# Composite Power System Reliability Assessment Considering Uncertainty of Electric Vehicle Charging and PV Power Generation

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***Abstract*—Modern power systems are facing several challenges with the increasing penetration of inverter-based resources (IBRs) and electric vehicles (EVs). The problem arises due to intermittency and uncertainties associated with IBR-based resources and electric vehicles. It is indispensable from the perspective of power system planning and operation to consider these factors in reliability assessment. The reliability assessment of modern power systems that are heavily penetrated with renewable generators should consider their uncertainties to quantify the reliability index and include EVs charging load in their framework as well. Therefore, this paper proposes an approach for composite power system reliability assessment combined with the probabilistic prediction interval of PV power along with the integration of electric vehicles. An electric vehicle load model developed considering the different locations of charging stations, types of EV, and drivers' behavior is integrated. Finally, a sequential Monte Carlo simulation is used to determine the range of the reliability index after an interval forecast of the PV and EV load model is developed. The impact of different levels of EV penetration on the reliability of power system integrated with PV is also investigated. The significance of this work is to provide an accurate reliability assessment framework that takes PV uncertainties and electric vehicles into consideration.**

***Keywords*—Electric vehicle (EV), interval forecast, PV uncertainty, reliability, sequential monte carlo simulation**

## I. Introduction

The generation portfolio of the modern power system has transitioned from synchronous generators, which traditionally provide services necessary for stable grid operation, to inverter-based resources (IBRs) such as wind solar photovoltaic (PV) and battery storage. Also, the aggressive electric vehicle (EV) integration target goals of different countries clearly depict the exponential rise of EVs and their impact on the existing power system. Some of the challenges associated with their integration are related to power system stability, degradation of power quality, and unexpected overloading due to EV charging loads [1], [2]. Furthermore, the intermittence and uncertainty associated with PV power generation and the heavy penetration of electric vehicles have restricted their large-scale integration and pose challenges to power system reliability [3], [4]. With an evident expectation of heavy penetration of EV and PV power in near future, this calls for assessing the impact of PV uncertainty and EV penetration on power system reliability.

Several methods have been proposed to conduct reliability assessments of power systems. In [5], a generalized analytical reliability assessment method has been proposed for smart grids considering the integration of renewable and nonrenewable distributed generations with plug-in hybrid electric vehicles. In [6], the reliability of integrated transportation and electrical power system has been investigated. Furthermore, a bidirectional EV charging station has been incorporated to model the interaction between the power and transportation system. In [7]–[9], EV's effect on the load profile of power systems along with the improvement of power system reliability has been investigated. The impact of EVs using battery exchange mode on power system reliability has been investigated in [10]. The impact of wind power uncertainty on power system reliability has been studied in [11] along with the development of the wind power interval forecasting model. In addition, a Bayesian estimation approach has been used in estimating the parameters of the wind power point prediction model. An analytical method has been implemented to evaluate the reliability of the Roy Billinton Test system considering PV and energy storage in [12]. In [13], the capacity outage probability and frequency table (COPAFT) has been used to model the PV system for composite power system reliability along with the sensitivity analysis of PV location on power system reliability. The impact of correlations between wind speed, solar irradiance, and load curve on composite power system reliability has been investigated in [14]. A combined reliability assessment and risk analysis framework have been developed to examine the impact of wind and solar integration on the grid [15]. Most of these studies have focused on determining the reliability of power systems with the integration of either renewable power generation or EVs alone. However, the combined impact of electric vehicles and renewable like PV on power system reliability considering their uncertainty is crucial to develop a practical basis for their integration into existing power systems. Also, several past research works are focused on determining the reliability of the system, however, the calculation of a range of reliability will provide more flexibility to the system operator in terms of renewable integration planning, power scheduling, and dispatch.

Therefore, this paper proposes a composite system reliability assessment to evaluate the combined impacts of different penetration levels of EVs along with the consideration of PV power uncertainty. A PV power point forecasting model is developed using a machine learning algorithm along with successive interval forecasting. The PV power interval prediction has been done for one year to make it suitable for its integration for power system reliability assessment. A load demand model, superimposing IEEE-RTS79 system load and EV load, is constructed. The EV load model is constructed considering 30,000 EVs with different energy consumption per mile and 30 miles as an average daily driving distance along with consideration of the different locations of charging stations (i.e., residential and public charging stations). Finally, a sequential Monte Carlo simulation is used to calculate the reliability index of the IEEE-RTS79 reliability test system integrating EV load and PV power interval forecast. The range of power system reliability indices is calculated by taking interval forecasting of PV power into consideration. Furthermore, the impact of different levels of EV penetration is also investigated.

The remainder of the paper is organized as follows. Section II provides a description of the PV power interval forecasting model and EV load modeling. Section III explains the optimization problem formulation for power system reliability assessment. Section IV shows various test cases on the IEEE-RTS79 reliability test system along with the determination of the range of reliability indices and investigation of EV's impact on power system reliability. Finally, Section V summarizes the paper and provides concluding remarks.

## II. PV Power Interval Prediction and EV Load Modeling

### A. PV Power Interval Prediction

The output of PV power is associated with randomness and uncertainty because of their dependence on several environmental factors such as temperatures and solar irradiance [16]. These uncertainties related to PV power are the major reasons for inaccurate point forecasting which in turn leads to ineffective generation scheduling decisions and risk analysis. Furthermore, a deterministic point forecast neglects those uncertainties which are detrimental from the perspective of safe and reliable operation of the power grid. Therefore, an interval forecast model that takes uncertainties into consideration is developed. The PV interval forecast provides the lower and upper bound of PV power at each hour of the forecasting interval with a certain degree of confidence. The significance of interval forecasting is that it facilitates the system operator to calculate the range of power system reliability. A real-world dataset collected from PV installed site Henderson, Nevada has been used to obtain the PV profile for one year.

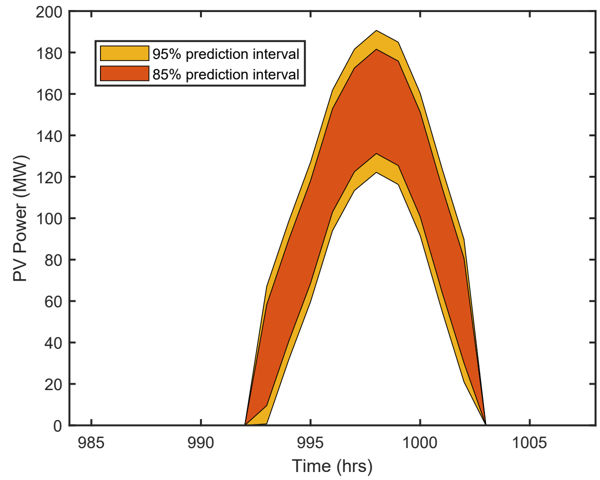


Fig. 1. PV Power Output Interval Prediction for 24 hours

Two scenarios with confidence degrees of 85%, and 95% are taken into consideration to forecast the PV interval and see the impact of the confidence interval on power system reliability. A commonly used non-parametric technique known as k-nearest neighbors (kNN) has been adopted in this work for time series point forecasting. As the PV profile dataset used in this paper is a univariate time series, lagged values of the variable to be forecasted has been used as features for kNN regression. The intuition behind the application of kNN is based on its ability to find seasonal patterns present in the time series and used it to forecast future values [17].

The prediction interval evaluates the likelihood that PV generation will fall within a range of values for a certain proportion of instances. This interval is derived from the standard error of measurement. In this section, we report the outcome for a 95% prediction interval and validate our forecast by confirming that the actual value falls within the interval range 95% of the time. The power output of PV was predicted utilizing an 85% and a 95% prediction interval. Test analysis was conducted on the entire 8,760 hours for a 95% prediction interval to assess the precision of the interval forecast model. The evaluation indicated a 94.3% accuracy rate, demonstrating a strong correlation between the forecasted and actual values. The forecast interval areas for a 24-hour timeframe are depicted in Fig. 1. Prediction interval enables consideration of the PV power output variability.

### B. EV Load Model

A suitable EV load model is required to superimpose it with the system load and investigate the impact of the charging load for power system reliability assessment. The EV load profile developed in [18] along with the constructed hourly, daily, and weekly load demand for EV charging is adopted in this paper. Factors governing the EV load such as driver's behavior, location (residential and public), and time (weekdays and weekends) are considered to construct a yearly EV charging load profile.

Furthermore, $30,000$ different types of EVs are adopted from [18] and presented in Table I with their respective consumption per unit distance to calculate the peak demand for residential and public charging. The average daily driving distance of 30 miles is assumed. The proportion of daily EV charging load in the residential and public charging stations is considered as 60 to 40 percent. Based on the report [19], the public charging demand profile for weekdays and weekends are considered similar. Based on the calculation, the peak load for the residential and public charging stations is 199 MW and 132 MW. The EV load profile is constructed by manipulating the hourly (weekdays and weekend), daily, and weekly load profile shown in Fig. 2(a), Fig. 2(b), Fig. 3(a), and Fig. 3(b) respectively. These loads are expressed as percentages of daily, weekly, and annual peak loads respectively.

TABLE I
EVs CHARGING CONSUMPTION

| EV Class | Number | KWh/mile | Average Daily Driving (mile) | Daily Consumption (MWh) |
|---|---|---|---|---|
| Sedan | 18255 | 0.3225 | 30 | 176.62 |
| Mid-Sedan | 3582 | 0.3605 | 30 | 38.74 |
| Mid-SUV | 3930 | 0.4375 | 30 | 51.58 |
| Full-SUV | 4233 | 0.5075 | 30 | 64.48 |

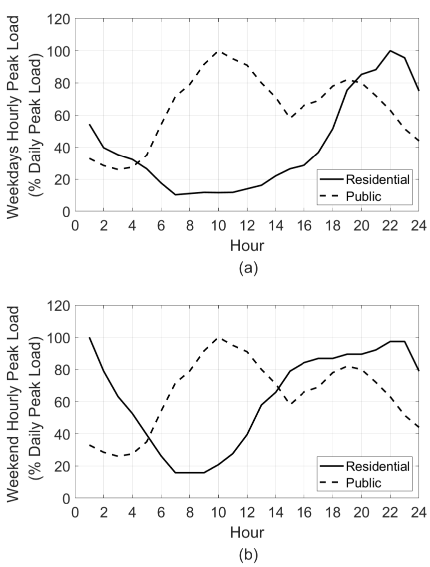


Fig. 2. EV Load Profile (a) Hourly Load (Weekdays) (b) Hourly Load (Weekend)

## III. Optimization Problem Formulation

### A. Network Modeling

Composite power system reliability assessment which involves heavy computation requires a suitable DC power flow model to overcome the issues of computation burden [20]. Furthermore, DC power flow models are accurate enough for composite power system reliability evaluation. Therefore,

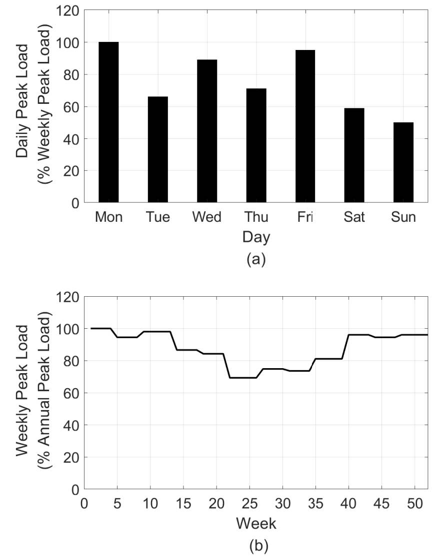


Fig. 3. EV Load Profile (a) Daily Load (b) Weekly Load

a DC power flow model [21] combined with constraints of power balance equation, generation capacity limits, and transmission line capacity is considered to formulate a linear programming problem with an objective of minimizing the amount of load curtailment. Consider a transmission network with $N_B$ buses and $N_T$ transmission lines. Equation (1) represents the objective function to minimize the load curtailment $C_i$ at each bus, where, $C_i$ is the difference between the generation and load at each bus.

$$min \sum_{i=1}^{N_B} C_i \tag{1}$$

subject to:

$$B\delta + G + C = L \tag{2}$$

$$B_T A\delta \leq T^{max} \tag{3}$$

$$-B_T A\delta \leq T^{max} \tag{4}$$

$$G^{min} \leq G \leq G^{max} \tag{5}$$

$$0 \leq C \leq L \tag{6}$$

$$-\pi \leq \delta \leq \pi \tag{7}$$

The equality constraint (2) describes the power balance constraint at each bus, where $B_{(N_B \times N_B)}$ is a bus susceptance matrix, $\delta_{(N_B \times 1)}$ represents vector of angle of bus voltages, $G_{(N_B \times 1)}$ represents the vector of generator's power at each bus, $L_{(N_B \times 1)}$ and $C_{(N_B \times 1)}$ are the vectors of the load and load curtailment at each bus respectively. The inequality constraints presented in equations (3) and (4) limits the transmission line capacity, where $B_{T\,(N_T \times N_T)}$ is a transmission line susceptance matrix, $A_{(N_B \times N_B)}$ is the element-node incidence matrix, $T^{max}_{(N_T \times 1)}$ represents the maximum transmission line capacity limit. Equation (5) represents the generator's power constraint, where $G^{min}$ and $G^{max}$ are both vectors of size $(N_B \times 1)$ representing lower and upper bound of generator power at each bus. As the load curtailment $C_i$ at each bus is positive and cannot be more than the respective load $L_i$, $C_i$ is bounded between zero and load of the respective bus as given by the equation (6). And the inequality constraint given in (7) represents the bounds for bus voltage angles.

### *B. Sequential Monte Carlo Simulation*

In this paper, a Sequential Monte Carlo technique is used to simulate a sequential time evolution of the system state and assess the power system reliability. Sequential simulation techniques can provide additional time-related indices such as duration and frequency of load loss. Reliability indices such as loss of load probability (LOLP), expected demand not supplied (EDNS), and loss of load frequency (LOLF) are evaluated. A brief description and expression to determine the aforementioned indices are presented as follows.

- Loss of Load Probability (LOLP): LOLP accumulates the individual probability of a system when the total amount of generation is not sufficient to meet the load. In other words, LOLP calculates the failure probability of a system. The expression to calculate the LOLP is given in (8), where $N$ is the total number of samples taken.

$$LOLP = \frac{1}{N}\sum_{k=1}^{N} p_k \qquad \begin{cases} p_k = 0, & C_k = 0 \\ p_k = 1, & 0 < C_k < L_k \end{cases} \tag{8}$$

- Expected Demand Not Supplied (EDNS): EDNS is defined as the weighted sum of load curtailment. The curtailed load at each time step of the simulation is added and averaged by the duration of the simulation to calculate EDNS which is given by (9).

$$EDNS = \frac{1}{N}\sum_{k=1}^{N} C_k \tag{9}$$

- Loss of Load Frequency (LOLF): It is defined as the expected number of loss of load occurrences in a given period. The expression to calculate the LOLF is given by (10).

$$LOLF = \frac{1}{N}\sum_{k=1}^{N} \phi_k \tag{10}$$

where,

$$\phi_k = \begin{cases} 1, & C_{k-1} = 0 \ \& \ C_k \neq 0 \\ 0, & else \end{cases} \tag{11}$$

The LOLF gives the expected frequency of generation deficiency per unit time, therefore, if LOLF is recorded per hour, it should be multiplied by 8760 to calculate LOLF (Occ/yr). To calculate the LOLF, two consecutive curtailments over the whole simulation are observed to record the frequency of failure instances in a given time.

TABLE II
COMPARISON AND EVALUATION OF RANGE OF RELIABILITY INDICES FOR PV INTERVAL FORECAST WITH DIFFERENT CONFIDENCE INTERVAL

| System | Confidence Degree (%) | LOLP | EDNS (MW/yr) | LOLF (Occ/yr) |
|---|---|---|---|---|
| IEEE-RTS | - | 0.0013 | 0.151 | 1.99 |
| IEEE-RTS with EV | - | 0.0034 | 0.487 | 6.56 |
| IEEE-RTS with EV & PV (Lower Limit) | 95 | 0.0022 | 0.2981 | 6.21 |
| | 85 | 0.002 | 0.2591 | 5.78 |
| IEEE-RTS with EV & PV (Upper Limit) | 85 | 0.0016 | 0.2219 | 5.2 |
| | 95 | 0.0013 | 0.1601 | 4.9 |

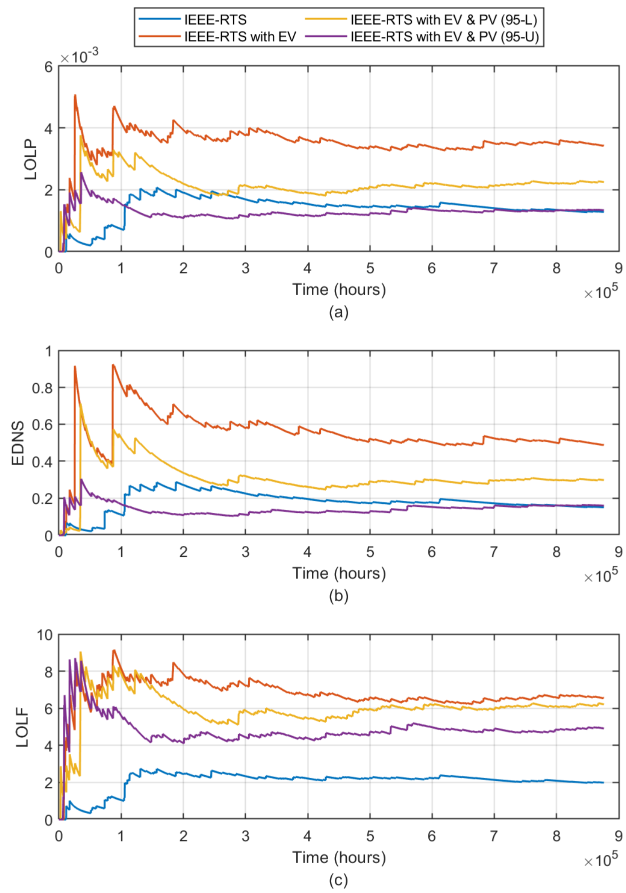


Fig. 4. Comparison of Reliability Indices for Different Degrees of PV Interval Forecast (a) Convergence of LOLP (b) Convergence of EDNS (c) Convergence of LOLF

## IV. CASE STUDY AND RESULTS

The IEEE Reliability test system (IEEE-RTS79) is used to determine and compare reliability indices for several scenarios with PVs and EVs. The IEEE-RTS79 consists of 24 buses, 38 transmission lines, and 32 generators with their capacity ranging from 12 MW to 400 MW. All the data required for reliability analysis such as generators' capacity, loads (hourly, daily, weekly), and transmission line limits are obtained from [22]. For the analysis, the yearly generation profile of three PVs with a maximum capacity of 200 MW, 200 MW, and 100 MW are aggregated and distributed across all the buses where loads are connected. The first case study involves the investigation of the impact of different confidence degrees of PV forecast on the composite reliability of power systems with a fixed base load of EV. The second case study investigates the impact of different levels of EV penetration on power system reliability considering a fixed confidence degree of PV interval forecast.

### A. Composite Reliability Evaluation for Different Confidence Degrees of PV Interval Forecast

The consideration of interval forecast of renewable generation for reliability assessment is to consider their uncertainty and variability. Operational reliability assessment using point forecast provides a fixed set of generation scheduling which gives no flexibility to the system operators. The significance of integrating interval forecast for reliability analysis are: (i) it considers uncertainty (ii) it allows system operators to calculate the range of reliability indices (iii) it provides more flexibility in generation planning and scheduling for operational reliability.

In this case study, PV interval forecast with 85% and 95% confidence level has been integrated with a fixed base load penetration of EV on the IEEE-RTS79. The sequential Monte Carlo simulation is used to calculate the LOLP, EDNS, and LOLF. The simulation is carried out for 100 years as the considered duration is sufficient for all the scenarios to converge. Each of the reliability indices is calculated considering both the lower and upper limits of PV forecast and subsequently, the range of reliability indices are determined. Furthermore, the significance of this case study is to evaluate the impact of adding PV on power system reliability and compare it with the reliability of the original system with and without EV. Table-II illustrates the value of reliability metrics for different degrees of PV forecasting confidence interval. The result demonstrates that the original system without the integration of PV and EV is more reliable than a system with PV and EV. As the second scenario in Table-II involves only EV integration, the system is more stressed because of increasing load. The addition of PV increases the reliability of the system which can be seen from the scenarios of system with both EV and PV. In terms of magnitude, the generation profile of PV associated with the upper and lower limit of 95% confidence interval is the highest and lowest respectively in comparison to other considered scenarios. Therefore, among the PV considered scenarios, the most reliable system is observed when the upper limit at 95% confidence interval is taken as the generation profile for PV.

Fig. 4 illustrates the comparison of power system reliability before and after the integration of PV on the IEEE-RTS79 with and without EV. The convergence of reliability metrics over the simulation period is shown for a specific case with 95% confidence interval of PV forecast. Fig. 4 also illustrates that when the PV output takes the upper limit of 95% confidence interval, the system is able to retain the level of reliability (in terms of LOLP and EDNS) as in the case of original IEEE-RTS79 with no PV and EV. The particular result gives an idea of the amount of extra generation required to retain the reliability of the original system. The results presented in Table-II can also be validated through Fig. 4.

### B. Composite Reliability Evaluation with Different Levels of EV Penetration and a Fixed Degree of PV Interval Forecast

*1) EV Load Distributed Across all the Load Buses Based on their Proportion:* In this case study, a composite reliability assessment of IEEE-RTS79 is conducted considering its annual load profile in hourly granularity with different penetration levels of EV load. The PV interval forecast with the confidence degree level of 95% has been used for all the scenarios. Furthermore, the penetration of EV load is increased with the step of 20% up to 100% to analyze the impact of different levels of EV charging load on reliability. With such case study, modern utilities can prepare themselves for future scenarios of heavy penetration of EVs. Furthermore, utilities can plan for generation expansion, network reconfiguration, the addition of renewable, etc. in advance if such realization of future scenarios can be done early. One of the main advantages of this case study is that it provides a foundation to determine the extra generation required to retain the reliability of the system when the system load increases.

Table-III represents the annual reliability indices for different penetration levels of EV load. The result presented in Table-III illustrates that the system reliability decreases as the penetration level of EV increases. As the reliability metrics such as LOLP, EDNS, and LOLF are all related to loss of load or curtailments, the higher value indicates a less reliable system. Furthermore, it can be observed that the reliability indices calculated with a lower interval limit of PV are higher compared to the values calculated with an upper interval limit. As the generation profile of PV associated with the upper limit of the interval forecast is larger compared to that of the lower limit, the system is more reliable when the upper limit is taken as the generation profile for PV. Furthermore, the values of LOLP and EDNS demonstrate significant differences between any two scenarios, however, the respective difference is not observed in the case of LOLF. As LOLF is just an indicator of the frequency of loss of load in a year, two scenarios with the same value of LOLF can have different amounts of curtailments per year. Therefore, it is imperative to observe either LOLP or EDNS combined with LOLF to analyze the reliability of the system.

*2) EV Load Distributed Assuming Demographic Characteristics of Load Buses:* In this case study, the EV load is distributed across all the load buses based on the demographic characteristics of each of these buses. Here, the term demographic characteristics mean the greater tendency to have EV charging. Among 17 load buses in the IEEE-RTS79, load buses are categorized into four categories; Group_1 (1, 2, 5, 7, 8), Group_2 (3, 4, 6, 9, 10), Group_3 (13, 14, 15, 16), and Group_4 (18, 19, 20). The distribution of EV load in each group is 40%, 25%, 20%, and 15% respectively which depicts the higher EV charging tendency of Group_1. The significance of this study is to investigate the impact of demographic characteristics on power system reliability and compare the

TABLE III
EVALUATION OF RELIABILITY INDICES FOR DIFFERENT PENETRATION LEVEL OF EV
(EV LOAD DISTRIBUTED BASED ON THE PROPORTION OF LOAD BUS)

| System | PV lower limit (95%) | | | PV upper limit (95%) | | |
|---|---|---|---|---|---|---|
| | LOLP | EDNS (MW/yr) | LOLF (Occ/yr) | LOLP | EDNS (MW/yr) | LOLF (Occ/yr) |
| IEEE-RTS with EV | 0.0022 | 0.2981 | 6.21 | 0.0013 | 0.1601 | 4.9 |
| IEEE-RTS with 1.2*EV | 0.0025 | 0.3178 | 7.27 | 0.0019 | 0.2398 | 6.84 |
| IEEE-RTS with 1.4*EV | 0.0031 | 0.4473 | 8.69 | 0.0024 | 0.3174 | 8.38 |
| IEEE-RTS with 1.6*EV | 0.0034 | 0.4614 | 10.23 | 0.0029 | 0.4411 | 10.12 |
| IEEE-RTS with 1.8*EV | 0.0038 | 0.599 | 11.82 | 0.0034 | 0.4779 | 10.76 |
| IEEE-RTS with 2.0*EV | 0.0047 | 0.745 | 12.99 | 0.0038 | 0.6067 | 12.63 |

TABLE IV
EVALUATION OF RELIABILITY INDICES FOR DIFFERENT PENETRATION LEVEL OF EV
(EV LOAD DISTRIBUTED ASSUMING DEMOGRAPHIC CHARACTERISTICS OF LOAD BUSES)

| System | PV lower limit (95%) | | | PV upper limit (95%) | | |
|---|---|---|---|---|---|---|
| | LOLP | EDNS (MW/yr) | LOLF (Occ/yr) | LOLP | EDNS (MW/yr) | LOLF (Occ/yr) |
| IEEE-RTS with EV | 0.0021 | 0.3046 | 5.49 | 0.0011 | 0.1488 | 4.2 |
| IEEE-RTS with 1.2*EV | 0.0024 | 0.3248 | 6.94 | 0.002 | 0.2785 | 6.67 |
| IEEE-RTS with 1.4*EV | 0.003 | 0.4163 | 8.81 | 0.0026 | 0.3916 | 8.44 |
| IEEE-RTS with 1.6*EV | 0.0033 | 0.4698 | 10.2 | 0.003 | 0.4444 | 9.6 |
| IEEE-RTS with 1.8*EV | 0.0046 | 0.6754 | 13.01 | 0.0036 | 0.5225 | 12.86 |
| IEEE-RTS with 2.0*EV | 0.0055 | 0.8454 | 15.47 | 0.0045 | 0.6896 | 15.24 |

results with the scenario of EV load distributed based on the proportion of the bus's load. In this case study as well, the $95\%$ PV interval forecast has been used for the purpose of analysis.

Table-IV represents the annual reliability indices for different penetration levels of EV load along with the distribution based on the assumed demographic characteristics of load buses. Comparing the results presented in Table-IV with Table-III, the system reliability index is found to be almost similar up to $60\%$ increment in penetration of EV. However, the impact of EV load distribution based on the assumed demographic characteristic is significant when the EV penetration is increased by $80\%$ and $100\%$ of its base load. The reason behind the insignificant difference in the indices up to $60\%$ increment in EV load can be attributed to the ability of the impacted transmission line to carry the incremented power. However, in the case of $80\%$ and $100\%$ EV load increment, the transmission line capacity is not enough to accommodate the increased power flows. In order to observe the impact of assumed demographic characteristics based EV load distribution, the calculation of the local reliability index is imperative rather than the calculation of system reliability.

## V. CONCLUSION

The paper has proposed a detailed reliability analysis of a power system taking PV power uncertainty and the impact of EVs into consideration. A machine learning-based PV power forecasting model along with the interval prediction was developed. The impact of electric vehicle load was investigated through modeling of EV load profile considering different locations of charging stations, types of EV, and drivers' behavior. A sequential Monte Carlo simulation incorporating the forecasted PV power interval was used to calculate the range of reliability indices. The significance to calculate the range of reliability indices is to provide utility planners and system operators with the range of reliability of their system. The IEEE Reliability Test System (IEEE-RTS79) was used to demonstrate the proposed approach. The results demonstrate the effectiveness of the proposed approach to calculate the range of reliability indices and investigate the impact of EV on power system reliability.

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