Evaluation of Electric Vehicles Hosting Capacity Based on Interval Undervoltage Probability in a Distribution Network

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\textbf{ABSTRACT} The rapidly growing market for electric vehicles (EVs) and chargers has a considerable influence on the operation of the distribution network. Accurate evaluation of the number of EVs penetrating the distribution network, that is, the hosting capacity (HC) of EVs, is beneficial to distribution network planning and efficient operation. Further, EVs have uncertainties in terms of arrival time, departure time, battery state of charge (SOC), and choice of charging station, which collectively affect the system difficult, but important, step of modeling EV uncertainties on system performance. This paper presents a methodology to model how many EVs can penetrate a low voltage distribution network, especially microgrid. First, EV load modeling incorporating uncertainties is performed by applying interval and affine arithmetic. Second, to analyze the effects of voltage, the same arithmetic methods are extended to perform power flow calculation. Thirdly, interval undervoltage probability (IUP) is introduced to evaluate the HC of the EVs. Subsequently, a voltage violation index (VVI) is introduced, and an EV HC evaluation method is proposed, assisting in the flexible operation of the network based on VVI. The utility of the proposed method is demonstrated by modeling the network of Seoul National University in South Korea, which is subsequently compared with the conventional approach of determining EV HC. The model incorporated Seoul National University’s practical cable data, load data, and vehicle access data, along with the number of EVs penetrating the target network.

\textbf{INDEX TERMS} Affine arithmetic, distribution network, electric vehicle, electric vehicle hosting capacity, interval arithmetic, uncertainties, under voltage probability.

\textbf{NOMENCLATURE}

\textit{Sets:}

\begin{itemize}
  \item $\Omega_D$: Set of Monte Carlo sampling days.
  \item $\Omega\Omega_D^1$: Set of electric vehicle (EV) loads at time period $t$ greater than the average value.
  \item $\Omega\Omega_D^2$: Set of EV loads at time period $t$ less than the average value.
\end{itemize}

\textit{Indices:}

\begin{itemize}
  \item $m$: Index for the number of EVs.
  \item $i$: Bus index.
  \item $j$: EV access case index.
\end{itemize}

\textit{k}: EV charging station selection index.

$\lambda_{\text{max}}$: Maximum interval undervoltage probability (IUP) set by the network operator.

$N_{\text{EV}}$: Total number of EV access cases after the number of EVs are determined.
The Real value of voltage in interval form.

The Imaginary value of voltage in interval form.

Upper and lower bounds of interval form.

Interval form of IUP for the

Interval form of IUP for the

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Energy Agency, the EV market size could reach 230 million worldwide in 2020. Considering the growing EV and charger market, increasing load is being placed on power distribution networks through voltage deviation, power losses, and transformer overheat [2]–[6]. Given EVs have such a significant effect on distribution networks, numerous studies have been conducted to calculate how many EVs a network can accommodate, i.e., EV hosting capacity (HC).

For EV HC, studies have mainly focused on determining the number of EVs, or the chargeable capacity, within a range that does not exceed voltage constraints. In [8], [9], the load was modeled for domestic EVs in a stochastic manner, with power loss optimization. Actual system modeling has also been conducted [2], [9]–[14], where the influence of EV and charger penetration on actual distribution networks was analyzed in different locations, including Gothenburg in Sweden, Toronto in Canada, and Budapest in Hungary, as well as Britain and America. There are also studies that assume the actual vehicle operation data to be those of an EV [15]–[17]. In [15], EV demand modeling was performed on randomly selected vehicle operation data of the Atlanta regional commission and the electric power efficiency of an EV. EV charging characteristics have also been studied using Guangzhou traffic data [16]. EV demand modeling has further been performed. Using representative load profiles according to the application [18], [19]; additionally, in [13], demand modeling was performed using stochastic method. Other studies have also been conducted to maximize the use of EVs as resources through charging strategies, such as vehicle to grid (V2G), or to evaluate the maximum capacity of EVs through proper placement of chargers [14], [15], [20]–[27]. However, a common limitation of these studies is that they do not sufficiently consider the uncertainties of EV operation. EVs have a time to arrive at charger, time to leave, state of charge (SOC), and required amount of charge. In consideration of these factors, a more thorough assessment of the influence of EVs on the system and the use of resources can be made.

In previous studies, probability methods using probability density functions (PDFs) were used to consider uncertainty. However, the performance was dependent on the accuracy of the PDFs, which is generally difficult to obtain [28]. In these situations, the interval method is suitable for improving the performance, because it expresses uncertain variables only if the exact lower and upper bounds are clear [28]–[31]. However, a disadvantage of the interval method is that it usually returns a conservative result when considering uncertainty [29]. This shortcoming can be resolved if interval arithmetic is realized with affine arithmetic [28]. In [31], a three-phase forward-backward sweep power flow method using interval and affine arithmetic was proposed. In addition, the photovoltaics (PV) HC, including load uncertainty, was evaluated using interval and affine arithmetic and interval overvoltage probability (IOP); IOP is a method of expressing HC by probability as presented in [28]. The interval, affine

\[ N_{SOC} \] - Total number of state of charge (SOC) cases of each EV after the EV access cases are determined.

\[ N_{CH} \] - Total number of charging station selection cases after the SOC cases are determined.

Variables:

\[ P_{EV}^t \cdot P_{EV}^t \] - Upper and lower bounds of the interval form EV load model at time period \( t \).

\[ P_{EV}^t \] - Affine form of EV load at time period \( t \).

\[ N_{GD} \] - Sizes of sets \( \Omega_D \).

\[ N_{GD_1} \] - Sizes of sets \( \Omega_{D_1} \).

\[ N_{GD_2} \] - Sizes of sets \( \Omega_{D_2} \).

\[ V_{t,j,k} \] - Interval form voltage of \( i \)-th bus and \( k \)-th scenario.

\[ V_{t,j,k} \] - Affine form of \( V_{t,j,k} \).

\[ V_{t,i,k} \] - Real value of voltage in interval form.

\[ V_{t,i,k} \] - Imaginary value of voltage in interval form.

\[ V_{min,k} \] - Minimum interval voltage in \( k \)-th scenario.

\[ \alpha_{m,j,k} \] - Decision variables (0-1) for calculating \( N_{m,j,over}^{\prime} \).

\[ \beta_{m,j,k} \] - Decision variables (0-1) for calculating \( N_{m,j,over}^{\prime} \).

\[ \gamma_{m,i,j,k} \] - Decision variables (0-1) for calculating \( \alpha_{m,j,k} \).

\[ N_{m,j,over}^{\prime} \] - Total number of “absolute undervoltage” values for evaluating interval form of HC.

\[ N_{m,j,over}^{\prime} \] - Total number of “partial undervoltage” values for evaluating interval form of HC.

\( \delta \) - Voltage violation index, representing the number of buses that violate the voltage constraint.

\[ \overline{\gamma_{m,j}}, \underline{\gamma_{m,j}} \] - Interval form of IUP for \( j \)-th charging station selection case.

\[ \overline{\gamma_{m,j}}, \underline{\gamma_{m,j}} \] - Interval form of IUP for the \( m \)-th EV case.

\[ EV \] - Minimum number of EVs.

I. INTRODUCTION

Carbon free has become a global concern. With the transport sector making the most severe contribution to CO2 emissions, interest in electric vehicle (EV) is growing. Currently, there are 10 million EV in operation worldwide [1]. As cited in [1], EV registrations have increased by 41% in 2020, in stark contrast to the worldwide downturn in car sales of 16% attributed the Covid-19 pandemic. According to the Sustainable Development Scenario proposed by the International Energy Agency, the EV market size could reach 230 million by 2030 if countries around the world work to reach their climate goals. With the expansion of the EV market, the charger market is also developing [1]. The number of publicly accessible chargers reached 1.3 million units in 2020. Considering the growing EV and charger market, increasing load is being placed on power distribution networks through voltage deviation, power losses, and transformer overheat [2]–[6]. Given EVs have such a significant effect on distribution networks, numerous studies have been conducted to calculate how many EVs a network can accommodate, i.e., EV hosting capacity (HC).

For EV HC, studies have mainly focused on determining the number of EVs, or the chargeable capacity, within a range that does not exceed voltage constraints. In [8], [9], the load was modeled for domestic EVs in a stochastic manner, with power loss optimization. Actual system modeling has also been conducted [2], [9]–[14], where the influence of EV and charger penetration on actual distribution networks was analyzed in different locations, including Gothenburg in Sweden, Toronto in Canada, and Budapest in Hungary, as well as Britain and America. There are also studies that assume the actual vehicle operation data to be those of an EV [15]–[17]. In [15], EV demand modeling was performed on randomly selected vehicle operation data of the Atlanta regional commission and the electric power efficiency of an EV. EV charging characteristics have also been studied using Guangzhou traffic data [16]. EV demand modeling has further been performed. Using representative load profiles according to the application [18], [19]; additionally, in [13], demand modeling was performed using stochastic method. Other studies have also been conducted to maximize the use of EVs as resources through charging strategies, such as vehicle to grid (V2G), or to evaluate the maximum capacity of EVs through proper placement of chargers [14], [15], [20]–[27]. However, a common limitation of these studies is that they do not sufficiently consider the uncertainties of EV operation. EVs have a time to arrive at charger, time to leave, state of charge (SOC), and required amount of charge. In consideration of these factors, a more thorough assessment of the influence of EVs on the system and the use of resources can be made.

In previous studies, probability methods using probability density functions (PDFs) were used to consider uncertainty. However, the performance was dependent on the accuracy of the PDFs, which is generally difficult to obtain [28]. In these situations, the interval method is suitable for improving the performance, because it expresses uncertain variables only if the exact lower and upper bounds are clear [28]–[31]. However, a disadvantage of the interval method is that it usually returns a conservative result when considering uncertainty [29]. This shortcoming can be resolved if interval arithmetic is realized with affine arithmetic [28]. In [31], a three-phase forward-backward sweep power flow method using interval and affine arithmetic was proposed. In addition, the photovoltaics (PV) HC, including load uncertainty, was evaluated using interval and affine arithmetic and interval overvoltage probability (IOP); IOP is a method of expressing HC by probability as presented in [28]. The interval, affine
arithmetic and IOP evaluation method are appropriate methods to consider the uncertainties of EVs.

In this paper, EV load modeling with uncertainty using interval and affine arithmetic, which was also used in calculating the interval undervoltage probability (IUP) to evaluate the EV HC of the test network. We subsequently propose an index that allows the network operator to flexibly reflect EV HC. The effect of the proposed method is simulated on a test network modeled on real-world data form the microgrid system of Seoul National University in South Korea. The major contributions of this work are as follows.

1) EV load modeling using interval and affine arithmetic considering the uncertainties of EV arrival time, SOC, and location of the charging station that did not consider all conditions at the same time in previous studies.

2) Network modeling using practical cable data of Seoul National University, with the load modeled by collecting the power consumption of each building, along with EV load modeling using actual vehicle access data.

3) Calculation of EV HC through IUP evaluation via the number of EVs form the model-based load and network.

4) Provision of an index that allows network operators to offer flexibility in EV load management.

The rest of this paper is organized as follows. Section II provides the methodology on interval and affine arithmetic and the procedure of EV HC evaluation. Section III describes the mathematical formulation for EV load modeling and IUP modeling including uncertainty. Section IV focuses on a case study in which we evaluated EV HC for the Seoul National University distribution network. Lastly, Section V concludes the paper.

II. METHODOLOGY
Traditionally, Various studies have been conducted to model with uncertainty problems. Here, the general approach is to process the model numerous times with the input parameters randomly drawn from the measured data over their respective ranges. In this section, we explain the uncertainty and methodology applied in this study.

A. INTERVAL AND AFFINE ARITHMETIC
Interval arithmetic is a suitable method for solving uncertainty problems. The interval method can be used to calculate wide range of numbers over a define range simultaneously. The basic form of interval arithmetic is presented in (1); further, (2)-(3) are the real and imaginary components of the complex number, respectively.

\[ \hat{x} = x_r + i x_i \]  
\[ x_r = [x_r, \bar{x}_r] = \{x_r \in \mathbb{R} | x_r \leq x_r \leq \bar{x}_r \} \]  
\[ x_i = [x_i, \bar{x}_i] = \{x_i \in \mathbb{R} | x_i \leq x_i \leq \bar{x}_i \} \]

Here, \(x_r\) and \(x_i\) have upper and lower limits, which are given by \(\bar{x}_r, x_r\) and \(\bar{x}_i, x_i\) respectively. Interval arithmetic has four basic arithmetic operations: addition, subtraction, multiplication and division \[29\]. The interval method returns a very conservative solution boundary if there is a dependency on the real and imaginary components of the operands. Affine arithmetic is a method that returns a much tighter solution boundary in the same situation. The basic form of affine arithmetic is given in \(4\). \(x_0\) is a central value, and \(\varepsilon_{new}\) is an error variable whose values are unknown and lie in the range of \([-1, 1]\). The interval form and affine form can be converted between each other using basic formulas \(5\)-(7).

\[ x = x_0 + x_{new1} \varepsilon_{new1} + x_{new2} \varepsilon_{new2} \]  \[ x_0 = \frac{(x_r + x_i) + i (x_r - x_i)}{2} \]  \[ x_{new1} = \frac{x_r - x_r}{2} \]  \[ x_{new2} = \frac{i (x_r - x_i)}{2} \]

As a demonstration of interval and affine arithmetic, considering the following example, where \(f = (\hat{x}_1, \hat{x}_2) = \hat{x}_1 \times \hat{x}_2, \hat{x}_1 = [3, 5] + i[2, 4]\) and \(\hat{x}_2 = [5, 9] + i[5, 11]\). In interval form, that the result is \(= f = (\hat{x}_1, \hat{x}_2) = [25, 89] + i[-45, 21]\). This can be converted to affine form \(x_1\) and \(x_2\) using \(5\)-(7).

\[ x_1 = (4 + \varepsilon_1) + i (3 + \varepsilon_2) \]  \[ x_2 = (7 + 2\varepsilon_2) - i (8 + 3\varepsilon_4) \]

Fig. 1 shows multiplication results for the example using interval and affine along with the true solution boundary, depicted by dotted, dashed, and solid lines, respectively. The example show that the affine method returns a much tighter solution boundary than the interval method.

![FIGURE 1. Example solution boundary for interval and affine multiplication.](image)

B. PROCEDURE FOR EV HC EVALUATION
The procedure for evaluating EV HC is described in general terms below and depicted in detail by the flowchart in Fig. 2.
First, based on existing vehicle access records, we find the number of EVs entering and exiting based on the time. A case number $N_{EV}$ is generated using a normally distributed random number, according to the average of the existing vehicle access records. Second, we determine the SOC for each EV with a normally distributed random number between the minimum and maximum SOC. Third, we determine the charging stations where each EV will be deployed. For EVs, the charging connection time is determined according to the SOC; if the number of EVs at a charging station exceeds maximum capacity, further EVs cannot be connected. Then, we calculate the interval charging load for each EV deployed at each charging station, and convert the obtained interval charging load into affine form. Subsequently, after obtaining the voltage in the affine form by performing a power flow using the affine form charge load, we convert the voltage to the interval form. Finally, we evaluate the HC of EVs using the IUP method. The method for IUP calculation is described in detail in Section III.

III. MATHEMATICAL FORMULATION

In this section, we formulate an equation to calculate the HC of an EV using interval and affine arithmetic. The HC is determined by the number of EVs that can be accommodated in the case where the voltage constraint of the target network is not violated. The main procedure of EV HC evaluation is as follows.

A. POWER FLOW USING AFFINE ARITHMETIC

For a radial LV distribution network, a method of calculating the forward-backward sweep power flow by applying affine arithmetic is as proposed in [31]. The net power injection for power flow expressed as a complex affine variable as arithmetic is as proposed in [31]. The net power injection for the forward-backward sweep power flow by applying affine forms is not violated. The main procedure of EV HC evaluation is in the case where the voltage constraint of the target network is satisfied. The equation (10) is based on the general forward-backward sweep power flow, wherein the power flow to which the affine variable is applied is calculated using the following three steps.

1) NODAL CURRENT CALCULATION

Set the initial voltage of the terminal bus and determine the affine form of the current (11).

$$\hat{I}_b = \left( \frac{S_b}{U_b} \right)^* = [(I_b)_0 + (I_b)_1\varepsilon_1 + \cdots + (I_b)_n\varepsilon_n]$$ (11)

2) BACKWARD SWEEP CALCULATION

Starting from the terminal bus, update the current using Kirchhoff’s current law to calculate the branch current (12).

$$\hat{I}_{m+1} = -\hat{I}_b + \sum_{j \in A} \hat{I}_j = [(I_{m+1})_0 + (I_{m+1})_1\varepsilon_1 + \cdots + (I_{m+1})_n\varepsilon_n]$$ (12)

3) FORWARD SWEEP CALCULATION

Update the nodal voltage from the starting bus and terminal bus using (13).

$$U_{m+1} = U_m - Z_{m,m+1}\hat{I}_m = [(U_{m+1})_0 + (U_{m+1})_1\varepsilon_1 + \cdots + (U_{m+1})_n\varepsilon_n]$$ (13)

Stop the iteration following the three steps if the iterative value calculated satisfies (14).

$$\max(|(U_b)_k - (U_b)_{k-1}|, |(U_b)_k - (U_b)_{k-1}|) < \varepsilon_{err}$$ (14)

B. EV HC EVALUATION METHOD BASED ON INTERVAL UNCERTAINTY

The IOP based HC has previously been proposed to evaluate the maximum penetration level of PV systems [28]. In this paper, EV penetration level is evaluated using a modified IOP method as follows.

Load uncertainty on the bus is dependent on the required charging time for an EV arriving at a charging station. Considering the output of the charger and the battery capacity of the EV, the time required for charging the EV is distributed within a specified range for which it is assumed that the charging time is uniformly distributed.

1) EV CHARGING LOAD INTERVAL UNCERTAINTY MODELING

In the interval uncertainty modeling of the EV charging load, the SOC of each EV is generated by random numbers. If the upper and lower limit of the SOC is determined from such randomly generated SOC, the interval load of the EV can be determined in proportion to the EV charger output. The load interval of the EV required by each bus
can thus be expressed as
\[
P_{EV}^t = \frac{1}{N\Omega_1} \sum_{d \in N_{D1}} P_{EV,d}^t \\
\Omega_{D1}^t = \left\{ d_1 \in \Omega_D | P_{EV,d_1}^t \geq P_{EV,avg}^t \right\}
\]
\[
\Omega_{D2}^t = \left\{ d_2 \in \Omega_D | P_{EV,d_2}^t < P_{EV,avg}^t \right\}
\]

(15)

Based on (15) and (16), we convert to the affine form \(P_{EV}^t\), as in (17), according to the conversion method that is detailed in [29]. If the power flow calculation is performed using (17), the output variable is as presented in (18), according to the affine arithmetic power flow method that is discussed in [31]. In (18), \(\varepsilon_p\) is the polynomial of the k-th scenario \(\varepsilon_{EV}\) with the detailed basis of such noise element calculations described further in [29].

\[
P_{EV}^t = \frac{1}{2} \cdot (P_{EV}^t + P_{EV}^d) + \frac{1}{2} \cdot (P_{EV}^t - P_{EV}^d) \cdot \varepsilon_{EV} \tag{17}
\]

\[
V_{i,j,k}^t = \left( V_{i,j,k,R}^t + iV_{i,j,k,I}^t \right) + \sum_{p=1}^{P} \left( V_{i,j,k,R}^{t,p} + iV_{i,j,k,I}^{t,p} \right) \cdot \varepsilon_p \tag{18}
\]

\[
\varepsilon_p = F_p (\varepsilon_{EV}), \quad \forall p = 1, 2, \ldots, P \tag{19}
\]

Interval \(V_{i,j,k}^t\) is acquired using (20)-(24), which are converted from affine form \(V_{i,j,k}^t\) (18). Equation (26) is the minimum interval voltage for the k-th scenario, which can be obtained using (25).

\[
V_{i,j,k,R}^t = V_{i,j,k,R}^{t,0} - \sum_{p=1}^{P} V_{i,j,k,R}^{t,p} \tag{21}
\]

\[
V_{i,j,k,L}^t = V_{i,j,k,L}^{t,0} + \sum_{p=1}^{P} V_{i,j,k,L}^{t,p} \tag{22}
\]

\[
V_{i,j,k,R}^{t,0} = V_{i,j,k,R}^{t,0} - \sum_{p=1}^{P} V_{i,j,k,R}^{t,p} \tag{23}
\]

\[
V_{i,j,k,L}^{t,0} = V_{i,j,k,L}^{t,0} + \sum_{p=1}^{P} V_{i,j,k,L}^{t,p} \tag{24}
\]

\[
\left| V_{i,j,k}^t \right| = \sqrt{\left( V_{i,j,k,R}^t \right)^2 + \left( V_{i,j,k,I}^t \right)^2} \tag{25}
\]

\[
V_{max,k} = \left[ \min_{1 \leq i \leq N_{bus}} \left| V_{i,j,k}^t \right| \cdot \min_{1 \leq j \leq N_{case}} \left| V_{i,j,k}^t \right| \right] \tag{26}
\]

2) IUP INTERVAL MODELING

On the foundation of the PV-based IOP that is described in [28], we propose an IUP to evaluate EV HC. In (28), \(\beta_{m,j,k}\) is a case where the lower limit of the interval voltage among all buses is lower than \(V_{min}\) in the charging situation in case \(j\) for the k-th scenario. In (27), \(\alpha_{m,j,k}\) is the case where the number of buses whose lower bound voltage is less than \(V_{min}\) is greater than the voltage violation index (VVI) that is denoted as \(\delta\), which is determined by the network operator depending on the situation.

\[
\alpha_{m,j,k} = \begin{cases} 
1, & \sum_{i=1}^{N_{bus}} \gamma_{m,i,j,k} \geq \delta \\
0, & \text{otherwise.}
\end{cases} \tag{27}
\]

\[
\beta_{m,j,k} = \begin{cases} 
1, & V_{min,j,k} < V_{min} \\
0, & \text{otherwise.}
\end{cases} \tag{28}
\]

\[
\gamma_{m,i,j,k} = \begin{cases} 
1, & V_{min,j,k} < V_{min} \\
0, & \text{otherwise.}
\end{cases} \tag{29}
\]

\[
N_{m,j,over} = \sum_{k=1}^{N_{m,j,total}} \alpha_{m,j,k} \tag{30}
\]

3) EV HC INTERVAL MODELING

If the HC for EV is expressed in interval form based on IUP, HC can be evaluated using (31)-(34). The upper bound of the IUP \(\lambda_m\) is the probability that \(N_{m,j,over}\) occurs for the entire scenario. The lower bound of IUP \(\lambda_m\) for the entire scenario, refers to the probability that occur \(N_{m,j,over}\), which is the case where the smallest lower bound voltage on each bus violates the voltage constraint. The upper bound of HC (33) is value the value of the minimum number of EVs whose lower bound of IUP is greater than \(\lambda_{max}\) which is
determined by the network operator.

\[
\lambda_{m,j} = \frac{N'_{m,j,\text{over}}}{N_{m,j,\text{total}}} \\
\bar{\lambda}_{m,j} = \frac{N''_{m,j,\text{over}}}{N_{m,j,\text{total}}}
\]

(31)

\[
\bar{\lambda}_{m} = \frac{1}{N_{\text{case}}} \sum_{j=1}^{N_{\text{case}}} \lambda_{m,j}
\]

(32)

\[
\begin{align*}
\bar{HC} &= \min_{1 \leq m \leq m_{\text{max}}} \left\{ EV \mid \lambda_{m} \geq \lambda_{\text{max}} \right\} \quad \text{(33)} \\
HC &= \min_{1 \leq m \leq m_{\text{max}}} \left\{ EV \mid \bar{\lambda}_{m} \geq \bar{\lambda}_{\text{max}} \right\} \quad \text{(34)}
\end{align*}
\]

IV. CASE STUDY

The proposed method was applied to data from the campus microgrid network of Seoul National University in South Korea. Although Seoul National University comprises several networks, the College of Engineering, which is conducting a project related to EV chargers, was set as the test system. This system is 22.9 kV feeder, as shown in Fig. 3.

The majority of the system is composed of 6.6 kV terminals, although some terminals are at 220V. On each bus in Fig. 3, the upper number is the building number and the lower number is the bus number. For the dataset obtained at 16:00 June 24, 2018, the total load was 6301 KVA. To perform simulations using the proposed method, it was assumed that six charging stations were installed in 6.6 kV lines, where each station could accommodate up to 500 EVs.

A. EV SCENARIO GENERATION AND INTERVAL FORMULATION USING VEHICLE ACCESS RECORDS

With the test system being a microgrid system, servicing a consistent number of members, the daily entry and exit records of the vehicles were similar. Therefore, the electric vehicle access scenario was assumed based on the vehicle access records obtained. The average access value was determined using a proportional formula comparing the number of assumed EVs to the actual number of vehicles entering and existing, the network. The EV access scenario was then constructed with normally distributed random numbers around this average.

To calculate the power flow to which affine arithmetic is applied, the net power injection (10) is must be expressed in affine form. The uncertainties considered were those typical for EVs: arrive time, SOC, and charger station location. As vehicle access is regular owing to the characteristics of the test system, normally distributed random numbers were used.

1) ARRIVE TIME

Using the entry record of existing vehicles, the average value of EV entry and exit was calculated using a proportional formula according to the number of EVs. \( N_{\text{EV}} \) cases were then generated using a normally distributed random number around the average value. In Fig. 4, the black line is the actual number of vehicles entering the test network totaling 3800, and the blue lines are the \( N_{\text{EV}} \) cases generated based on 1500 EVs.

2) SOC

The SOC is directly related to the required charging time. Considering the battery capacity and charger output of the latest electric vehicles, the required charging time was set between 1 to 4.

3) LOCATION OF CHARGER STATION

It was assumed that charging stations were located in six areas where the main building of the test system is located, and that 500 EVs could be accommodated per charging station.

By generating an EV scenario using interval formulation, data on the required amount of charge can set, that is, the load for each time on the bus where the charger is installed.
We obtain the interval form using (15) and (16) for the load data, and calculate the power flow that is introduced in Section III.

B. EV HC EVALUATION

1) CONVENTIONAL EV HC EVALUATION

The conventional method to evaluate HC is to calculate and display voltages for all cases and analyze the violation of voltage accordingly. The EVs were increased from 500 to 1500 at intervals of 10 units, given 101 cases calculated. For each case unit, $N_{EV}$ is 10, $N_{SOC}$ is 10, and $N_{CH}$ is 50, forming 505,000 scenarios. In Fig. 5, we follow this approach and plot the minimum voltage according to the number of EVs. The minimum number of EVs that violate the voltage constraint 0.95 p.u. is represented by the red dotted line in Fig. 5, which equals 1120 according to the conventional HC evaluation method.

2) IUP-BASED EV HC EVALUATION

The scenario for IUP-based evaluation was identical to that of the conventional method. IUP was calculated for each number of EVs considering the undervoltage risk. Fig. 6 is a chart that shows IUP after calculating, for each case unit, the lower bound, which exceeds the voltage limit among the interval value of the bus for each scenario. If the maximum value of IUP is set to 0.1, HC is 1150 according to the IUP evaluation method. In a real-world scenario, the maximum value of IUP would be determined by the network operator.

3) EV HC EVALUATION BASED ON INTERVAL AND AFFINE ARITHMETIC

IUP modeling was used to evaluate the EV HC, according to the mathematical formulation that is provided in Section III. Considering the uncertainties specified for EV, the charging load was expressed in interval form as given by (15) and (16). The lower bound is the case where the lower bound of the interval voltage values of the bus are smaller than $V_{min}$ using (34), whereas the upper bound uses (33); $\delta$ is set to 3 which is the number of buses whose lower bound voltage is less than $V_{min}$.

Fig. 7, is a plot of EV HC evaluation for the upper and lower bounds using only interval and affine methods and without using IUP evaluation method. Within these bounds, the minimum number of EVs that violated the same voltage constraint of 0.95 p.u., as set for Fig. 5, was between 1060 to 1080. The lower bound of 1060 is less than lower bound of 1120 that is calculated conventional method, owing to the process of calculating the interval form of EV using (15) and (16).

Fig. 8, shows the EV HC using the IUP evaluation method. The IUP, which represents the voltage violation probability, increased sharply beyond a certain number of EVs. As the maximum IUP is determined by the network operator, it seems correct to set it to approximately 0.1, as beyond this value it increased rapidly. With the IUP maximum set to 0.1, the test network can be penetrated by between 1155 to 1269 EVs.
4) EV HC EVALUATION ACCORDING TO VVI CHANGE

EV HC evaluation was performed according to the upper bound change by altering the VVI incrementally, as shown in Fig. 9. The VVI can be set by the network operator, the value is smaller, it is closer to the lower bound, and a narrower and thus more conservative range for EV HC is obtained. For example, if δ is set to 2 instead of 3 in the above scenario, the EV HC falls in the range of 1155 to 1228, not 1155 to 1269. The IUP value is zero in the range of 1500 EV units from VVI above 5, which means that the 5-th bus in the test network needs more 1500 EVs in order for the voltage to violate the voltage constraint. That is, it is a good condition for the operator of the test network to set VVI between 1 and 4.

Table 1 shows the EV HC values according to VVI change for the given IUP application. The HC evaluation method to which the IUP is applied indicates the acceptable number of EVs within a given range that the network operator can afford. Consequently, when the IUP according to the network simulation is set and applied to network planning, the degree of impact of EVs with large uncertainties on the network can be more sensitively evaluated.

![Figure 9. IUP chart according to the number of EVs and VVI.](image_url)

**TABLE 1.** HC according to each maximum IUP value.

| \( \lambda_{\text{max}} \) | IUP based HC | HC according to VVI change |
|-----------------|-------------|---------------------------|
| 0.01            | 1100        | [1100, 1190] [1100, 1230] |
| 0.02            | 1122        | [1122, 1196] [1122, 1124] |
| 0.03            | 1128        | [1128, 1202] [1128, 1246] |
| 0.04            | 1133        | [1133, 1210] [1133, 1253] |
| 0.05            | 1137        | [1137, 1215] [1137, 1259] |
| 0.06            | 1142        | [1142, 1219] [1142, 1261] |
| 0.07            | 1147        | [1147, 1222] [1147, 1263] |
| 0.08            | 1151        | [1151, 1224] [1151, 1265] |
| 0.09            | 1153        | [1153, 1226] [1153, 1267] |
| 0.1             | 1155        | [1155, 1228] [1155, 1269] |

V. CONCLUSION

This paper proposes an EV HC evaluation method for a microgrid using IUP, which is an index of the probability of occurrence of low voltage. Load formulation was performed considering the uncertainty of EV operation using interval and affine arithmetic. Uncertainties regarding the number of EVs, arrival time, SOC, and charging station selection were also considered. The HC of the proposed method was evaluated and compared with that of the conventional approach, for which the approach was found to return a less conservative solution owing to the formulation and EV uncertainties. The system’s EV HC can thus be set according to the network operator’s choice for the maximum IUP, allowing for much more flexible system operation. To achieve this, we proposed the VVI, which can enable the determination of an upper bound for the EV HC. Given the upper bound of HC increases as the VVI value is increases, the network operator can stipulate more degrees of freedom in network operation. The propose method on real-world data, the microgrid system of Seoul National University in South Korea was modeled using the parameter and length data of the actual cabling. Building load data were modeled by applying the load usage of each building by time. In addition, actual vehicle access records were analyzed, and EV load modeling was performed assuming 500 to 1500 EVs out of about 3,800 vehicles per day. The proposed method has limitations in not considering charging control such as V2G. Also, depending on the probability, voltage violation can occur even with EV penetrated within a safe range. As a future work, we will propose a method to evaluate the EV HC in consideration of V2G for various purposes.

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