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Reliability Evaluation of Composite Power Systems: Evaluating the Impact of Full and Plug-in Hybrid Electric Vehicles

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ABSTRACT The rising concerns over global climate change and depleting fossil fuel reserves are two of the main reasons for the ongoing efforts towards the electrification of the transportation sector. While greenhouse gases (GHGs) emissions from other sectors are generally falling, emissions from the road transport have increased over the past few decades, with both full electric vehicles (FEVs) and plug-in hybrid electric vehicles (PHEVs) being recognized as potential alternatives to combat climate change and reduce GHG emissions. However, wide-spread integration of FEVs and PHEVs will substantially increase the load on the power system which will eventually affect the reliability of existing power systems. In this paper, a probabilistic model for integrating FEVs and PHEVs with existing power grids is proposed that incorporates important FEV and PHEV characteristics, such as battery capacity, charge depleting distance, and charging rates. In addition, user behavior is taken into account through time of recharging, arrival and departure times, and daily miles driven. Furthermore, different charging strategies, i.e., opportunistic charging and controlled charging with and without vehicle-to-grid (V2G) scheme have been considered to evaluate the impact of FEVs and PHEVs on the composite power system. IEEE-RTS-79 system is used to examine the proposed probabilistic technique considering different FEV and PHEV penetration levels as well as charging strategies. Simulation results show that even a relatively low penetration level of FEVs or PHEVs might have a significant impact on the system reliability unless a proper charging and/or discharging schemes are utilized.

INDEX TERMS Composite power system, full electric vehicles, plug-in hybrid electric vehicles, reliability.

NOMENCLATURE

A. INDICES

b	Index of bus number
f	Index of FEV class
h	Index of PHEV class
d	Index of day
i	Index of sampled state
j	Index of load level
k	Sample of an EV class
m	Index of system component
t	Index of time

B. STOCHASTIC VARIABLES

κ	Energy supplied by the PHEV battery
ψ	Battery capacity of a PHEV
x	Daily miles driven
$\overline{\tau}$	Departure time
$\underline{\tau}$	Arrival time

C. OTHER VARIABLES

α	Minimum limit of load level range
β	Maximum limit of load level range
ℓ	Load level
p^{ℓ}	Non EV hourly load
λ^{ℓ}	Load level probability

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λ^{phev}	Percentage of PHEVs
λ^{fev}	Percentage of FEVs
λ^{ς}	Percentage of EVs preferring fast charging
λ^{v2g}	Percentage of EVs participating in V2G
e	Energy needed for battery charging
e^{v2g}	Energy supplied by EV battery during V2G
δ^{v2g}	Set of EVs participating in V2G
τ	Charging time
v	Charging voltage
i	Charging current
ℓ^{phev}	PHEV load
ℓ^{fev}	FEV load
$\hat{a}$	$n_t \times n_b$ connection matrix
$\hat{s}$	$n_b \times n_b$ susceptance matrix
θ	n_b column vector of bus voltage angles
ℓ	n_b vector of bus load levels
g	n_b vector of bus generation levels
c	n_b vector of bus load curtailments
s	$n_t \times n_t$ transmission line susceptance matrix
$\overline{g}$	n_b vector of maximum bus generation levels
f	n_t vector of transmission line flow levels
$\overline{f}$	n_t vector of maximum line flow levels
$\Im$	Component status
Θ	Loss of load probability
$V(\Theta)$	Loss of load probability variance
σ	Standard deviation
N	Number of sampled states
Ω	State of load
p_{phev}	PHEV penetration level
p_{fev}	FEV penetration level
n_{phev}	Number of PHEVs
n_{fev}	Number of FEVs
n_{v2g}	Number of EVs participating in V2G

D. PARAMETERS AND CONSTANTS

T	Total number of hours per day
T_D	Total number of days
S_D	Total number of summer days
W_D	Total number of winter days
n_ℓ	Total number of load levels
n_v	Total number of vehicles
$\overline{x}$	Charge depleting distance for an EV
π^{phev}	Number of PHEV classes
π^{fev}	Number of FEV classes
ρ	Correlation factor between κ and ψ
$\underline{\kappa}$	Minimum energy supplied by the PHEV battery
$\overline{\kappa}$	Maximum energy supplied by the PHEV battery
$\underline{\psi}$	Minimum battery capacity of a PHEV
$\overline{\psi}$	Maximum battery capacity of a PHEV
y	Parameter required for PHEV energy calculation
z	Parameter required for PHEV energy calculation
ξ	Battery capacity of FEV
n_s	Number of samples of each EV class
n_t	Number of transmission lines
n_b	Number of buses

Λ_{dp}	Average departure time
Λ_{ar}	Average arrival time
T_{v2g}	Discharging period for EVs used in V2G process
$MTTR$	Mean time to repair
$MTTF$	Mean time to failure
FOR	Forced outage rate

I. INTRODUCTION

Fossil fuels consumption is constantly increasing while the resources are depleting. Consequently, dependence on fossil fuels is a problem that needs to be urgently addressed. Vehicles and automobiles consume tremendous amounts of fossil fuels. To decrease their dependence on fossil fuels, combustion engine-based cars can be converted into electric vehicles (EVs). Plug-in hybrid electric vehicles (PHEVs) and full electric vehicles (FEVs), which are in this paper referred to as electric vehicles (EVs), are an upcoming technology that will help reduce the dependency on conventional resources. It is posited that a wide use of all types of EVs will greatly help in reducing carbon emissions, thus alleviating environmental challenges [1], [2].

This paper makes distinction between FEVs, which use only energy from the on-board batteries for driving, and PHEVs, which use both internal combustion engine and on-board batteries for driving, with the capability of charging from electric grid. EVs benefit society by diminishing greenhouse gas (GHG) emissions, reducing our dependence on foreign oil and, at times of peak power demand, supply energy to the grid by using vehicle-to-grid (V2G) technology [3]–[6]. These statements are reinforced by the fact that the cost of fueling PHEVs by gasoline is greater than the electricity cost, so it is estimated in [7] that a full electric driving capacity of 40 miles could result in a two-third reduction in oil consumption [7]. Practically all car manufacturers are now offering different types of EVs, ranging from small and medium size passenger cars, to sub-urban vehicles (SUVs), and vans. As a result of an increasing awareness of the numerous benefits of EVs, it has been predicted that approximately 37 million hybrid electric vehicles (HEVs) will be available in the US market by 2030 [7]. Moreover, it has been anticipated that the penetration level of FEVs will reach 15% in Switzerland by 2020 [8] while it will become 62% in the US by 2050 [9].

The benefits of EVs are many and varied, but energy demand for charging their batteries may cause considerable problems when they are connected to the power system for charging since they put an ample burden on the electric grid [10] which is already being noticed by system operators [11]. As the number of EVs is presently small, their effect on the power system is minimal. However, a rapid increase in the number of EVs and their widespread integration will have a strong impact on the reliability of power systems. Moreover, the increased charging load may lead to under voltages, higher losses, phase unbalance, load peaking, line and transformer overloads. To mitigate these problems, research has been initiated to evaluate the effects that EVs could have on existing power systems. Several studies have focused on developing EV charging load models and their implementation to study the impact and alleviate various power system problems [12]. For example, many researchers have investigated the integration of EVs into distribution power system with respect to dynamic behavior of a power system [13]–[16]; economic and financial analyses [17]; short- and long-term planning issues [18], [19]; and market policies and opportunities [3], [20], [21]. However, the reliability assessment of power system, when EVs are integrated into the system, has not been given much attention so far. Since the EVs mainly affect the local distribution systems, the previous work mostly tried to determine how different distribution system characteristics will be affected by the EVs.

A condition-dependent outage model is used to estimate the failure rate of transformer in order to assess the reliability of a PHEVs integrated residential distribution system [22]. In [23], an interruptible FEV charging load model is used to evaluate the reliability of an urban distribution system in China. The reliability of the distribution power system is also assessed in [24] considering vehicle-to-home (V2H) and V2G charging schemes while battery exchange mode is considered in modelling the FEV charging load in [25]. In [26], the impact of EV penetration level on the reliability of distribution system is evaluated for the scheduled and unscheduled V2G discharging modes. The work in [22]–[26] is targeted towards the evaluation of EV charging load in a distribution system. Moreover, the focus is on assessing the distribution power system facilities provisioning the energy to end users while satisfying the minimum allowable range of service continuity without considering the supply-demand balance. Although the effects of EVs will be most clearly seen in distribution systems, the increasing penetration of EVs will also have a cumulative effect on the entire grid, and this additional load will affect the power system reliability at both transmission and generation levels. However, limited research has been conducted to evaluate the impact of EVs on the generation and transmission side, and currently no detailed model exists for analysis of related EV impact.

Few studies have focused on evaluating the impact of EVs on composite power system, i.e., transmission and generation side [1], [27]–[31]. In [27], the author has investigated the impact of PHEVs on the U.S. electricity supply. But some important modelling parameters have been ignored, in addition, some unrealistic assumptions have been made. For example, it is assumed that all the PHEVs would drive 20 miles per day with all the energy in the batteries being consumed. In [28], a bidirectional charging power control is developed to manage the load and generation balance. The authors in [29] have considered PHEVs to improve the power system reliability when wind energy resources are utilized. Some important factors related to user behavior that affect the EV charging profiles, such as, vehicles arrival and departure time, miles driven, time of recharging etc. are not considered in [27]–[29]. In [30], the authors have developed the PHEV charging load model to evaluate the reliability of the U.S. Northwest Power Pool area considering different penetration levels. The methodology to estimate the generation expansion required to maintain the reliability of the system in the presence of PHEVs is proposed in [31]. In [1], an analytical approach is utilized to assess the power system reliability when PHEVs are integrated in the grid under different charging scenarios. In [1], [30], [31], random variables are used to incorporate varying daily mileages and arrival times. However, the EV charging load modelling is based on oversimplified assumptions; for example, small batteries with fixed charge depleting distance are assumed for all the EVs. Moreover, it is assumed that all the EVs will be fully charged regardless of the randomness of driver stay-at home habits. In addition, the EVs uncontrolled charging in a reliability analysis tends to be deterministic, i.e., only one charging scenario is developed and utilized over the reliability assessment time horizon (typically one year). In fact, the EV charging load is completely dependent on the driving pattern variations and the EV profiles (market share, penetration level, charging levels, battery specifications, etc.). It is evident that a detailed realistic model of FEVs and PHEVs is still lacking in existing literature.

In order to fill that gap, this paper presents a detailed probabilistic modeling of PHEV and FEV loads, which is specifically aimed at assessing the reliability of a composite power system. Moreover, different charging strategies such as; opportunistic charging and controlled charging with and without V2G are presented. The analysis is conducted on an hourly basis for both summer and winter season, considering different classes of PHEVs and FEVs. The probabilistic load model considers different loading ranges for each hour. The modeling of PHEVs and FEVs incorporates a number of important EV characteristics: (1) battery capacity, (2) charge depleting distance, and (3) charging rates, while user behavior is taken into account through: (4) time of recharging, (5) vehicle arrival and departure time, (6) discharge rate, and (7) miles driven. The proposed methodology is illustrated on a widely used IEEE RTS-79 network, where generator, transmission line, and transformer outages are analyzed using Monte Carlo simulation (MCS) approach. The loss of load probability (LOLP) index is used to evaluate the system reliability for different EV penetration levels. The results demonstrate that even a relatively low penetration levels of EVs might have a significant impact on the system reliability unless a proper charging strategy is implemented.

II. MATHEMATICAL MODELLING

This section provides a detailed mathematical formulation of the probabilistic modeling employed to evaluate the reliability of a composite power system.

A. LOAD MODELLING

Different load levels are considered in the proposed probabilistic model, based on available hourly demand data from [32]. The probability of system load to have value within two different load ranges, α_j and β_j, in each hour can be calculated as follows:

$$p^{\ell}_{t,d} = p^{\ell}\left(t + T * (d-1)\right), \quad \forall t, d \tag{1}$$

$$s_{t,\ell_j} = \mathbf{1}_{\left(\alpha_j < p^{\ell}_{t,d} < \beta_j\right)}, \quad \forall t, d, j \tag{2}$$

$$\ell_j = \frac{\alpha_j + \beta_j}{2}, \quad \forall j \tag{3}$$

$$\lambda^{\ell}_{t,\ell_j} = \frac{1}{T_D}\sum_{d=1}^{T_D} s_{t,\ell_j}, \quad \forall t, j, \; T_D = [S_D, W_D] \tag{4}$$

$$\sum_{j=1}^{n_\ell} \lambda^{\ell}_{t,\ell_j} = 1, \quad \forall t \tag{5}$$

$$\tilde{p}^{\ell}_t = \sum_{j=1}^{n_\ell} \ell_j . \mathbf{1}_{\left(\sum_{\hbar=0}^{j-1} \lambda^{\ell}_{t,\ell_\hbar} \leq r \leq \sum_{\hbar=0}^{j} \lambda^{\ell}_{t,\ell_\hbar}\right)} \tag{6}$$

where:

$$\lambda^{\ell}_{t,\ell_0} = 0 \tag{7}$$

and

r is a uniform random number between 0 and 1.

$$p^{\ell}_t = \tilde{p}^{\ell}_t + \frac{\vartheta}{2}\left(\mathbf{1}_{0 \leq r < 0.5} - \mathbf{1}_{0.5 \leq r \leq 1}\right) \tag{8}$$

where:

$$\vartheta = \beta_j - \alpha_j = \beta_{j+1} - \alpha_{j+1}, \quad \forall j \tag{9}$$

and

r is a uniform random number.

Note: Symbols, parameters, and variables that are listed in Nomenclature section are not repeated in (1)-(9) and in all subsequent equations.

B. PHEV MODELLING

To correctly analyze the impact of PHEVs on a power system, it is essential to develop a comprehensive PHEV model that takes into account both the PHEV characteristics and PHEV users' behavior. The adopted probabilistic model is appropriate for a non-sequential MCS, as it avoids guessing where a PHEV will be found at any given time and it is generally superior, i.e. more computationally efficient, to using an agent-based simulation technique. Different PHEV classes are considered, with each class characterized by following seven parameters: y_h, z_h, $\underline{\kappa}_h$, $\overline{\kappa}_h$, $\underline{\psi}_h$, $\overline{\psi}_h$, and $\overline{x}_h$.

These values are used to calculate the mean values and standard deviations of energy supplied by battery (κ) and battery capacity (ψ) of PHEVs. Mean values and standard deviations are respectively defined as $\tilde{\kappa}$, $\tilde{\psi}$, $\hat{\kappa}$, and $\hat{\psi}$.

$$\tilde{\kappa}_h = \frac{\underline{\kappa}_h + \overline{\kappa}_h}{2}, \quad \forall h \tag{10}$$

$$\tilde{\psi}_h = \frac{\underline{\psi}_h + \overline{\psi}_h}{2}, \quad \forall h \tag{11}$$

$$\hat{\kappa}_h = \frac{\overline{\kappa}_h - \underline{\kappa}_h}{4}, \quad \forall h \tag{12}$$

$$\hat{\psi}_h = \frac{\overline{\psi}_h - \underline{\psi}_h}{4}, \quad \forall h \tag{13}$$

The total number of PHEVs in each class is:

$$n_{phev} = n_v . p_{phev} \tag{14}$$

$$n_{phev_h} = normal\left(\mu_h, \sigma_h\right), \quad \forall h \tag{15}$$

where:

$$\mu_h = n_{phev} . \lambda^{phev}_h, \quad \forall h \tag{16}$$

$$\sigma_h = 0.01 . \mu_h, \quad \forall h \tag{17}$$

and

$$\sum_{h=1}^{\pi^{phev}} \lambda^{phev}_h = 1 \tag{18}$$

After calculating the number of PHEVs in each class, other characteristics of that class must also be determined. By using a bivariate normal distribution with a correlation factor (ρ), κ and ψ can be determined. The correlation represents the intuitive relationship between the design parameters κ and ψ, which are mathematically defined in (19) and (20), where subscripts 0 and 1 indicate the first and second random numbers, respectively [33].

$$\kappa_h = \tilde{\kappa} + bivariate(\hat{\kappa}, \hat{\psi})_0, \quad \forall h \tag{19}$$

$$\psi_h = \tilde{\psi} + bivariate(\hat{\kappa}, \hat{\psi})_1, \quad \forall h \tag{20}$$

To correctly model PHEV users' behavior, miles driven, departure and arrival times for all the PHEV samples on each day for an entire year are calculated using a lognormal distribution [33]. The charging time is considered to be between the arrival time at day '*d*' and the departure time at day '*d+1*' for each PHEV when controlled charging strategy is utilized.

$$\aleph_{k,h,d} = logNormal\left(3.37, 0.5\right), \quad \forall k, h, d \tag{21}$$

$$\overline{\tau}_{k,h,d} = logNormal\left(\Lambda_{dp}, \sqrt{3}\right), \quad \forall k, h, d \tag{22}$$

$$\underline{\tau}_{k,h,d} = logNormal\left(\Lambda_{ar}, \sqrt{3}\right), \quad \forall k, h, d \tag{23}$$

The daily energy required to charge each vehicle can be calculated based on the miles driven every day. It is assumed that only λ^{ς} percent of PHEV owners will prefer to charge their vehicles using Level 2 type charger as shown in Table 1. Therefore, charging voltage and current can be obtained as follows:

$$\begin{aligned} e_{k,h,d} = {} & \psi_h . \mathbf{1}_{\left(x_{k,h,d} \geq \overline{x}_h\right)} \\ & + x_{k,h,d} . y_h . \kappa_h^{z_h} . \mathbf{1}_{\left(x_{k,h,d} < \overline{x}_h\right)}, \quad \forall k, h, d \end{aligned} \tag{24}$$

where y and z are the parameters that allow the calculation of the energy required per mile driven. It is assumed that only λ^{v2g}_h percent of PHEV owners in class h will participate in V2G process.

$$n_{v2g_h} = n_{phev_h} . \lambda^{v2g}_h, \quad \forall h \tag{25}$$

$$v_{k,h,d} = 120.\mathbf{1}_{(0 \leq r < 1 - \lambda^{\varsigma})} + 230.\mathbf{1}_{(1 - \lambda^{\varsigma} \leq r \leq 1)}, \; \forall k, h, d \tag{26}$$

$$A_{k,h,d} = 15.\mathbf{1}_{(0 \leq r < 1 - \lambda^{\varsigma})} + 30.\mathbf{1}_{(1 - \lambda^{\varsigma} \leq r \leq 1)}, \; \forall k, h, d \tag{27}$$

where: r denotes a uniform random number.

TABLE 1. Charging levels based on the SAE J1722 standard.

Charger Type	Voltage Level	Current	Power Rating
Level 1 (Normal Charging)	120 V	15 A	1.8 kW
Level 2 (Rapid Charging)	230 V	30 A	6.9 kW

The energy available to be supplied by PHEV during V2G period is calculated as follows:

$$e^{v2g}_{k,h,t,d} = min\left(\psi_h - e_{k,h,d}, v_{k,h,d}.A_{k,h,d}\right), \quad \forall h, d \quad (28)$$

where:

$$t \in T_{v2g}$$

and

$$k \in \delta^{v2g}_{h}$$

The time available to charge PHEV is calculated based on the arrival and departure times as follows:

$$\tau_{k,h,d} = \left(T - \underline{\tau}_{k,h,d}\right) + \overline{\tau}_{k,h,d}, \quad \forall k, h, d, k \notin \delta^{v2g}_{h} \quad (29)$$

After calculating the available charging time, the charging load of PHEVs which are not participating in the V2G process is calculated as follows:

$$i_{k,h,d} = \min\left(\frac{e_{k,h,d}}{v_{k,h,d} * \tau_{k,h,d}}, A_{k,h,d}\right), \quad \forall k, h, d, k \notin \delta^{v2g}_{h} \quad (30)$$

$$\ell^{phev}_{k,h,t,d} = v_{k,h,d}.i_{k,h,d}, \quad \forall k, h, d, k \notin \delta^{v2g}_{h} \quad (31)$$

where:

$$\underline{\tau}_{k,h,d} < t \le T, \quad t \le \overline{\tau}_{k,h,d} \quad (32)$$

In order to calculate the charging load of PHEVs participating in V2G process, the amount of energy supplied during the V2G must be considered. So,

$$\ell^{phev}_{k,h,t,d} = \min\left(\frac{e_{k,h,d}}{T_{g2v}} + e^{v2g}_{k,h,t,d}, v_{k,h,d}.A_{k,h,d}\right), \quad \forall h, d \quad (33)$$

where:

$$t \in T_{g2v}$$

and

$$k \in \delta^{v2g}$$

Now, the total load of each PHEV class can be calculated as follows:

$$\ell^{phev}_{h,t} = \frac{n_{phev,h}}{n_s}.\sum_{d=1}^{T_D}\sum_{k=1}^{n_s}\ell^{phev}_{k,h,t,d}, \quad \forall h, t \quad (34)$$

where the total load for all PHEVs at any time t is equal to the summation of PHEV loads from all the classes:

$$\ell^{phev}_{t} = \sum_{h=1}^{\pi^{phev}}\ell^{phev}_{h,t}, \quad \forall t \quad (35)$$

C. FEV MODELLING

Similar to PHEVs, the integration of FEVs is based on both FEV users' behavior and FEV characteristics. Different classes of FEVs are considered, with each class characterized by its charge-depleting distance ($\overline{\aleph}$) and battery capacity (ξ). The total number of EVs in each FEV class can be obtained using FEV's penetration levels as follows:

$$n_{fev} = n_v.p_{fev}, \quad \forall f \quad (36)$$

$$n_{fev_f} = n_{fev}.\lambda^{fev}_{f}, \quad \forall f \quad (37)$$

On the other hand, user behavior is accounted for by applying (21)-(23). Once the miles driven and the arrival and departure times are obtained, energy needed to charge batteries can be calculated, assuming that FEVs will discharge linearly with respect to the distance travelled:

$$e_{k,f,d} = \xi_f.\mathbf{1}_{(x_{k,f,d}=\bar{x}_f)} + x_{k,f,d}.\frac{\xi_f}{\bar{x}_f}.\mathbf{1}_{(x_{k,f,d}<\bar{x}_f)}, \quad \forall k, f, d \quad (38)$$

After the energy required for charging by each vehicle in each FEV class is obtained, charging voltage and current can be again determined using (26)-(30). The energy delivered in V2G process can be found as follows:

$$e^{v2g}_{k,f,t,d} = min\left(\xi_f - e_{k,f,d}, v_{k,f,d}.A_{k,f,d}\right), \quad \forall f, d \quad (39)$$

where:

$$t \in T_{v2g}$$

and

$$k \in \delta^{v2g}_{f}$$

The load of each sample of FEV class can be computed using (30)-(33). Afterwards, the total FEV load at any time t can be obtained as follows:

$$\ell^{fev}_{f,t} = \frac{n_{fev,f}}{n_s}.\sum_{d=1}^{T_D}\sum_{k=1}^{n_s}\ell^{fev}_{k,f,t,d}, \quad \forall f, t \quad (40)$$

$$\ell^{fev}_{t} = \sum_{f=1}^{\pi^{fev}}\ell^{fev}_{f,t}, \quad \forall t \quad (41)$$

D. DC LOAD FLOW CALCULATION

The DC optimal power flow (DC-OPF) is run to determine whether the total demand (system load plus different penetration levels of PHEVs and FEVs) can be met at all the time and with respect to possible generators and transmission lines and/or transformer contingencies. The objective function (minimization of curtailed load at all network buses) and the constraints of the DC-OPF are defined below:

$$\min \sum_{b=1}^{n_b} c_b \quad (42)$$

$$\text{subject to}: \hat{s}\theta = g - l + c \quad (43)$$

$$s\hat{a}\theta \le \overline{f} \quad (44)$$

$$-s\hat{a}\theta \leq \overline{f} \tag{45}$$

$$g \leq \overline{g} \tag{46}$$

$$c \leq l \tag{47}$$

$$g, c \geq 0 \tag{48}$$

III. RELIABILITY EVALUATION ALGORITHM

The probabilistic models of system load, PHEV, and FEV are considered to determine the composite reliability, with loss-of-load probability (LOLP) index used to assess the reliability performance. First, a uniform random integer value is generated to select the time of a day.

$$t = randi(1, T) \tag{49}$$

Once the time of a day is selected, other random numbers are used to generate possible values for the system load, PHEV load, and FEV load at all buses, based on the probabilistic models described in Section II. The status of each generator, transmission line, and transformer are determined by generating and comparing the uniform random numbers with the related forced outage rates (FORs) [32].

$$\Im_m = \mathbf{1}_{(r_m \leq FOR_m)} \tag{50}$$

where:

$$FOR_m = \frac{MTTR_m}{MTTR_m + MTTF_m} \tag{51}$$

and

r denotes a uniform random number.

Once the state is sampled, the DC-OPF is run to classify each sampled state either as a loss-of-load state or non-loss-of-load state, as the reliability of the composite power system can be determined once the state is classified. After sampling and classifying each state, the LOLP and its variance are calculated. The MCS is set to terminate when the variation of LOLP reaches a certain value, e.g., $\sigma \leq 0.02$, when the final LOLP value is achieved. This value of σ is selected so that the variations in final LOLPs are minimized since the probabilistic model is utilized. Moreover, the computational burden does not exceed the available computational capability. The mathematical relationships are described in (52)-(55). Here, N is the total number of states that are sampled up to this point. The process of reliability evaluation is shown in Fig. 1.

$$\Theta_t = \frac{1}{N_t}\sum_{i=1}^{N_t} \Omega_{i,t}, \quad \forall t \tag{52}$$

$$V(\Theta_t) = \frac{1}{N_t}(\Theta_t - \Theta_t^2), \quad \forall t \tag{53}$$

$$\sigma_t = \frac{\sqrt{V(\Theta_t)}}{\Theta_t}, \quad \forall t \tag{54}$$

where:

$$\Omega_{i,t} = \mathbf{1}_{\left(\sum_{b=1}^{n_b} c_b \neq 0\right)}, \quad \forall i, t \tag{55}$$

TABLE 2. PHEV classes and parameters [33].

Description	Compact passenger car	Full-size passenger car	Medium SUVs	Large SUVs
Class	h_1	h_2	h_3	h_4
λ^{phev}	20%	30%	30%	20%
y	0.3790	0.4288	0.6720	0.8180
z	0.4541	0.4179	0.4040	0.4802
$\underline{\psi}$	8 kWh	10 kWh	17 kWh	19 kWh
$\overline{\psi}$	12 kWh	14 kWh	21 kWh	23 kWh
$\underline{\kappa}$	0.2447 kWh	0.2750 kWh	0.3217 kWh	0.3224 kWh
$\overline{\kappa}$	0.5976 kWh	0.6151 kWh	0.5428 kWh	0.4800 kWh
$\overline{\varkappa}$	40 mi	40 mi	40 mi	40 mi

TABLE 3. FEV classes and parameters.

Class	Description	FEV Percentage	ξ	$\overline{\varkappa}$
f_1	Compact passenger car	50%	24 kWh	100 mi
f_2	Full-size passenger car	50%	30 kWh	126 mi

IV. CASE STUDY

The method presented in Section III was tested on IEEE RTS-79 [32], which is a 24-bus system with 38 transmission lines and transformers and 32 generators, Fig. 2. Non-EV peak load is 2,850 MW, whereas the maximum generating capacity is 3,405 MW. The FORs of generators, transformers, and transmission lines are obtained from [32].

The integration of EVs includes four PHEV classes, namely compact passenger cars, full size passenger cars, medium SUVs and large SUVs, as well as two classes of FEVs, i.e., compact passenger cars and full-size passenger cars. The parameters of all the considered PHEV and FEV classes are given in Tables 2 and 3 [33], [35], [36]. The total number of vehicles in the test system is considered to be 0.8 million. Note that 10% PHEV penetration level means there will be 80,000 PHEVs available in the system. Among the total PHEVs, 16,000 PHEVs belong to compact passenger class and large SUVs class each. Similarly, 24,000 PHEVs belong to full-size passenger class and medium SUVs class each (see Table 2). The total number of PHEVs in the system will be doubled when PHEV penetration level reaches 20%. Similar calculations, for a given FEV penetration level, can be done to calculate the actual number of vehicles in each FEV class, as per the percentages given in Table 3.

V. RESULTS AND DISCUSSION

The DC-OPF results are obtained using software [37]. The impact of PHEVs and FEVs on the composite power system in both summer and winter seasons is studied. The months from April to September and from October to March are considered as summer and winter seasons, respectively. The hourly load data of IEEE RTS-79 from [32] is used to analyze the impact of EVs, with average load profiles for summer and winter shown in Fig. 3.

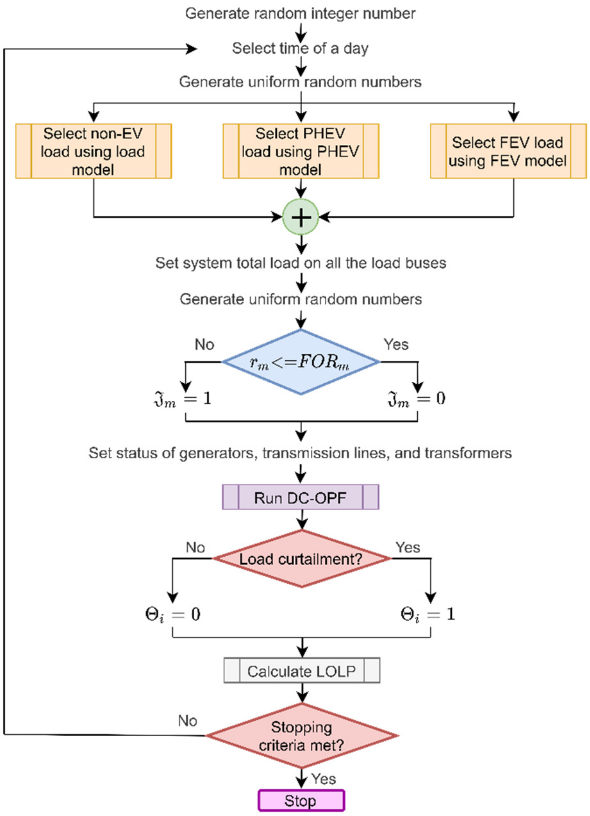

FIGURE 1. Flow chart of reliability evaluation process.

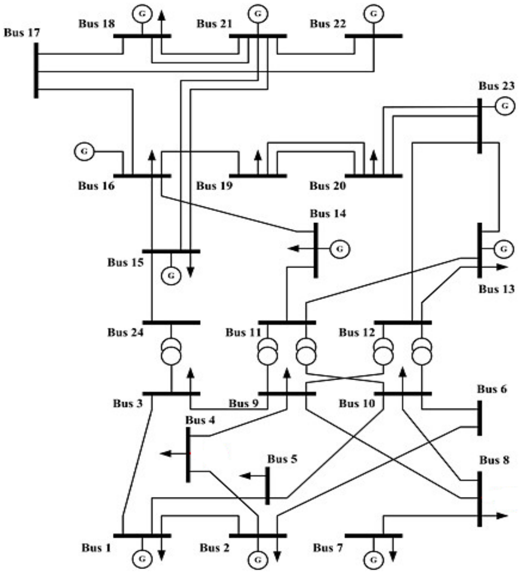

FIGURE 2. IEEE RTS-79 system [32].

A. BASE CASE (i.e., WITHOUT PHEVs AND FEVs)

The summer and winter loading conditions are used to calculate the LOLP of the system when there are no PHEVs and FEVs. The base case results are shown in Fig. 4. It can be seen that the LOLP in winter season is higher as compared to summer season which is in accordance with the average seasonal system loads (see Fig. 3). The LOLP in winter and summer seasons are less than 0.95% and 0.4%, respectively.

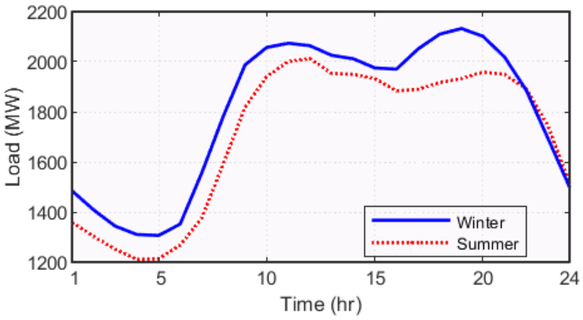

FIGURE 3. Average seasonal system load profiles.

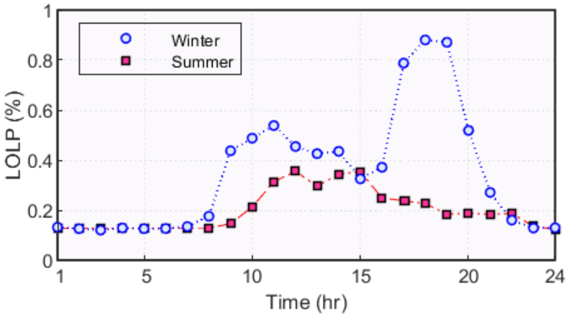

FIGURE 4. Base case LOLP for summer and winter seasons.

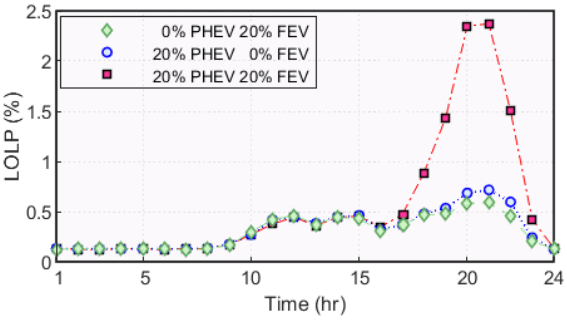

FIGURE 5. LOLP for summer season due to opportunistic charging.

B. OPPORTUNISTIC CHARGING

EVs start charging at their maximum charging rates in opportunistic charging scheme once they get connected into the system [38]. The impact of the EVs on the system would be worst due to this uncontrolled charging strategy. The reliability of the system for summer and winter seasons for different PHEV and FEV penetration levels are shown in Figs. 5 and 6, respectively. It is clear from the figures that the system's reliability is severely affected specially when there are 20% PHEV and 20% FEV since the total charging load is maximum for this case. The LOLP reaches 6.89% during the winter season which is highly unacceptable. Note that the LOLP is almost same for different penetration levels of PHEV and FEV from 1 a.m. to 3 p.m. (see Figs. 5 and 6). It is due to the fact that most of the EVs will be charged in the evening.

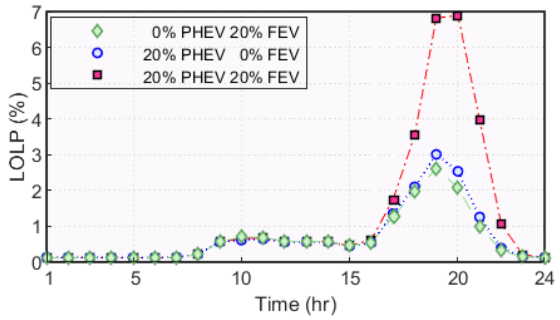

FIGURE 6. LOLP for winter season due to opportunistic charging.

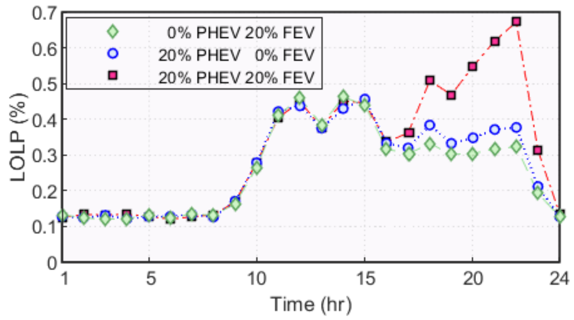

FIGURE 7. LOLP for summer season due to controlled charging without using V2G.

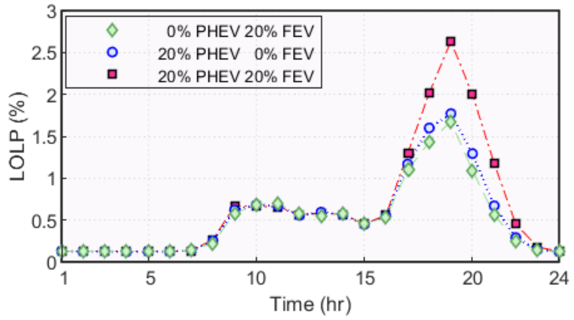

FIGURE 8. LOLP for winter season due to controlled charging without using V2G.

C. CONTROLLED CHARGING WITHOUT V2G

As mentioned earlier that the opportunistic charging strategy impacts the system reliability adversely, therefore, charging load of PHEVs and FEVs must be controlled [39]. In controlled charging without V2G strategy, PHEVs and FEVs are charged based on the arrival and the departure times. If there is enough charging time available, EVs are charged slowly in such a way that each EV is fully charged before the next trip. The LOLP of system for summer and winter seasons are shown in Figs. 7 and 8, respectively. It can be seen that the LOLP has been reduced from 2.37% to 0.67% and 6.89% to 2.63% for summer and winter seasons, respectively when there are 20% PHEV and 20% FEV penetrations in the system. Note that the system reliability has been considerably improved by throttling the charging rates of PHEVs and FEVs. It can also be noticed that the peaks are shifted from 9 p.m. to 10 p.m. and 8 p.m. to 7 p.m. in summer and winter seasons, respectively.

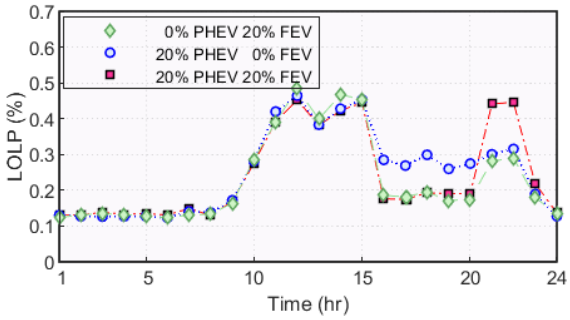

FIGURE 9. LOLP for summer season due to controlled charging with V2G.

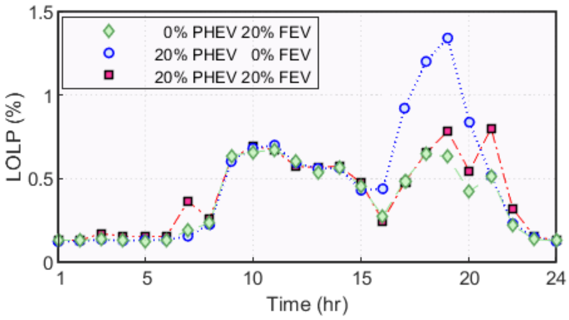

FIGURE 10. LOLP for winter season due to controlled charging with V2G.

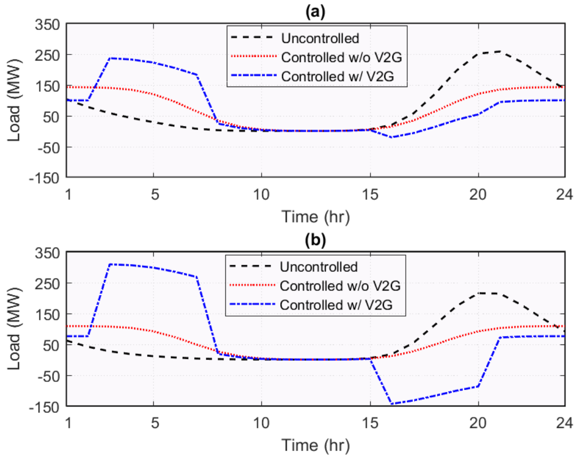

FIGURE 11. (a) PHEV load (b) FEV load.

D. CONTROLLED CHARGING WITH V2G

In V2G, EVs provide energy to the grid. Therefore, in controlled charging with V2G strategy it is assumed that PHEVs and FEVs deliver energy to the grid from 4 p.m. to 8 p.m. because the peak of non EV load appears during this time (see Fig. 3). Furthermore, it is considered that the EVs participating in V2G process can be recharged from 3 a.m. to 7 a.m. since the system load is insignificant during this time. It is also important to note that only 30% of PHEVs and FEVs are assumed to participate in V2G process to make the case more realistic. The results for summer and winter seasons are provided in Figs. 9 and 10, respectively. It is clear from the figures that the system reliability has been improved significantly specially during the time span when V2G process is being taken place. Most of the time the system LOLP is less than 1% which shows that the higher penetration of PHEVs and FEVs can be incorporated in the existing power system if proper charging and discharging strategies are formulated. It is important to note that the LOLP for 20% PHEV case is higher from 4 p.m. to 8 p.m. as compared to other cases. The reason is that the PHEVs usually have much smaller battery bank capacities as compared to FEVs, hence, their participation in V2G process gets reduced as shown in Fig. 11.

VI. CONCLUSION

In this paper, a probabilistic method for load and EVs modeling with different penetration levels is presented. The reliability of the composite power system is evaluated considering forced outage rates (FORs) of generators, transmission lines, and transformers. Moreover, different charging strategies, i.e., opportunistic and controlled charging with and without vehicle-to-grid (V2G) scheme are used to evaluate the reliability of the power system. The proposed methodology is validated using IEEE RTS-79. Different classes of full electric vehicles (FEVs) and plug-in hybrid electric vehicles (PHEVs) are considered to assess their impact on the composite power system. As expected, the results indicate that loss of load probability (LOLP) increases as the load increases and becomes particularly pronounced during the peak hours. The LOLP for PHEVs is higher than FEVs due to the higher consumption by the medium and large SUVs.

These results further suggest that the reliability issues caused by the integration of EVs can be mitigated significantly by implementing controlled charging strategies. Moreover, bidirectional EV chargers can be utilized to perform V2G process that can considerably improve power system reliability by supplying energy to grid during the peak hours. To implement these remedial strategies, EV owners should be given reasonable incentives to ensure their active participation.

In future, a comprehensive model can be developed to incorporate other demand response (DR) resources, such as thermostatically controlled loads. Moreover, the impact of demand side management (DSM) on power system reliability can be evaluated.

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