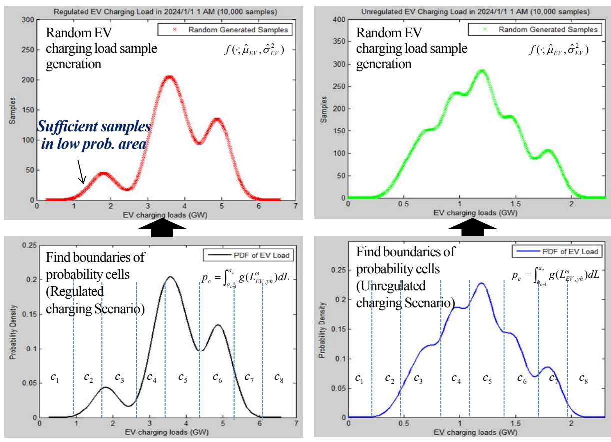

Fig. 3. Probabilistic distribution of EV charging loads estimated by the Latin-hyper rectangle sampling (LHRS) for different scenarios

In order to analyze the impact of EV deployment on power system planning, two EV charging scenarios are considered in this case study as follows: (1) regulated charging scenario and (2) unregulated charging scenario. For the purpose of comparison, it is also assumed in the basecase that does not consider the EV deployment.

The volume of new vehicle registrations during the planning horizon is forecasted by using past transportation statistical data obtained from the National Statistics Office in Korea [26]. In this study, the Bass diffusion model described in [22] is used to forecast the penetration growth rates of EVs. Furthermore, the saturation level of the Bass diffusion model is also determined by using the EV penetration rates forecasted by the Roland Berger Strategy Consultants [21]. It is also assumed based on the transportation survey data in [26] that the average vehicle replacement cycle is six years in order to estimate the volume of EVs disposed of over the planning horizon. In this study, two types of EV model used by Korea's EV demonstration project are considered; these models are the i10 manufactured by Hyundai Motors and the SM3

Table 5. Estimated annual volumes of EVs in Korea

Year	2013	2014	2015	2016	2017	2019	2020	2021	2022	2023	2024
Volume	59,279	166,129	323,352	533,873	800,750	1,516,475	1,806,006	2,118,114	2,391,003	2,622,040	2,808,467

manufactured by Renault Samsung. The actual fuel efficiency of these EVs has been estimated to be 5.25 km/kWh and 4.38 km/kWh, respectively. Further, the average daily driving distance for conventional vehicles is assumed to be 42 km based on the transportation statistical data of Korea in 2010 [26]. The arrival time of EVs is estimated by using the hourly traffic patterns collected by the Seoul Metropolitan Police Agency. In addition, the travel time to commute is set to about 1 hour based on the traffic statistics data in [26]. Table 5 lists the estimated annual volumes of EVs in Korea during the planning horizon.

The optimal investment decisions of the stochastic IRP problem with EV charging load are determined by the proposed iterative procedure presented in Section 3. The

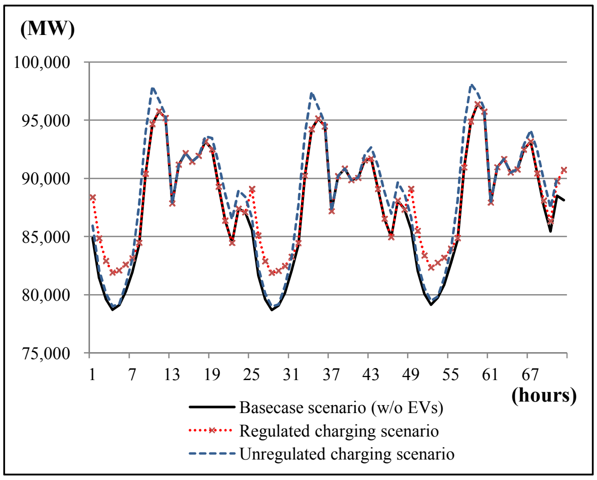

Fig. 4. Hourly system load profiles for different scenarios in 2024

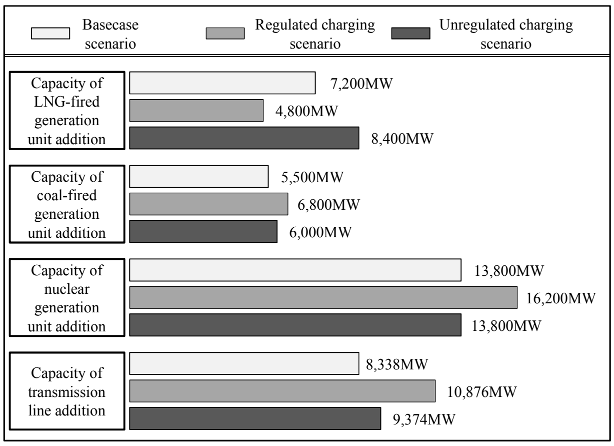

Fig. 5. Capacity of generation unit and transmission line addition in 2024

boundary gap tolerance ε, which determines the stopping criterion, is set to 10^{-1}. Fig. 3 shows the probabilistic distribution of EV charging loads in 2024 for each scenario, estimated by the LHRS. Fig. 4 shows the representative hourly system load profiles of each scenario for three days (72 hours) of the first week in 2024.

It can be seen from Fig. 4 that in the unregulated charging scenario, the system load at peak time can be increased due to EV charging loads. The generation and transmission investment decision results for each scenario in 2024 are shown in Fig. 5. The number of generation unit additions and transmission line additions for each scenario are also shown in Tables 6 and Table 7, respectively.

In Tables 6 and 7, the generation and transmission investment decision results for each scenario are shown to be different due to different EV charging loads.

In the regulated charging scenario, due to the increase in system loads at off-peak time, candidate base-load generation units are given more consideration for investment than in the other scenarios. In contrast, candidate peaking generation units are given less consideration for investment. The increase in base-load generation capacity in non-metropolitan area also requires more new transmission line additions between metropolitan and non-metropolitan areas since most of candidate base-load generation units are located far from the metropolitan area and cause transmission congestion between metropolitan and non-metropolitan areas.

Table 6. Number of generation unit addition by scenario

Scenario	Basecase scenario (w/o EVs)	Regulated charging scenario	Unregulated charging scenario
LNG-fired#1	5	3 (▼2)	6 (▲1)
LNG-fired#2	6	4 (▼2)	7 (▲1)
Coal-fired#1	3	3 (-)	4 (▲1)
Coal-fired#2	5	6 (▲1)	5 (-)
Nuclear#1	4	5 (▲1)	4 (-)
Nuclear#2	7	8 (▲1)	7 (-)

Table 7. Number of transmission line addition by scenario

Scenario	Basecase scenario (w/o EVs)	Regulated charging scenario	Unregulated charging scenario
Transmission line	17	22 (▲5)	19 (▲2)

In the unregulated charging scenario, due to the increase in system loads at peak and intermediate times, the amount of new generation and transmission additions is increased compared to that of base scenarios. When it comes to generation mix, the proportion of peaking generations is increased compared to the basecase scenario.

It is concluded from the numerical results that different EV charging patterns have a different impact on integrated generation and transmission planning. The numerical results imply that if appropriate price signals to regulate EV charging loads are provided, EV charging would be at off-peak hours; thereby provide an investment signal for base-load generation units.

5. Conclusion

This paper presents two-stage stochastic decomposition method with LHRS to solve the integrated generation and transmission planning problem incorporating EV deployment. In this paper, a stochastic EV charging load model is proposed to handle the uncertainties involved in the prospective conditions for estimating EV charging loads. Also, the probabilistic distribution of EV charging loads is estimated by LHRS to enhance the computational performance of the proposed method. Two-stage stochastic decomposition method is applied to decompose the original IRP problem into the deterministic expansion problem and the stochastic operation problem. The results of this study imply that different EV charging patterns have a different impact on integrated generation and transmission planning.

EV charging loads can be influenced by EV mix since daily consumed energy and hourly charging patterns vary with the type of EVs such as commuter EVs and business EVs. Therefore, future research is needed to study the effect of EV mix on EV charging loads. In addition to EV deployment, it is also a challenging task to integrate the other smart grid resources such as demand response (DR), renewable generation, and electric energy storage systems into generation and transmission planning. The next phase of this research is to extend the proposed method to incorporate these smart grid resources into the integrated generation and transmission planning.

Acknowledgements

This work was supported by the Power Generation and Electricity Delivery of the Korea Institute of Energy Technology Evaluation and Planning (KETEP) grant funded by the Korea government Ministry of Knowledge Economy (No. 20111020400290). This research was also supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (2010-0006346). This research was supported by a Korea University Grant.

References

[1] Roadmap: Revolutionizing Transportation and Achieving Energy Security, Nov. 2009. [Online]. Available: http://www.electrificationcoalition.org/.

[2] J. Wang, C. Liu, D. Ton, Y. Zhou, J. Kim, and A. Vyas, “Impact of Plug-in Hybrid Electric Vehicles on Power Systems with Demand Response and Wind Power,” *Energy Policy*, Vol. 39, No. 7, pp. 4016-4021, July 2011.

[3] K. Clement-Nyns, E. Haesen, and J. Driesen, “The Impact of Charging Plug-in Hybrid Electric Vehicles on a Residential Distribution Grid,” *IEEE Trans. Power Systems*, Vol. 25, No. 1, pp. 371-380, Feb. 2010.

[4] C. Weiller, “Plug-in Hybrid Electric Vehicle Impacts on Hourly Electricity Demand in the United States,” *Energy Policy*, Vol. 39, No. 6, pp. 3766-3778, June 2011.

[5] L. Goransson, S. Karlsson, and F. Johnsson, “Integration of Plug-in Hybrid Electric Vehicles in a Regional Wind-Thermal Power System,” *Energy Policy*, Vol. 38, No. 10, pp. 5482-5492, Oct. 2010.

[6] L. Wang, L. Anhua, and C. Yihsu, “Potential Impact of Recharging Plug-in Hybrid Electric Vehicles on Locational Marginal Prices,” *Naval Research Logistics*, Vol. 57, No. 8, pp. 686-700, Dec. 2010.

[7] K. C. Divya, O. Jacob, L. Esben, C. Kern, T. Wittman, and M. Weinhold, “Integration of Electric Drive Vehicles in the Danish Electricity Network with High Wind Power Penetration,” *Euro. Trans. on Elect. Power*, Vol. 20, No. 7, pp. 872-883, Oct. 2010.

[8] K. J. Dyke, N. Schofield, and M. Barnes, “The Impact of Transport Electrification on Electrical Networks,” *IEEE Trans. Indus. Elect.*, Vol. 57, No.12, pp. 3917-3926, Dec. 2010.

[9] X. Yu, “Impacts Assessment of PHEV Charge Profiles on Generation Expansion Using National Energy Modeling System,” in *Proc. IEEE Power and Energy Soc. General Meeting*, Pittsburgh, PA, July 2008.

[10] J. Kiviluoma and P. Meibom, “Influence of Wind Power, Plug-in Electric Vehicles, and Heat Storages on Power System Investments,” *Energy*, Vol. 35, No. 3, pp. 1244-1255, Mar. 2010.

[11] A. H. Hajimiragha, C. A. Caňizares, M. W. Fowler, S. Moazeni, and A. Elkamel, “A Robust Optimization Approach for Planning the Transition to Plug-in Hybrid Electric Vehicles,” *IEEE Trans. Power Systems*, Vol. 26, No. 4, pp. 2264-2274, Nov. 2011.

[12] J. Á. López, K. Ponnambalam, and V. H. Quintana, “Generation and Transmission Expansion Under Risk Using Stochastic Programming,” *IEEE Trans. Power Systems*, Vol. 22, No. 3, pp. 1369-1378, Aug. 2007.

[13] G. H. Moon, S. K. Joo, D. Hur, H. S. Jeong, H. S. Ryu, and K. W. Cho, “Stochastic Integrated Generation and

Transmission Planning Method with Gradient Radar Step (GRS),” *IEEE Trans. & Distr. Conference & Exposition: Asia and Pacific*, Seoul, 2009.
[14] M. R. Busseick, “Stochastic Optimization: Solvers and Tools,” *Stochastic Optimization in the Energy Industry*, Aachen, Germany, 2007.
[15] D. Mease and D. Bingham, “Latin Hyper-Rectangle Sampling for Computer Experiments,” *Technometrics*, Vol. 48, No. 4, pp. 467-477, Nov. 2006.
[16] Y. Ding, P. Wang, L. Goel, P. C. Loh, and Q. Wu, “Long-term Reserve Expansion of Power Systems with High Wind Power Penetration Using Universal Generating Function Methods,” *IEEE Trans. Power Systems*, Vol. 26, No. 2, pp. 766-774, May 2011.
[17] S. Kamalinia and M. Shahidehpour, “Generation Expansion Planning in Wind-Thermal power systems,” *IET Gener. Transm. Distrib*., Vol. 4, No. 8, pp. 940-951, Aug. 2010.
[18] S. W. Hadley, “Evaluating the Impact of Plug-in Hybrid Vehicles on Regional Electricity Supplies,” *Proc. Bulk Power System Dynamics and Control VII Symp., IREP*, Charleston, SC, Aug. 2007.
[19] M. Kintner-Meyer, K. Schneider, and R. Pratt, “Impacts Assessment of Plug-in Hybrid Vehicles on Electric Utilities and Regional us Power Grids Part 1: Technical Analysis,” *Pacific Northwest National Lab*., 2007.
[20] Z. Darabi and M. Ferdowsi, “Plug-in Hybrid Electric Vehicles: Charging Load Profile Extraction Based on Transportation Data,” *2011 IEEE Power and Energy Society General Meeting*, July 2011.
[21] Roland Berger Strategy Consultants, “Powertrain 2020: The Future Drives Electric,” *Automotive Competence Center Client Magazine*, No. 02_2008, 2008.
[22] W. Short and P. Denholm, “A Preliminary Assessment of Plug-in Hybrid Electric Vehicles on Wind Energy Markets,” *National Renewable Energy Lab*., April 2006.
[23] A. R. Mugdadi and E. Munthali, “Relative Efficiency in Kernel Estimation of the Distribution Function,” *Journal of Statistical Research*, Vol. 37, No. 2, pp. 203-218, 2003.
[24] H. Heitsch and W. Romisch, “Scenario Tree Reduction for Multistage Stochastic Programs,” *Compu. Manag. Scien.*, Vol. 6, No. 2, pp. 117-133, May 2009.
[25] Korea Power Exchange (KPX), “The 5th Basic Plan for Long-Term Electricity Supply and Demand (2010-2024),” Ministry of Knowledge Economy in Korea, Dec. 2010.
[26] Statistics Korea: Transport Survey, Nov. 2011. [Online]. Available: http://kostat.go.kr/portal/english/survey Outlines/6/3/index.static.

Guk-Hyun Moon He received B.S. degree from Korea University, Seoul, Republic of Korea, in 2007. He is currently pursuing Ph.D. degree in Electrical Engineering at Korea University. His research interests include optimization and power system planning.

Seong-Bae Kong He received B.S. degree from Dankook University, Seoul, Republic of Korea, in 2009, and M.S. degree from Korea University, Seoul, Republic of Korea, in 2011. He is currently pursuing Ph.D. degree in Electrical Engineering at Korea University. His research interests include electric vehicle and probabilistic load flow.

Sung-Kwan Joo He received M.S. and Ph.D. degrees from the University of Washington, Seattle, in 1999 and 2004, respectively. He is currently an Associate Professor in Electrical Engineering at Korea University. His research interests include multi-disciplinary research related to power systems, involving economics, information technologies, optimization, and intelligent systems.

Heon-Su Ryu He received B.S., M.S., and Ph.D. degrees in Electrical Engineering from Yonsei University, Seoul, Republic of Korea, in 1992, 1996, and 2002 respectively. He joined KPX (Korea Power Exchange) in 2002, and currently works in power system planning department. His research interests include power system planning and control.

Tae-Hoon Kim He received B.S. degree from Yonsei University, Seoul, Republic of Korea, in 1988, and he is currently pursuing M.S. degree at Korea University. From 1990 to 2001, he worked for KEPCO, and currently works for KPX. His research interests include Korean network configuration for the future, related to effective grid expansion.